Security-Oriented Sensor Placement in Intelligent Buildings

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Abstract

Intelligent buildings are beginning to utilize sensor networks for monitoring and protecting indoor air quality against contamination events. This paper presents a methodology for determining where to install such sensors. In particular, a multi-objective optimization problem is formulated for minimizing the sensor cost, the average and the worst-case impact damage corresponding to a set of contamination event scenarios. Each contamination scenario is comprised of parameters characterized by some given probability distribution. Based on these distributions, a set of representative contamination scenarios is constructed through grid and random sampling, and the overall impact of each scenario is computed, thus providing a solution to the sensor placement problem. The proposed methodology is illustrated by two case studies, a simple building with five rooms and a realistic building with 14

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rooms.

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1. Introduction

Intelligent buildings are beginning to utilize networked sensors for monitoring the Indoor Air Quality (IAQ) by measuring temperature, humidity, carbon dioxide and many other parameters of interest throughout the building environment. This information can be utilized in order to better control the mechanical systems (rollers, blinds, doors and windows) and the electrical systems (heating, ventilation and air conditioning) to create a healthy and comfortable living environment while at the same time minimizing the amount of consumed energy. More critical, sensor information can be utilized to alert the occupants about the presence of dangerous contaminants in the building air. These contaminants may be the result of an accident (e.g., *Carbon Monoxide* leakage from a faulty furnace) or a malicious attack. Under these safety-critical situations, it becomes of paramount importance that the contaminant is promptly detected and localized so that appropriate control actions are taken to mitigate the damage and ensure the safety of the people.

The first step in designing such an IAQ sensor network is to decide the number, location and type of sensors to use. Ideally, it would be desirable to have sensors in every room of the building, measuring all different types of contaminants, but the cost and sophistication of most IAQ sensors today makes this an elusive goal (at least for a class of high-cost sensors). In this paper, it is assumed that a limited number of sensors is available, able to measure the concentration of the contaminants of interest. The overall objective is to develop a procedure for finding suitable locations for these sensors, in order to achieve the maximum possible security of the indoor building environment with the minimum cost.

Deciding where to install these sensors is in general a difficult task due to the complex and dynamic conditions of the indoor building environment. For example, a sensor placement solution designed for a wind blowing from the west and assuming fully open doors and windows will seize to be optimal if the wind changes direction or if we close some of the doors and windows. In fact, the optimal solution depends on a number of parameters like the wind direction and speed, the status of the various leakage paths (doors and windows openings), the contamination source properties (location, duration, release rate) and the people characteristics (average occupancy in each zone, inhalation rate). In the proposed approach, since most of these parameters are not known in advance, probability distributions are used to describe them, which incorporate the existing knowledge about the building environment and the contamination event. Then, a representative scenario set is constructed through grid and randomized sampling of the probability distributions.

Each of the different scenarios is simulated using a multi-zone formulation that has been developed in our previous work [1] together with CONTAM [2], a multi-zone building simulation software. For assessing the damage caused by each scenario (e.g., number of people infected) we calculate an impact metric based on the total amount of contaminant inhaled and depending on the number of people, their age and type of their activity within the building. Finally, for deciding on where to place the sensors we solve an optimization problem that may involve multiple objectives, for instance to minimize (i) the average impact damage, (ii) the worst-case impact damage and (iii) the cost/number of sensors.

The main contribution of this work is to present a design methodology for formulating and solving the sensor placement problem in intelligent buildings, based on a multi-zone state-space representation of the dispersion dynamics, by taking into account the impact dynamics and existing knowledge of the building environment and contaminant event parameters in the form of probability distributions. In general, compared to existing simpler methods, the proposed methodology can better handle more complex scenarios which involve many parameters and different optimization functions. Note that one of the novelties of this work is that the proposed approach takes into consideration the building usage, which is something that has not been considered in previous related works.

This work offers to the decision maker a useful tool that analyses all the different parameters involved in the building environment and gives the most informed recommendations on where to place the available sensors, in order to effectively detect and localize contamination events, while taking security into consideration. The simulation results illustrate the proposed methodology on a realistic building scenario representing a typical house with 14 rooms, referred to as the "Holmes's house" [3].

The remaining of this paper is organized as follows: in Section 2, related work in the indoor air quality sensor networks and the general sensor placement problem is presented. In Section 3, the problem formulation is proposed which couples dispersion and impact dynamics. Furthermore, the section provides intuition on how to construct the contamination scenario set and formulate the multiple risk-objective optimization program. In Section 4, two case studies are presented to illustrate the effectiveness of the proposed algorithm. Finally, Section 5 concludes the paper and future work is discussed.

2. Related Work

Indoor Air Quality sensor networks are typically designed based on empirical rules of thumb and simple guidelines which are often subjective. A common approach is to evenly distribute the sensors to cover the facility (assuming equal coverage areas for the sensors) without taking into account the building aerodynamics or any information about the building utilization. As indicated in [4], there is a lack of system-level research in scientific design and evaluation of sensor systems to meet the IAQ design goals. The need of design principles for IAQ in buildings including the architecture (topology, number and placement of sensors) is also highlighted in [5]. There have been a few attempts in the literature to address issues related to the indoor sensor placement problem. These can be classified into two categories according to the method employed for simulating the indoor building environment: those based on (i) Computational Fluid Dynamics (CFD) and those based on (ii) Multi-zone analysis.

In the first category, some CFD software tool is used to study the contaminant transport. In general, CFD techniques have the advantage of increased accuracy in modeling airflows and contaminant propagation. In [6], the optimal sensor locations were determined for detecting releases in a building by using a CFD tool to estimate the distribution of contaminants. In [7], CFD techniques were also applied to predict chemical and biological agent dispersion in an office complex for finding the best locations for sensors and for developing effective ventilation strategies. Similarly, in [8], a CFD software program was employed to study contaminant transport in a nine-row section of a Boeing 747 aircraft cabin with airborne contaminants released under different scenarios for determining the optimal number and location of sensors.

