A Distributed Framework for Contaminant Event Detection and Isolation in Multi-zone Intelligent Buildings

Vasso Reppa, Michalis Michaelides, Marinos Christodoulou, Christos Panayiotou and Marios Polycarpou

Abstract— **An intelligent building is required to provide safety to its occupants against any possible threat that may affect the indoor air quality, such as accidental or malicious airborne contaminant release in the building interior. In this work, we design a distributed methodology for detecting and isolating multiple contaminant events in a large-scale building. Specifically, we consider the building as a collection of interconnected subsystems and we design a contaminant event monitoring agent for each subsystem. Each monitoring agent aims to detect the contamination of the underlying subsystem and isolate the zone where the contaminant source is located, while it is allowed to exchange information with its neighboring agents. The decision logic implemented in the contaminant event monitoring agent is based on the generation of observer-based residuals and adaptive thresholds. We demonstrate our proposed formulation using a 14-zone building case study.**

I. INTRODUCTION

A key emerging control application is the monitoring of intelligent buildings, where by incorporating various sensing devices and distributed computing it is possible to enhance the building environment in terms of saving energy and providing a more comfortable environment for the occupants [1]–[4]. Besides energy efficiency and comfort, an intelligent building is required to also provide safety to its occupants against possible threats that affect the indoor air quality as a result of airborne contaminants released in the building interior. These contaminant events could be the result of an accident or a planned attack. Under such safety-critical conditions, real-time collected data from sensors that monitor the contaminant concentration can be used to alert the occupants and determine appropriate control solutions like indicating safe spaces, or isolating and cleaning contaminated spaces. Therefore, the accurate and prompt detection and isolation of contaminant events (sources) is an essential part of the intelligent building design.

For indoor air and contaminant simulation there are two main modeling approaches: Computational Fluid Dynamics (CFD) and multi-zone modeling. Multi-zone models (i.e. CONTAM [5]) offer a computational efficient solution by representing a building as a network of well-mixed zones. Both multi-zone and CFD models can predict the behavior and transport characteristics of indoor contaminants given the source conditions. This is referred to as the forward problem: given certain inputs (e.g., a contaminant source location and emission rate) and system parameters, find the output of the model (contaminant concentration in all areas). For event detection and isolation applications, what we are interested in is actually the inverse reconstruction problem: given the system parameters and output, find out which input has led to this output. A detailed report on related literature on the inverse tracking of pollutants in both groundwater and air fields is presented in [6]. Two methods that have successfully been applied to the problem of contaminant source isolation in indoor building environments are the Bayesian updating method [7] and the Adjoint probability method [8]. However, both of these methods require some form of prior knowledge in the results demonstrated so far, either in the form of a constructed scenario database before the event or concerning one of the source characteristics during the event (location or the time of release).

In a recent work [9], we developed a state space method using a multi-zone formulation for the problem of contaminant event monitoring. In the proposed formulation, the contaminant event source is modeled as a fault in the process, which we would like to detect and isolate. This enables the application of advanced fault diagnosis tools to the problem of contaminant event monitoring in intelligent buildings. Furthermore, we developed Contaminant Detection and Isolation (CDI) estimator schemes with adaptive thresholds for the detection and isolation of a single contaminant source in the presence of measurement noise and modeling uncertainty. The proposed solution does not require any prior information of the source characteristics (onset time, location and generation rate). In our previous work, however, we consider a centralized approach, where the building is treated as a monolithic system so the complexity of the developed schemes increases with the number of zones considered. In fact, when the scale of the building is large, the calculation of the adaptive thresholds can become a formidable task.

The main objective of this paper is the development of a distributed CDI scheme by considering the building as a collection of interconnected subsystems. Buildings offer a natural candidate for such a decomposition, because they are distributed in space and a particular building zone is only interconnected with a limited number of neighboring zones, mainly through doors and windows. The structural decomposition applied in this work is chosen in a way to minimize the interconnections between the various sub-

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systems involved and ensure the structural observability of each subsystem. The advantages of distributed fault diagnosis architectures and frameworks have been documented in [10]–[12]. Specifically, following a distributed approach may: (i) simplify the design of a CDI method, since it applies to a smaller part of the global model of the system (building), (ii) make the problem of isolating multiple contaminant sources in a large-scale building tractable (the centralized method can lead to combinatorial explosion because the CDI method should be designed to handle faults globally), (iii) decrease the communication requirements, because there is no need of transmitting all the information to a central computing core, (iv) increase the reliability of the CDI method against security threats, since there are more than one computing cores (a central computing core corresponds to a single-point of failure), and (v) improve the scalability of the CDI method, since it can easily be adapted in the case that more zones should be monitored.

The paper is organized as follows. First, in Section II, we formulate the distributed framework for the problem of contaminant event monitoring in the indoor building environment, followed by the development of the proposed distributed CDI scheme in Section III. Section IV illustrates how the developed method can be applied to the problem of detection and isolation of multiple contaminant sources through a 14-zone representative building case study. Finally, Section V provides some concluding remarks.

II. PROBLEM FORMULATION

Considering a n-zone building as a *monolithic* system, the contaminant dispersion in the indoor environment of the building is described by the following multi-zone model

$$\Sigma: \quad \dot{x}(t) = (A+\Delta A)x(t) + Q^{-1}Bu(t) + Q^{-1}Gg(t), \quad (1)$$

$$y(t) = Cx(t) + w(t), \quad (2)$$

where $x \in \mathbb{R}^n$ represents the concentrations of the contaminant in the building zones ($x^{(i)}$ is the element of x, denoting the concentration in the i-th zone), while $A \in \mathbb{R}^{n\times n}$ is the state transition matrix with its element $A(i,j)$ be zero, if there is no leakage path (door, window, etc) between between zone i and zone j, otherwise $A(i,j)$ models changes in contaminant concentration between zone i and zone j, primarily as a result of the air-flows. The term $\Delta A \in \mathbb{R}^{n\times n}$ collectively accounts for the presence of modeling uncertainty in the building envelope as a result of changing wind speed, wind direction and variable leakage openings. The controllable inputs in the form of doors, windows, fans and air handling units are represented by $u \in \mathbb{R}^p$, while $B \in \mathbb{B}^{n\times p}$ is a zone index matrix concerning their locations, with $\mathbb{B} = \{0,1\}$. The last term of (1) involves the location and evolution characteristics of the contaminant sources, represented by $G \in \mathbb{B}^{n\times s}$ and $g \in \mathbb{R}^s$ respectively. Note that $Q \in \mathbb{R}^{n\times n}$ is a diagonal matrix with the volumes of the zones, i.e. $Q = \text{diag}(Q^{(1)}, Q^{(2)}, \dots, Q^{(n)})$ where $Q^{(i)}$ is the volume of the i-th zone. In (2), $y \in \mathbb{R}^m$ represents the output of the sensors monitoring Σ, $C \in \mathbb{B}^{m\times n}$ is a zone index matrix for the sensor locations and $w \in \mathbb{R}^m$ characterizes the additive measurement noise. More details on the state-space model formulation can be found in [9]. It is worth pointing out that in the context of fault diagnosis, the last term in (1), i.e. $Q^{-1}Gg(t)$, is equivalent to process faults that impact the normal system operation.