The second category involves multi-zone models for calculating the airflows and contaminant transportation under different scenarios followed by an optimization method for estimating the sensor locations. In [9], six attack scenarios for a small commercial building were simulated, and a genetic algorithm was applied for each attack scenario to optimize the sensor sensitivity, location, and number to achieve the best system behavior while minimizing system cost. In [10], the impact of zonal and multi-zone modeling techniques on indoor air protection systems was analyzed for a typical office environment and a large hall. The proposed methodology could also be considered under this category. Compared to the aforementioned work, our approach uses sampling from probability distributions and additionally considers changing environmental conditions, the building utilization and people distribution in constructing the different scenarios.

Closely related to sensor placement is also the problem of contaminant source isolation and identification. Some representative work in this area includes the Bayesian interpretation approach (see [11] and [12]), to assess the effect of various sensor characteristics on the overall system performance regarding the time needed to characterize the release (location, amount released and duration). The optimal sensor placement, however, was not investigated. Furthermore, in [13], an inverse modeling method was proposed (the adjoint probability) for designing the sensor network and identifying potential contaminant source locations. The sensor placement solution provided, however, depends on certain information about the source (location or release time) that need to be given *a priori*, making this approach more suitable for the case of mobile sensors. The problem of contaminant isolation was also investigated in our previous work [1] using a state-space multi-zone formulation.

The problem of selecting locations to install sensors for optimizing some parameters such as controllability or security, has also received significant interest from other research disciplines, such as operational research [14] and control systems [15]. In addition, significant research has been conducted by the water research community, for improving the security of water distribution networks from deliberate or accidental contaminations [16]. When a contaminant enters at some location in the network, it propagates along the water flow, and may affect the consumers who use the contaminated water. In [17], a security-oriented sensor placement problem formulation for water distribution systems was presented, considering multiple risk-objective functions, and a solution methodology was proposed based on evolutionary computation.

Compared to the existing work in the literature, to the best of our knowledge, the approach presented in this paper is the first to provide a formal mathematical treatment to the problem of sensor placement in buildings for minimizing the impact damage, while taking into account contamination scenario parameter variability and multiple risk objectives, and can be used for CFD and multi-zone models. However, in this work a multi-zone model is used to aid better understanding and to limit the computational efforts required to simulate multiple contaminant dispersion scenarios. In specific, the overall impact is a function of the contaminant concentration in the various zones as well as the people distribution and characteristics. To evaluate the overall impact, a finite set of contamination scenarios is considered taking into account the parameter probability distributions.

3. Design Methodology

In this section, the sensor placement design methodology is described. The intuition behind the problem is to formulate and solve an optimization problem, to identify in which building zones to install contaminant concentration sensors, in order to reduce the possibility of a severe damage due to an airborne contamination event. An outline of the proposed sensor placement design methodology is as follows:

- Model the indoor contaminant dispersion dynamics
- Model the impact dynamics
- Construct the set of representative contamination event scenarios and simulate the contamination event scenarios to compute their event detection-times.

- Compute the overall impact damage of each contamination scenario
- Select the risk objective functions, construct and solve the optimization problem and select one solution out of the Pareto solution set.

3.1. Indoor Contaminant Dispersion Dynamics Model

In general, CFD or multi-zone models can be used for modelling the indoor contaminant, including particulate contaminant, dispersion dynamics; in the proposed work we consider the use of a multi-zone model, whose details can be found in [1], along with the relation of the different model components and the mass-balance equations. The model used can represent both naturally and mechanically ventilated buildings, as illustrated in the case studies. In addition, sources and sink elements can be incorporated in the model.

Let $\mathcal{R}$ represent the set of real numbers and $\mathcal{Z} = \{0, 1\}$ the set of binary numbers. The state space equations for contaminant dispersion in an indoor building environment with N_z zones are described by

$$\dot{x} \quad = A(p_x)x + Bu(x; p_u) + \xi(x, u) + d(x) + \phi(p_\phi). \tag{1}$$

The vector $x \in \mathcal{R}^{N_z}$ represents the concentration of the contaminant in the building zones (measured in mass per volume). The state matrix $A \in \mathcal{R}^{N_z \times N_z}$ models the changes in the contaminant concentrations between the different building zones as a result of the airflows and is a function of a set of parameters p_x which influence the resulting airflows between the different building zones, such as external wind speed and wind direction. The state matrix A can be calculated using a multi-zone simulation software, such as CONTAM

[2]. The input $u \in \mathcal{R}^{N_u}$ represents the changes in air-flow caused by the N_u controllable inputs, and p_u is the set of parameters affecting the input, such as the degree of door openings (e.g., half open) or the fan operation mode (e.g., half speed). The binary zone index matrix $B \in \mathcal{Z}^{N_z \times N_u}$ indicates the relationship between the zones and the controllable parameters (e.g., $B_{ij} = 1$ means that the i-th building zone is affected by the j-th controllable parameter). The vector field $\xi : \mathcal{R}^{N_z} \times \mathcal{R}^{N_u} \mapsto \mathcal{R}^{N_z}$ characterizes the modeling uncertainties, which can be the result of unaccounted leakages in the building envelope (e.g., around windows and doors), inaccuracies in modeling the nonlinear relationship between pressure and flow across each leakage path, as well as inaccuracies in accounting for changing environmental conditions (e.g., temperature). The disturbances $d \in \mathcal{R}^{N_z}$ in the interior building environment are caused by flows coming from the outside, uncontrollable openings, or chemical reactions between the different contaminants present in the zones. Note that controllable inputs, uncertainties and disturbances become important if they have a large impact on the building airflow dynamics and the contaminant propagation. Finally, the contamination event term $\phi \in \mathcal{R}^{N_z}$ represents the location and evolution characteristics of the sources generating the contamination event, or the sinks. Let p_ϕ be the set of source parameters affecting the event profile, such as its onset time, its duration, its generation rate and its location.