In this work, the monolithic system Σ is decomposed into K interconnected subsystems Σ_I, $I \in \{1,\dots,K\}$, where each subsystem corresponds to the concentration of the contaminant in an area of n_I zones and is described by:

$$\Sigma_I: \quad \dot{x}_I(t) = (A_I + \Delta A_I)x_I(t) + Q_I^{-1}B_I u_I(t) + Q_I^{-1}G_I g_I(t) + (H_I + \Delta H_I)z_I(t), \quad (3)$$

$$y_I(t) = C_I x_I(t) + w_I(t), \quad (4)$$

where $x_I \in \mathbb{R}^{n_I}$, $u_I \in \mathbb{R}^{p_I}$ and $y_I \in \mathbb{R}^{m_I}$ are the local state, local control input, and local measured output vectors, respectively, and $z_I \in \mathbb{R}^{\ell}$ is the vector of the interconnection variables. In particular, x_I represents a column vector made up of n_I elements of x (correspondingly for u_I and y_I), i.e. there is an index mapping function M_{x_I} such that $M_{x_I}: \{1,\dots,n\} \to \{1,\dots,n_I\}$ and $M_{x_I}^{-1}$ its inverse mapping function such that $M_{x_I}^{-1}: \{1,\dots,n_I\} \to \{1,\dots,n\}$, satisfying

$$M_{x_I}(k) = \left\{ j:\ x_I^{(j)} = x^{(k)},\ k \in \{1,\dots,n\}, j \in \{1,\dots,n_I\} \right\}, \quad (5)$$

$$M_{x_I}^{-1}(j) = \left\{ k:\ x^{(k)} = x_I^{(j)},\ k \in \{1,\dots,n\}, j \in \{1,\dots,n_I\} \right\} \quad (6)$$

In a similar way, we determine the index mapping functions for u and y, i.e. M_{u_I} such that $M_{u_I}: \{1,\dots,p\} \to \{1,\dots,p_I\}$ and M_{y_I} such that $M_{y_I}: \{1,\dots,m\} \to \{1,\dots,m_I\}$. The interconnection variables z_I refer to the states of the neighboring subsystems in the building structure graph having a direct connection with the subsystem I, i.e. z_I is made up of states of x that belongs to subsystems different from Σ_I. The term $g_I \in \mathbb{R}$ represents the local contaminant source, $G_I \in \mathbb{R}^{n_I}$ is a vector with zeros except for a single row with one, which represents the location zone of the contaminant source and $w_I \in \mathbb{R}^{m_I}$ corresponds to the local noise vector. Note that, in this work, we assume a maximum of a single contaminant source per subsystem. Finally, A_I, ΔA_I, Q_I, G_I and C_I are sub-matrices of appropriate dimensions of the corresponding matrices of the monolithic system Σ, while H_I (ΔH_I) is a sub-matrix of A (ΔA) related to the interconnection variables z_I.

In this work, the decomposition of the monolithic system (1) is conducted as follows; taking into account the structural graph of the building, whose nodes are the state variables of the system (i.e. the concentration in a specific building zone), Σ is decomposed such that (i) there is no overlapping between subsystems, i.e. a particular building zone can only belong to a single subsystem, (ii) the subsystems' interdependencies are minimized, (iii) the components of the interconnection vector z_I are made of measurable variables, and (iv) the subsystem Σ_I is structurally observable for all $I \in \{1,\dots,K\}$ as defined in [13], [14]. It is noted that the thorough treatment of the decomposition problem is beyond the scope of this paper. This is an important issue that will be further investigated in our future research with respect to the building structure, contaminant event detectability, isolability and communication requirements.

III. DISTRIBUTED CONTAMINANT DETECTION AND ISOLATION

The objective of this section is to design a methodology for detecting and isolating multiple contaminant sources in the building subsystems, assuming a maximum of a single source per subsystem. For each of the interconnected subsystems Σ_I, a contaminant monitoring agent, denoted by $\mathscr{M}_I$, is designed to detect and isolate a contaminant source affecting the dynamics of Σ_I. The agent $\mathscr{M}_I$ is allowed to exchange information with its nearest neighboring contaminant event monitoring agents. The exchanged information is associated with the form of the physical interconnections, i.e. unidirectional or bidirectional interactions between the interconnected subsystems. The agent $\mathscr{M}_I$ consists of a contaminant detector, denoted by $\mathscr{D}_I$ and n_I isolators, denoted by $\mathscr{I}_{I,j}$, $j \in \{1,\ldots,n_I\}$.