3.2. Impact Dynamics Model

After an air contamination event has occurred, the contaminant will propagate through the various zones following the flow paths, and may be inhaled by people located inside the various zones. To measure the damage caused during a contamination scenario at the k-th zone, an impact value z_k can be computed. This corresponds to the damage caused on the system measured through some impact metric, e.g., the occupant exposure [18], the contaminant mass inhaled, the number of people affected/infected etc. In general, the impact dynamics are given by

$$\dot{z}_k = f_z(x_k; p_z) \tag{2}$$

where $f_z(\cdot)$ is the function for computing the change rate of the impact z_k for an airborne contamination event at the k-th zone. This depends on the contaminant concentration x_k and the set of impact parameters p_z, such as the average zone occupancy and the inhalation rate. It is important to note that in the proposed methodology, multiple impact metrics could be considered, e.g., the contaminant mass inhaled or the number of people infected.

3.3. Representative Contamination Event Scenarios

In general, the more information we have about the building the more accurate the simulation model will be. However, if some of the information is not available, then it can be considered as uncertainty, which can be accommodated using more scenarios. In the proposed methodology, some of the input information is described in the form of parameters, (such as wind speed and wind direction, door openings, room occupancy etc) and depending on prior knowledge these can be provided in terms of bounds or distributions. Note that the propagation of the contaminant is modelled directly using Eq. (1).

Let $p = \{p_x, p_u, p_\phi, p_z\}$ be the set of all the unknown system parameters which correspond to the states, the inputs, the contamination events and the impact dynamics respectively. For example, if the wind direction mean value and standard deviation is known, a normal distribution could be considered and bounds could be selected, typically within 2 standard deviations. Note that the proposed methodology easily allows to incorporate any uncertainty involved using additional scenarios. In addition, multiple-source contamination events at different zones can also be expressed using different scenarios.

Let $\mathcal{P}^*$ be the range set of all the possible parameter combinations, such that $p \in \mathcal{P}^*$. Since the number of all possible parameters is infinite, grid and random sampling can be applied to construct a subset $\mathcal{P} \subseteq \mathcal{P}^*$ of N_p sets of parameters. Grid sampling refers to the method of segmenting a distribution into a certain number of discrete intervals of constant length, whereas random sampling refers to applying a random number generator to select a certain number of parameters out of a probability distribution.

In general, the number and method of selection of the scenarios may affect the sensor placement. Ideally, the input scenarios should capture to the extent possible the real system characteristics and dynamics. Intuitively, the more scenario cases considered, the better the building parameter distributions will be represented and the sensor-placement solution results will be more reliable.

3.4. Overall-impact Matrix Calculation

For each contamination scenario in $\mathcal{P}$, the indoor contaminant dispersion dynamics are simulated for τ_s hours. Let $T \in \mathcal{R}^{N_p \times N_z}$ be the event detection-time matrix, for which its (i, j)-th element, T_{ij}, is the time when the contaminant concentration at the j-th zone exceeds a sensor detection threshold ϵ, under the i-th contamination scenario $p^i \in \mathcal{P}$. If the contamination cannot be detected by any sensor, then T_{ij} is considered equal to the simulation time τ_s. In general, T depends on the sensor detection threshold ϵ and if this threshold is large, some sensors may not detect certain contamination events.

Let $\Omega \in \mathcal{R}^{N_p \times N_z}$ be the overall-impact matrix with respect to some impact metric; its (i,j)-th element, Ω_{ij} corresponds to the total impact damage due to the i-th contamination scenario from $\mathcal{P}$, when a sensor is monitoring the j-th zone, and this is given by

$$\Omega_{ij} = f_\omega(z(T_{ij})) \tag{3}$$

where $f_\omega : \mathcal{R}^{N_z} \mapsto \mathcal{R}$ is a function which computes the overall-impact with respect to the impact state z corresponding to time T_{ij}.

To illustrate how to construct the impact dynamics and the overall-impact matrix, consider the use of the "contaminant mass inhaled" impact metric. In general, the inhalation rate depends on the age group, sex and activity intensity of the people within one zone [19]. For simplicity, let h_k be the daily average rate of air volume inhaled by all the occupants within the k-th zone. In this case, the impact state dynamics become

$$\dot{z}_k(t) = x_k(t)h_k, \tag{4}$$

for $k \in \{1, ..., N_z\}$. Considering these dynamics, the overall-impact under the i-th contamination scenario, $i \in \{1, ..., N_p\}$ and for a sensor installed at the j-th zone, Ω_{ij}, is the sum of the contaminant mass inhaled at each zone until time T_{ij}, given by

$$\Omega_{ij} = \sum_{k=1}^{N_z} z_k(t) = \sum_{k=1}^{N_z} h_k \int_0^{T_{ij}} x_k(t)dt. \tag{5}$$

3.5. Optimization Problem Formulation

To address the security problem, it is necessary to use multiple metrics to estimate the risk with respect to some feasible sensor placement scheme. Based on these metrics, the optimization problem can be formulated and solved. However, it is possible that the optimal placement of sensors with respect to one objective (e.g., average impact damage), may not be optimal with respect to some other objective (e.g., sensor cost), across all contamination scenarios considered. Selecting the appropriate objective functions to optimize is an important part of the sensor placement design specification, which can influence the results.