Under normal conditions, the task of $\mathscr{D}_I$ is to detect the presence of a contaminant source in the subsystem Σ_I. If a contaminant is detected, then the corresponding isolators $\mathscr{I}_{I,j}$ are activated to localize the zone of subsystem Σ_I with the contaminant source. The decisions of the n_I isolators are combined for excluding the zones in the building subsystem Σ_I that are not contaminated. The decision logic of $\mathscr{D}_I$ and $\mathscr{I}_{I,j}$ relies on comparing some residuals to corresponding adaptive thresholds. Both the residuals and the adaptive thresholds are generated using an estimation model, which is produced by an observer. In the sequel, the dependence of the signals on time (e.g. $x(t)$) will be dropped for notational brevity.

A. Contaminant Event Detection

1) Residual Generation: The estimation model of $\mathscr{D}_I$ is formulated by selecting the following observer

$$\dot{\hat{x}}_I = A_I\hat{x}_I + Q_I^{-1}B_Iu_I + H_Iy_{z_I} + L_I\left(y_I - C_I\hat{x}_I\right), \quad (7)$$

where $\hat{x}_I \in \mathbb{R}^{n_I}$ is the estimation of x_I (with initial conditions $\hat{x}_I(0)=0$), $L_I \in \mathbb{R}^{n_I\times m_I}$ is the observer gain matrix selected such that the matrix $A_I - L_IC_I$ is stable and $y_{z_I} \in \mathbb{R}^{\ell_I}$ is the transmitted sensor information, defined based on (4) as

$$y_{z_I} = z_I + w_{z_I} \quad (8)$$

where $w_{z_I} \in \mathbb{R}^{\ell_I}$ is the corresponding noise vector.

The k-th residual of the detector $\mathscr{D}_I$, denoted by $\varepsilon_{y_I}^{(k)} \in \mathbb{R}$, is defined as

$$\varepsilon_{y_I}^{(k)} = y_I^{(k)} - C_I^{(k)}\hat{x}_I, \quad (9)$$

where $y_I^{(k)} \in \mathbb{R}$ is the k-th element of y_I and $C_I^{(k)}$ is the k-th row of C_I.

2) Computation of Adaptive Thresholds: The k-th adaptive threshold of $\mathscr{D}_I$, denoted by $\overline{\varepsilon}_{y_I}^{(k)}(t)$, is designed in order to ensure robustness of the detector $\mathscr{D}_I$ with respect to modeling uncertainties ΔA_I and ΔH_I and noise w; i.e. the adaptive threshold is computed such that

$$\left|\varepsilon_{y_I}^{(k)}(t)\right| \le \overline{\varepsilon}_{y_I}^{(k)}(t), \quad (10)$$

assuming that $|\Delta A_I| \le \overline{\Delta A}_I$, $|\Delta H_I| \le \overline{\Delta H}_I$ and $\left|w_I^{(k)}(t)\right| \le \overline{w}_I^{(k)}$, where $\overline{\Delta A}_I$, $\overline{\Delta H}_I$, $\overline{w}_I^{(k)} \in \mathbb{R}$ are known constant bounds.

The k-th adaptive threshold of the detector $\mathscr{D}_I$ is designed to bound the residual under healthy conditions, i.e. taking into account that $g_I = 0$. Based on (4), (9), the residual can be expressed as $\varepsilon_{y_I}^{(k)} = C_I^{(k)}\varepsilon_{x_I} + w_I^{(k)}$, where ε_{x_I} is the state estimation error, defined as $\varepsilon_{x_I} \triangleq x_I - \hat{x}_I$. Under healthy conditions, the state estimation error is described by:

$$\dot{\varepsilon}_{x_I} = A_{L_I}\varepsilon_{x_I} - H_Iw_{z_I} + \Delta H_Iz_I + \Delta A_Ix_I - L_Iw_I, \quad (11)$$

$$A_{L_I} = A_I - L_IC_I. \quad (12)$$

The adaptive thresholds $\overline{\varepsilon}_{y_I}^{(k)}(t)$ are computed taking into account (10) and the solution of (11), following a standard procedure in robust fault diagnosis methods [9]–[11].