The overall idea is to construct the solution set Y for the sensor placement problem. In the general case, Y is a Pareto front of solutions [20], for which a solution is Pareto optimal if there exists no other feasible solution which reduces some of the objective functions, while at the same time increases at least some other objective function. The multi-objective optimization problem is formulated as

$$Y = \underset{\chi \in \{1,0\}^{N_z}}{\operatorname{argmin}} \{F_0(\chi), F_1(\chi; \Omega), ..., F_{N_f}(\chi, \Omega)\}, \tag{6}$$

where χ is the zone index set for which $\chi_l = 1$ when a sensor is installed and $\chi_l = 0$ when there is no sensor installed at the l-th zone. Function $F_0 : \{1,0\}^{N_z} \mapsto \mathcal{R}$ corresponds to the total sensor cost. Let N_f be the number of impact-risk estimation functions considered, and for $k \in \{1, ..., N_f\}$, let $F_k : \{1,0\}^{N_z} \times \mathcal{R}^{N_p \times N_z} \mapsto \mathcal{R}$ be the k-th impact-risk estimation function. For instance, consider the case when the following two impact-risk objectives are utilized to estimate the average and the worst-case impact, i.e., $N_f = 2$:

a) the estimated average impact-risk, which is given by

$$F_1(\chi;\Omega) = \frac{1}{N_p} \sum_{i\in\{1,\ldots,N_p\}} \min_{j\in\{l \mid \chi_l=1\}} \Omega_{ij}, \tag{7}$$

and b) the estimated worst-case impact, which is given by

$$F_2(\chi;\Omega) = \max_{i\in\{1,\ldots,N_p\}} \min_{j\in\{l \mid \chi_l=1\}} \Omega_{ij}. \tag{8}$$

Note that in the formulation of the objective functions, the minimum overall-impact is computed with respect to the i-th contamination scenario, as it is considered that overall impact is counted up to the moment when it is detected by at least one of the sensors in the binary zone index set χ. For solving this optimization problem, exhaustive search could be used for a small number of scenarios, zones and sensors. For larger problems, an optimal solution is intractable. For instance, the cardinality of the solution set is 2^{N_z}, which grows exponentially with respect to the number of zones N_z. For this reason, sophisticated optimization algorithms, e.g., based on computational intelligence [21] could be considered for computing "good enough" solutions.

After solving the optimization problem and a Pareto solution set has been constructed, decision makers may use higher level reasoning to arrive at the final decision regarding the zones to install the air contamination sensors.

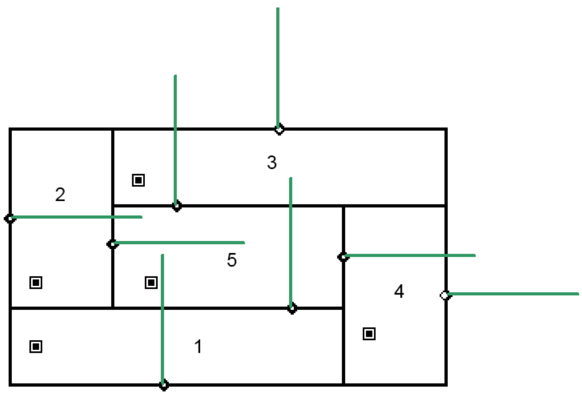
4. Case Studies

The objective of this section is to demonstrate the proposed algorithm and illustrate some of the key challenges. The first example describes a simple building with five rooms, while the second example describes a more realistic building (Holmes's house [3]) with 14 rooms. The objective for the first example is to illustrate the proposed methodology on a simple building that would provide some intuitive understanding. For the case studies, the parameter sets are defined as follows: Let the state parameters set be $p_x = \{w_s, w_d\}$, where w_s is the wind speed and w_d is the wind direction, and let the input parameters set $p_u = \{\theta\}$, where $\theta_i \in [0, 1]$ denotes the opening degree of a door or a window. In addition, let the contamination source parameter set be $p_\phi = \{\lambda_0, \tau_0, g_0, \tau_d\}$, where λ_0 is the zone index where a contamination has occurred, τ_0 is the time when the contamination has started, g_0 is the contaminant generation rate and τ_d is the contamination duration. Furthermore, let the impact parameters set be $p_z = \{h\}$, where h is the vector of the daily average rate of air volume inhaled by all the occupants of each zone.

4.1. Simple 5-Room Building Example

Consider a simple building with five connected rooms, depicted in Fig. 1, where each room is a zone, i.e. $N_z = 5$. The volume of each zone is 100 m^3. All doors between the zones are considered open. Fans in Zone 3 and Zone 4 provide a constant air inflow of 100 m^3/hr, and the air moves from Zone 1 and Zone 2 to Zone 5 and then to Zone 3 and Zone 4, where it exits the building. Let $x \in \mathcal{R}^5$ be the contaminant concentration state vector as described in the indoor contamination dispersion dynamic model using Eq. (1). For simplicity purposes, we consider that there are no controllable inputs, $u(x; p_u) = 0$, no modeling uncertainties, $\xi(x, u) = 0$, and no disturbances, $d(x) = 0$. To measure the impact damage using Eq. (2), the contaminant mass inhaled impact metric is considered as in Eq. (4). For this example, *Carbon Monoxide* (CO) contamination is considered, with the following parameters: for p_u, all

Figure 1: A simple building comprised of five connected zones. Air enters at Zone 1 and Zone 2, and exits at Zone 3 and Zone 4.



openings are fully open, i.e. $\theta = [1, 1, 1, 1, 1, 1]^\top$, for p_ϕ, contamination start time is $\tau_0 = 0$ hr, contaminant generation rate is $g_0 = 0.5$ kg/hr and contamination duration is $\tau_d = 2$ hr, whereas the location of the contamination is not known and could be at any zone with equal probability. The wind speed w_s and wind direction w_d are irrelevant in this example as flow is forced by the fans in Zone 3 and Zone 4. In addition, for p_z, the daily average rate of air volume inhaled is $h = [0.5, 0.5, 0.5, 0.5, 0.5]^\top$ m^3/hr, assuming an inhalation rate of 0.5 m^3/hr (which corresponds to a moderate physical exercise) and average occupancy of one person in each zone.

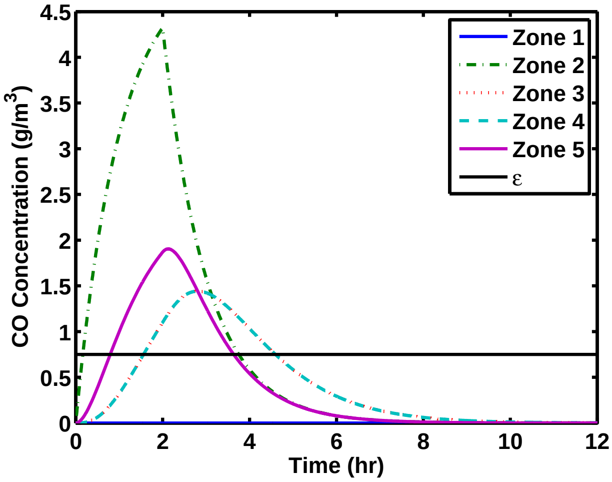
To demonstrate the proposed methodology, single-source contamination events are considered. A finite range set $\mathcal{P}$ with $N_p = 5$ possible contamination scenarios is constructed. All zones are assumed to be equally probable locations for a contamination event to occur. These scenarios correspond to the contamination event taking place in each of the five rooms; we exclude the case of multiple contamination events taking place simultaneously in different zones. The various contamination scenarios are simulated for $\tau_s = 24$ hours to compute the event detection-time matrix $T \in \mathcal{R}^{5\times5}$. The event detection-time is measured as the time when the contaminant concentration in one zone exceeds a certain threshold. In this example, the threshold is set to 600 ppm or $\epsilon = 0.75\text{g/m}^3$, at which concentration the occupants may experience headaches within one hour of exposure; CO sensors may trigger a detection alarm within a couple of minutes at this concentration, as required by standards, e.g., ANSI/UL 2034:2005 in the USA and EN50291:2001 in European Union.

To illustrate how event detection-time matrix T is constructed, consider the scenario where an event takes place in Zone 2. Figure 2 depicts the CO concentration within the first 12 hours after the CO injection in Zone 2. The contaminant concentration reaches a maximum at Zone 2 after two hours, and the concentration is reduced as the contaminant mass exits the building through the fans located at Zone 3 and Zone 4. The contaminant concentration at Zone 1 is zero, as there is no inflow into that zone from the adjacent zones. The event detection-time matrix is therefore given by

$$T = \begin{bmatrix} 0.2 & 24.0 & 1.6 & 1.6 & 0.8 \\ 24.0 & 0.2 & 1.6 & 1.6 & 0.8 \\ 24.0 & 24.0 & 0.2 & 24.0 & 24.0 \\ 24.0 & 24.0 & 24.0 & 0.2 & 24.0 \\ 24.0 & 24.0 & 0.8 & 0.8 & 0.2 \end{bmatrix}$$

where each row corresponds to a contamination scenario and each column to a zone where a sensor could be installed. Consider the second row of T which corresponds to the detection times of the previous scenario, where an event

Figure 2: Carbon Monoxide concentration in all zones when contaminant is injected at Zone 2 with 0.5 kg/hr, for 2 hours. The sensor detection threshold concentration is considered as $\epsilon = 0.75$ kg/m^3.



takes place in Zone 2. If a sensor was placed in Zone 2, detection would occur after $T_{2,2} = 0.2$ hours, whereas if a sensor was installed in Zone 4, detection would occur after $T_{2,4} = 1.6$ hours. On the other hand, if a sensor was placed in Zone 1, the event would never be detected, thus $T_{1,2} = 24.0$ hours (simulation duration). If multiple sensors were used, the specific contamination event would be detected by the sensor with the smallest detection time. Finally, the overall-impact matrix Ω is computed using Eq. (5), and is given by

$$\Omega = \begin{bmatrix} 0.1 & 50.0 & 11.6 & 11.6 & 3.1 \\ 50.0 & 0.1 & 11.6 & 11.6 & 3.1 \\ 20.0 & 20.0 & 0.1 & 20.0 & 20.0 \\ 20.0 & 20.0 & 20.0 & 0.1 & 20.0 \\ 30.0 & 30.0 & 2.9 & 2.9 & 0.2 \end{bmatrix}.$$

In the following, it is considered that all sensors have the same costs, and that the sensor cost objective corresponds to the number of sensors, i.e $F_0(\chi) = \sum_{i=1}^{N_z} \chi_i$. For the optimization problem, in addition to the sensor cost objective, two estimated impact-risk objectives are considered, the average impact-risk using Eq. (7) and the worst-case impact risk using Eq. (8). The optimization problem is therefore given by

$$Y = \underset{\chi \in \{0,1\}^5}{\operatorname{argmin}} \{F_0(\chi), F_1(\chi; \Omega), F_2(\chi, \Omega)\}. \tag{9}$$