3) Decision Logic: Detector $\mathscr{D}_I$,$I \in \{1,\ldots,K\}$ infers the presence of the contaminant in subsystem Σ_I, if there is a time instant t at which

$$\left|\varepsilon_{y_I}^{(k)}(t)\right| > \overline{\varepsilon}_{y_I}^{(k)}(t), \quad (13)$$

for at least one $k \in \{1,\ldots,m_I\}$. The rationale behind this decision is that the presence of the contaminant in subsystem Σ_I is guaranteed, when the behavior of Σ_I observed through y_I is not consistent with the expected behavior, represented by $\hat{x}_I$. The time instant of detection is defined as:

$$T_{D_I} = \min_t \bigcup_{k\in\{1,\ldots,m_I\}} \left\{\min_t\left\{t : \left|\varepsilon_{y_I}^{(k)}(t)\right| > \overline{\varepsilon}_{y_I}^{(k)}(t)\right\}\right\} \quad (14)$$

After the time instant of detection T_{D_I}, we determine the contaminant diagnosis set, denoted by $\mathcal{S}_{D_I}(t)$ that includes all zones in subsystem Σ_I as possibly contaminated. Hence, after the time of detection, the diagnosis set is defined as

$$\mathcal{S}_{D_I}(t) = \left\{Z^{(j)},\ \forall\ j \in \{1,\ldots,n_I\}\right\},\ \text{for } t \ge T_{D_I} \quad (15)$$

where $Z^{(j)}$ denotes the zone j.

B. Contaminant Event Isolation

Suppose that the contaminant source lies in the r-th zone of building subsystem Σ_I, $r \in \{1,\ldots,n_I\}$; i.e.,

$$\dot{x}_I = (A_I + \Delta A_I)x_I + Q_I^{-1}B_Iu_I + (H_I + \Delta H_I)z_I + Q_I^{-1}G_{I,r}g_I, \quad (16)$$

where $G_{I,r}$ is a vector with zeros except for the r-th row with ones. It is noted that the r-th zone of building subsystem Σ_I, $r \in \{1,\ldots,n_I\}$ corresponds to the $M_{x_I}^{-1}(r)$ zone of building system Σ.

At the time instant of detection T_{D_I}, the bank of n_I isolators $\mathscr{I}_{I,j}$, $j \in \{1,\ldots,n_I\}$ is activated, aiming at isolating the contaminated zone in the building subsystem Σ_I.

1) Residual Generation: The estimation model of $\mathscr{I}_{I,j}$ is formulated by selecting an adaptive observer, which is designed assuming the presence of the contaminant source in the zone j, $j \in \{1,\dots,n_I\}$; i.e.,

$$\begin{aligned}\dot{\hat{x}}_{I,j} &= A_I\hat{x}_{I,j} + Q_I^{-1}B_I u_I + H_I y_{z_I} + L_I(y_I - C_I\hat{x}_{I,j}) \\ &\quad + \Omega_{I,j}\dot{\hat{\phi}}_{I,j} + Q_I^{-1}G_{I,j}\hat{\phi}_{I,j}, \qquad (17)\\ \dot{\Omega}_{I,j} &= A_{L_I}\Omega_{I,j} + Q_I^{-1}G_{I,j} \qquad (18)\\ \dot{\hat{\phi}}_{I,j} &= P_I\left\{\Gamma_{I,j}(C_I\Omega_{I,j})^\top(y_I - C_I\hat{x}_{I,j})\right\} \qquad (19)\end{aligned}$$