In this simple example, all sensor placement schemes can be examined. The Pareto front is calculated as $\{(1, 9.2, 20.0), (1, 9.2, 20.0), (2, 5.3, 11.6), (3, 1.3, 3.1), (4, 0.7, 2.9), (5, 0.1, 0.2)\}$ which corresponds to the Pareto solutions $Y = \{(0, 0, 1, 0, 0), (0, 0, 0, 1, 0), (0, 0, 1, 1, 0), (0, 0, 1, 1, 1), (1, 1, 1, 1, 0), (1, 1, 1, 1, 1)\}$. Thus, if one sensor is to be installed, the average impact-risk objective is 9.2 and the worst-case impact risk is 20.0, which correspond to a sensor placement at either Zone 3 or Zone 4. If two sensors are to be installed, the average risk is 5.3 and the worst-case impact risk is 11.6, which correspond to Zone 3 and Zone 4. This analysis can provide assistance in deciding how many sensors to install. For example, the marginal benefit with respect to the worst-case impact risk in installing a fourth sensor may not be significant, thus 3 sensors should be adequate. The results for the single-source contamination events with respect to the number of sensors installed, are given in the first column of Table 1.

In the rest of the example, we consider the case when multiple contamination events can occur simultaneously in the different zones. All the problem parameters are kept the same as in the previous paragraph, however in this study all the possible source-location combinations are considered, i.e. $N_p = 31$ scenarios comprised of 5 one-source, 10 two-source, 10 three-source, 5 four-source and 1 five-source scenarios. Next, the event detection-time matrix $T \in \mathcal{R}^{31\times 5}$ is calculated and based on T the overall-impact matrix $\Omega \in \mathcal{R}^{31\times 5}$ is constructed.

To illustrate how the selection of objectives affects the solution of this case study, the optimization problem is solved for different objectives combinations: a) F_0 and F_1, b) F_0 and F_2 c) F_0, F_1 and F_2. The results are provided in Table 1, where each row corresponds to solutions with 1–5 sensors installed. We observe that the average impact objective (F_1) and the worst-case impact objective (F_2), when considered independently, may provide some different solutions. For instance, for the single-sensor placement problem and for the average impact objective, the Pareto optimal solution is at Zone 5, whereas for the the worst-case impact objective the corresponding Pareto optimal solution is at either Zone 3 or Zone 4. However, when all objectives are considered, all three rooms (Zone 3–5) are Pareto optimal solutions. This is similar for the two-sensor placement problem. However, in the case of 3 or more sensors, the results do not change, and there is a single optimal solution for the problem. Thus, the sensor placement solution depends on the selection of objectives, which is an important part of the design specification.

Regarding the use of multiple-source contamination scenarios, in comparison with the previous example where $N_p = 5$ and by considering all three objectives, there are differences in the solution with respect to the single-sensor placement problem (Zone 5), as well as in the two-sensor placement problem (Zones 4 and 5 or Zones 3 and 5) as seen in Table 1. Thus, including multiple contamination scenarios can influence the sensor placement solution.

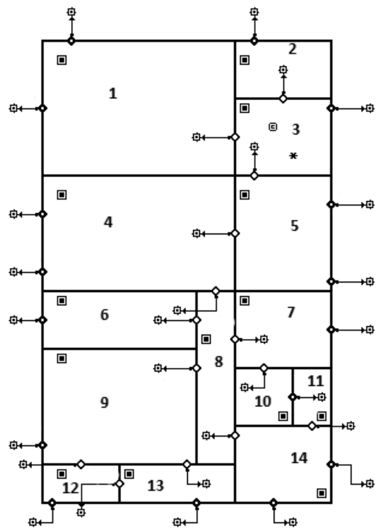
Table 1: Table of sensor locations solutions for single and multiple objectives for the simple 5-room building example, considering single and multiple-source contamination events with respect to the number of sensors

	Single Source	Multiple Sources		
	F_0,F_1,F_2	F_0, F_1	F_0,F_2	F_0,F_1,F_2
1	{3} or {4}	{5}	{3} or {4}	{3} or {4} or {5}
2	{3 4}	{4 5} or {3 5}	{3 4}	{4 5} or {3 5} or {3 4}
3	{3 4 5}	{3 4 5}	{3 4 5}	{3 4 5}
4	{1 2 3 4}	{1 2 3 4}	{1 2 3 4}	{1 2 3 4}
5	{1 2 3 4 5}	{1 2 3 4 5}	{1 2 3 4 5}	{1 2 3 4 5}

4.2. Holmes's House Example

Consider the Holmes's House building with $N_z = 14$ zones, depicted in Fig. 3. Details of the model can be found in [3]. The building is comprised of a garage (Zone 1), a storage room (Zone 2), a utility room (Zone 3), a living room (Zone 4), a kitchen (Zone 5), two bathrooms (Zones 6

Figure 3: The Holme's House with 14 zones.



and 13), a corridor (Zone 8), three bedrooms (Zone 7, 9 and 14) and three closets (Zones 10, 11 and 12). For the contamination scenarios, we consider that all zones are equally-probable locations for the *Carbon Monoxide* (CO) contamination. In practice, the parameter set p is unknown, however certain assumptions can be made in relation to some of its parameters. In this example, it is considered there are no controllable inputs and contaminant removal. In relation to uncertainties, the following are considered: The wind direction w_d has a uniform distribution $[70, 100]^\circ$ and the wind speed w_s has a uniform discrete distribution of $\{5, 10, 15\}$ m/s. The contaminant generation rate g_0 has a uniform distribution $[0.3, 0.7]$ kg/hr and the contamination duration is $\tau_d = 1.5$ hr. In this example it is considered that all doors are fully open, i.e. $\theta = [1, 1, ..., 1]^\top$ and the contamination event onset time is $\tau_0 = 0$. In relation to the impact parameters,

$h = [0.25, 0.05, 0.1, 2, 2, 0.1, 0.25, 0.5, 0.5, 0.05, 0.05, 0.05, 0.1, 0.5]^{\top}$ m^3/hr for zones '1' to '14' respectively, assuming an inhalation rate of 0.5 m^3/hr (which corresponds to a moderate physical exercise) and average occupancy $\{0.5, 0.1, 0.2, 4, 4, 0.2, 0.5, 1, 1, 0.1, 0.1, 0.1, 0.2, 1\}$ of each zone respectively.

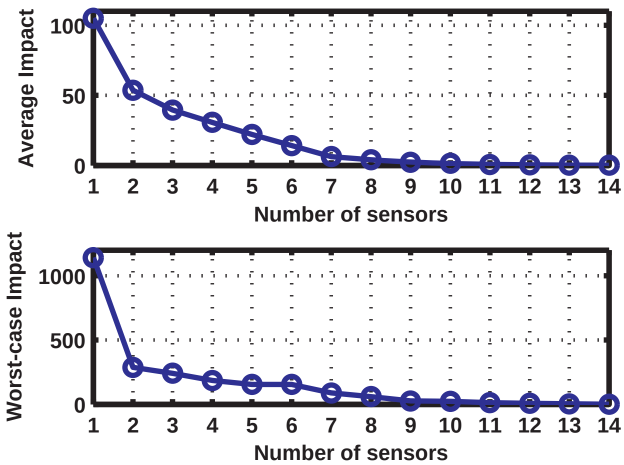
Through grid sampling and by taking into account the probability distributions, we construct $N_p = 2310$ scenarios corresponding to the finite parameter subset $\mathcal{P}$, considering 14 zones $\{1, ..., 14\}$, 11 generation rates $\{0.3, 0.34, 0.38, ..., 0.7\}$ kg/hr, 3 wind speeds $\{5, 10, 15\}$ m/s and 5 wind angles $\{70, 80, 90, 100, 110\}^\circ$ (thus, $N_p = 14 \times 11 \times 3 \times 5 = 2310$). Through simulation, the event detection-time matrix T is constructed and based on the impact dynamics, the overall-impact matrix Ω is computed. As in the previous example, three objectives are considered to minimize the sensor cost, the estimated average risk impact and the worst-case risk impact, with respect to the contamination scenarios in $\mathcal{P}$. The multi-objective optimization problem is formulated as

$$Y = \underset{\chi\in\{0,1\}^{14}}{\operatorname{argmin}} \{F_0(\chi), F_1(\chi; \Omega), F_2(\chi, \Omega)\}. \tag{10}$$

To compare on how the average and worst-case impact risk objectives are reduced, Fig. 4 is provided. The results indicate that as the number of sensors installed is increased, the change in the impact risk objectives is reduced and it may not be significant.

To illustrate how the selection of objectives affects the solution of this case study, the optimization problem is solved for different objectives combinations: a) F_0 and F_1, b) F_0 and F_2 c) F_0, F_1 and F_2. The results are provided in Table 2. In this example, all the solutions computed for 1 to 5 sensor placements with respect to the average-impact objective (F_0 and F_1),

Figure 4: The average and the worst-case impact-risk objective metrics with respect to the number of sensors installed.



also appear in the solution set when all objectives are considered (F_0, F_1 and F_2). On the other hand, this is not the case for all the solutions computed using the worst-case impact objective (F_0 and F_2). Consider the three-sensor placement problem, whose optimal solution with respect to the average impact objective would be $\{4\ 8\ 12\}$ (living room, corridor, south-west closet), whereas its optimal solution with respect to the worst-impact impact objective would be $\{4\ 6\ 9\}$ (living room, west bathroom, west bedroom). When all the objectives are considered, then both solutions are computed as Pareto optimal since for the solution $\{4\ 8\ 12\}$, $F_1 = 39.6$ and $F_2 = 288.7$, whereas for the solution $\{4\ 6\ 9\}$, $F_1 = 44.9$ and $F_2 = 240.5$. Thus, for example, if we had considered the average impact objective only, we would have neglected the other Pareto optimal solution which increases the average impact F_1 by 13%, but reduces worst-case impact F_2 by 17%.

Table 2: Table of sensor locations computed for single and multiple objectives with respect to the $\mathcal{P}$ scenario set.

F_0	F_0, F_1	F_0,F_2	F_0,F_1,F_2
1	{4}	{4} or {5}	{4}
2	{4 9}	{4 9}	{4 9}
3	{4 8 12}	{4 6 9}	{4 6 9} or {4 8 12}
4	{4 6 8 12}	{4 6 13 14} or {4 6 12 14} or {4 6 8 13} or {4 6 8 12}	{4 6 8 12}
5	{1 4 6 8 12}	{3 4 6 13 14} or {3 4 6 12 14} or {3 4 6 8 13} or {3 4 6 8 12} or {2 4 6 13 14} or {2 4 6 12 14} or {2 4 6 8 13} or {2 4 6 8 12} or {1 4 6 13 14} or {1 4 6 12 14} or {1 4 6 8 13} or {1 4 6 8 12}	{1 4 6 8 12}

5. Conclusions

In this paper, the problem of monitoring the air quality in buildings was investigated against the presence of contaminant threats. In specific, this paper presents a methodology for determining where to install indoor air quality sensors to increase security, and how many. In particular, a multi-objective optimization problem was formulated for minimizing the average and worst-case impact damage corresponding to a set of contamination event scenarios. Each contamination scenario was comprised of parameters which may be characterized by some probability distribution given in advance. Based on these distributions, a set of representative contamination scenarios was constructed through grid or random sampling, and the overall impact of each scenario was computed. The proposed methodology was illustrated on two case studies, a simple building with 5 rooms and a realistic building with 14 rooms.