where $\hat{x}_{I,j}$ is the estimation of x_I, $L_I \in \mathbb{R}^{n_I\times m_I}$ is the observer gain matrix selected such that the matrix A_{L_I} (defined in (12)) is stable and where $G_{I,j}$ is a vector with zeros except for the j-th row with ones. Moreover, the adjustable parameter of the adaptive approximator $\hat{\phi}_{I,j}(t) \in \mathbb{R}$ corresponds to the estimate of the contaminant source g_I. The initial parameter $\hat{\phi}(T_{D_I})$ and matrix $\Omega(T_{D_I})$ are chosen as $\hat{\phi}(T_{D_I}) = 0$ and $\Omega(T_{D_I}) = 0$, respectively. In the adaptive law (19), $\Gamma_{I,j} \in \mathbb{R}$ is a learning rate (positive), while the projection operator P_I restricts the adjustable parameter $\hat{\phi}_{I,j}(t)$ to the predefined interval Φ_I, within which g_I resides [15].

The k-th residual of the isolator $\mathscr{I}_{I,j}$, denoted by $\varepsilon^{(k)}_{y_{I,j}} \in \mathbb{R}$, is defined as

$$\varepsilon^{(k)}_{y_{I,j}} = y_I^{(k)} - C_I^{(k)}\hat{x}_{I,j}, \qquad (20)$$

where $y_I^{(k)} \in \mathbb{R}$ is the k-th element of y_I and $C_I^{(k)}$ is the k-th row of C_I.

2) Computation of adaptive thresholds: The adaptive threshold of the isolator $\mathscr{I}_{I,j}$ is designed to bound the residual $\varepsilon^{(k)}_{y_{I,j}}$, i.e.

$$\left|\varepsilon^{(k)}_{y_{I,j}}(t)\right| \le \overline{\varepsilon}^{(k)}_{y_{I,j}}(t), \qquad (21)$$

assuming that the contaminant source lies in the j-th zone, $j \in \{1,\dots,n_I\}$, i.e. $G_{I,r} = G_{I,j}$ in (16) and that the rate of evolution of the j-th contaminant $g^{(j)} \in \mathbb{R}$ (the j-th element of g), for all $j \in \{1,\dots,n_I\}$ is uniformly bounded, $\left|\dot{g}^{(j)}(t)\right| \le \bar{g}^{(j)}$, where $\bar{g}^{(j)} \in \mathbb{R}$ is a known constant bound.

Based on (4), (20), the residual can be expressed as $\varepsilon^{(k)}_{y_I} = C_I^{(k)}\varepsilon_{x_{I,j}} + w_I$, where $\varepsilon_{x_{I,j}} \triangleq x_I - \hat{x}_{I,j}$; taking into account (16) and (17), the state estimation error is described by:

$$\begin{aligned}\dot{\varepsilon}_{x_{I,j}} &= A_{L_I}\varepsilon_{x_{I,j}} - H_I w_{z_I} + \Delta A_I x_I + \Delta H_I z_I - L_I w_I \\ &\quad + Q_I^{-1}G_{I,r}g_I - Q_I^{-1}G_{I,j}\hat{\phi}_{I,j} - \Omega_{I,j}\dot{\hat{\phi}}_{I,j}. \qquad (22)\end{aligned}$$

The adaptive thresholds $\overline{\varepsilon}^{(k)}_{y_{I,j}}(t)$ are computed taking into account (21) and the solution of (22), following a standard procedure in robust fault diagnosis methods [9]–[11].

3) Decision Logic: Isolator $\mathscr{I}_{I,j}$ infers that zone j, $j \in \{1,\dots,n_I\}$, of the building subsystem Σ_I (or equivalently, zone $M^{-1}_{x_I}(j)$ of the building system Σ), has not been contaminated if there is a time instant at which

$$\left|\varepsilon^{(k)}_{y_{I,j}}(t)\right| > \overline{\varepsilon}^{(k)}_{y_{I,j}}(t), \qquad (23)$$

for at least one $k \in \{1,\dots,m_I\}$. The rationale behind this decision logic is that it is guaranteed that zone j is safe, i.e. the contamination of zone j is excluded, when the behavior of Σ_I observed through y_I is not consistent with the expected behavior represented by $\hat{x}_{I,j}$.