Future work will examine the sensor placement in the context of contamination source isolation. In addition, the proposed formulation will be examined on more complex buildings for which it is infeasible to exhaustively compute the best locations for sensor placement, but for which computational intelligent methodologies could be applied for solving the multi-objective optimization problems. Furthermore, the methodology will be extended to consider the multiple-sampling-point methodology [8], in which multiple air samples from one or more zones are combined to enhance detection.

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Nomenclature

A	State transition matrix
B	Controllable input zone-index matrix
χ	Zone index set

d	Disturbance
ϵ	Contaminant concentration detection threshold
f_z	Impact damage rate function
f_ω	Overall impact function
g_0	Contaminant generation rate
h	Daily average rate of air volume inhaled
λ_0	Contamination source zone index
N_f	Number of risk estimation functions
N_p	Number of contamination scenarios
N_u	Number of controllable inputs
N_z	Number of zones in building
Ω	Overall-impact matrix
p_u	Input parameters set
p_x	State parameters set
p_z	Impact parameters set
p_ϕ	Contamination source parameters set
p	Unknown system parameters set
$\mathcal{P}^*$	Range set of all parameter sets
$\mathcal{P}$	Contamination scenarios finite set
ϕ	Contamination event function
$\mathcal{R}$	Set of real numbers
T	Event detection-time matrix
τ_s	Simulation time length
τ_0	Contamination onset time

τ_d	Contamination duration time
θ	Control parameter vector
u	Controllable inputs
w_s	Wind speed
w_d	Wind direction
ξ	Modeling uncertainties
Y	Solution set
$\mathcal{Z}$	Set of binary numbers
z	Impact vector

References

[1] Michaelides, M., Reppa, V., Panayiotou, C., Polycarpou, M.. Contaminant event monitoring in intelligent buildings using a multi-zone formulation. In: Proc. of SAFEPROCESS. Mexico City, Mexico; 2012.

[2] Walton, G., Dols, W.. CONTAM 2.4 user guide and program documentation. National Institute of Standards and Technology; Gaithersburg, MD 20899-8633; 2.4c ed.; 2005. NISTIR 7251.

[3] Wang, L., Dols, W., Chen, Q.. Using CFD capabilities of CONTAM 3.0 for simulating airflow and contaminant transport in and around buildings. HVAC&R Research 2010;16(6):749–763.

[4] Wen, J.. A smart indoor air quality sensor network. In: Proc. of SPIE. 2006.

[5] Varshney, P.K., Mohan, C.K.. Advances in Pervasive Computing

and Networking; chap. On Sensor Networking and Signal Processing for Smart and Safe Buildings. Springer; 2005, p. 213–226.

[6] Arvelo, J., Brandt, A., Roger, R., Saksena, A.. An enhanced multi-zone model and its application to optimum placement of CBW sensors. ASHRAE Transactions 2002;108(2):818–826.

[7] Zhai, Z., Srebric, J., Chen, Q.. Application of CFD to predict and control chemical and biological agent dispersion in buildings. International Journal of Ventilation 2003;2(3):251–264.

[8] Zhang, T., Chen, Q., Lin, C.. Optimal sensor placement for airborne contaminant detection in an aircraft cabin. HVAC&R Research 2007;13(5):683–696.

[9] Chen, Y., Wen, J.. Sensor system design for building indoor air protection. Building and Environment 2008;43(7):1278–1285.

[10] Chen, Y., Wen, J.. Application of zonal model on indoor air sensor network design. In: Proc. of SPIE. 2007.

[11] Sohn, M.D., Sextro, R.G., Gadgil, A.J., Daisey, J.M.. Responding to sudden pollutant releases in office buildings: 1. Framework and analysis tools. Indoor Air 2003;13(3):267–276.

[12] Sreedharan, P., Sohn, M.D., Nazaroff, W.W., Gadgil, A.J.. Towards improved characterization of high-risk releases using heterogeneous indoor sensor systems. Building and Environment 2011;46(2):438 – 447.

[13] Liu, X., Zhai, Z.. Protecting a whole building from critical indoor contamination with optimal sensor network design and source identification methods. Building and Environment 2009;44(11):2276–2283.

[14] Toregas, C., ReVelle, C.. Optimal location under time or distance constraints. Papers in Regional Science 1972;28(1):131–143.

[15] Basseville, M., Benveniste, A., Moustakides, G., Rougee, A.. Optimal sensor location for detecting changes in dynamical behavior. IEEE Transactions on Automatic Control 1987;32(12):1067 – 1075.

[16] Ostfeld, A., Uber, J.G., Salomons, E., Berry, J.W., Hart, W.E., Phillips, C.A., et al. The battle of the water sensor networks (BWSN): A design challenge for engineers and algorithms. ASCE Journal of Water Resources Planning and Management 2008;134(6):556–568.

[17] Eliades, D.G., Polycarpou, M.M.. A fault diagnosis and security framework for water systems. IEEE Transactions on Control Systems Technology 2010;18(6):1254 –1265.

[18] Rudnick, S.N., Milton, D.K.. Risk of indoor airborne infection transmission estimated from carbon dioxide concentration. Indoor Air 2003;13(3):237–245.

[19] Moya, J., Phillips, L., Schuda, L., Wood, P., Diaz, A., Lee, R., et al. Exposure factors handbook: 2011 edition. Tech. Rep. EPA/600/R-09/052F; U.S. EPA; 2011.

[20] Rao, S.. Engineering Optimization: Theory and Practice. New York, USA: Wiley; 3rd ed.; 1996.

[21] Deb, K., Pratap, A., Agarwal, S., Meyarivan, T.. A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation 2002;6(2):182–197.