The decision of $\mathscr{I}_{I,j}$ is represented by a boolean function, $D_{I,j}$ defined as

$$D_{I,j}(t) = \begin{cases} 1, & \text{for } t < T_{I,j} \\ 0, & \text{otherwise} \end{cases}, \qquad (24)$$

$$T_{I,j} = \min_t \bigcup_{k\in\{1,\dots,m_I\}} \left\{\min_t\left\{t : \left|\varepsilon^{(k)}_{y_{I,j}}(t)\right| > \overline{\varepsilon}^{(k)}_{y_{I,j}}(t)\right\}\right\}. \qquad (25)$$

Hence, when $D_{I,j}(t) = 0$, the isolator $\mathscr{I}_{I,j}$ decides that zone j is safe (i.e. no contamination has occurred), or equivalently, zone $M^{-1}_{x_I}(j)$ in the building system Σ is safe.

The decision of the contaminant event monitoring agent $\mathscr{M}_I$, $I \in \{1,\dots,K\}$ on which zone in the building subsystem Σ_I is contaminated, is obtained by combining the decisions of the n_I isolators that update the diagnosis set $\mathcal{S}_{D_I}(t)$ defined by (15). In particular, the diagnosis set is determined as follows

$$\mathcal{S}_{D_I}(t) = \mathcal{S}_{D_I}(T_{D_I}) \setminus \left\{Z^{(j)},\ \forall\ j \in W_I\right\}, \qquad (26)$$

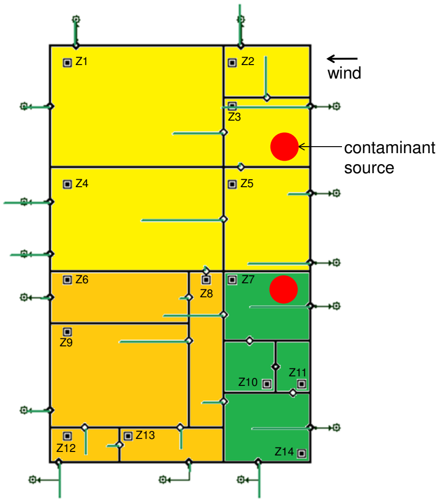
$$W_I = \left\{j : D_{I,j} = 0\right\} \qquad (27)$$

If there is a contaminant source in Σ_I and every isolator $\mathscr{I}_{I,j}$ except for isolator $\mathscr{I}_{I,r}$, $j \neq r$, $j,r \in \{1,\dots,n_I\}$ excludes the contamination of zone $Z^{(j)}$, then it is guaranteed that a contaminant source is located in zone r of the building subsystem Σ_I, or equivalently, in zone $M^{-1}_{x_I}(r)$ of the building system Σ.

IV. MULTI-ZONE BUILDING CASE STUDY

In this section, we demonstrate how the methodology developed in the previous section can be applied toward the distributed detection and isolation of multiple contaminant sources in an indoor building test case environment. We use the Holmes' House building case study with 14 zones, depicted in Fig. 1(a). Details of the model can be found in [16]. The building is comprised of a garage (Z1), a storage room (Z2), a utility room (Z3), a living room (Z4), a kitchen (Z5), two bathrooms (Z6, Z13), a corridor (Z8), three bedrooms (Z7, Z9, Z14) and three closets (Z10, Z11, Z12). The building is divided into three subsystems as demonstrated in Fig. 1(a), while the decomposition of the state transition matrix is demonstrated in Fig. 1(b). The structural decomposition is chosen in order to minimize the interconnections between the subsystems by taking advantage of the large number of zeros present inside the state transition matrix A shown in Fig 1(b), while the non-zero entries of A (the diagonal entries are indicated as $\lambda_i, i \in \{1,\dots,n\}$ while the non-diagonal as λ_{ij} for $i,j \in \{1,\dots,n\}$) are treated as free parameters. Note that the 3 subsystems are structurally observable for almost all wind directions, i.e. λ_{ij}, $i,j \in \{1,\dots,n\}$ are parameters independent of the wind direction.

For the contaminant scenario, we assume that at time $t = 1$ hour, two contaminant sources of generation rate $g_0 = 126.6$ g/hr are simultaneously activated in the utility room (Z3) and the Bedroom 1 (Z7) as shown in Fig. 1(a). During the release



(a) Holmes's house

	x1	x2	x3	x4	x5	x6	x8	x9	x12	x13	x7	x10	x11	x14
x1	λ1	0	λ31	0	0	0	0	0	0	0	0	0	0	0
x2	0	λ2	λ32	0	0	0	0	0	0	0	0	0	0	0
x3	λ13	λ23	λ3	0	λ53	0	0	0	0	0	0	0	0	0
x4	0	0	0	λ4	λ54	0	λ84	0	0	0	0	0	0	0
x5	0	0	λ35	λ45	λ5	0	0	0	0	0	0	0	0	0
x6	0	0	0	0	0	λ6	λ86	0	0	0	0	0	0	0
x8	0	0	0	λ48	0	λ68	λ8	λ98	0	0	λ78	0	0	λ148
x9	0	0	0	0	0	0	λ89	λ9	λ129	λ139	0	0	0	0
x12	0	0	0	0	0	0	0	λ912	λ12	λ1312	0	0	0	0
x13	0	0	0	0	0	0	0	λ913	λ1213	λ13	0	0	0	0
x7	0	0	0	0	0	0	λ87	0	0	0	λ7	λ107	0	0
x10	0	0	0	0	0	0	0	0	0	0	λ710	λ10	λ1110	0
x11	0	0	0	0	0	0	0	0	0	0	0	λ1011	λ11	λ1411
x14	0	0	0	0	0	0	λ814	0	0	0	0	0	λ1114	λ14

Subsystem 1
Subsystem 2
Subsystem 3

(b) State transition matrix (A)

Fig. 1. Structural decomposition of Holmes's house into 3 subsystems. Note that for $\Sigma_1 : \{1,2,3,4,5\} = M_{x_1}(\{1,2,3,4,5\})$, for $\Sigma_2 : \{1,2,3,4,5\} = M_{x_2}(\{6,8,9,12,13\})$ and for $\Sigma_3 :\ \{1,2,3,4\} = M_{x_3}(\{7,10,11,14\})$

it is assumed that natural ventilation is the dominant cause of air movement in the building with wind coming from the east 90° at a speed of 10 m/s. All the openings (doors or windows) are assumed to be in the fully open position and the resulting airflows are calculated using CONTAM and portrayed in Fig. 1(a) with green lines (the length of the line corresponds to the magnitude of the flow), while the state transition matrix A corresponding to these conditions can be found in [9]. There are sensors in 11 out of the 14 zones (Z1, Z2, Z4, Z6, Z7, Z8, Z9, Z10, Z11, Z12 and Z14) able to record the concentration of the contaminant at regular intervals at their own locations but the sensor measurements are corrupted by noise. Based on the sensor measurements, our goal is to detect and isolate the two sources in the presence of noise and modeling uncertainty. Specifically, we assume the following uncertainty conditions: wind direction in the range $w_d = 90 \pm 10°$, wind speed in the the range $w_s = 10 \pm 0.5$ m/s and leakage openings $\pm 10\%$ from the fully open position. For these uncertainty values, based on the results of [9], we use $\overline{\Delta A}_1 = 0.185$, $\overline{\Delta A}_2 = 0.23$, $\overline{\Delta A}_3 = 0.075$, $\overline{\Delta H}_1 = 0.0564$, $\overline{\Delta H}_2 = 0.162$ and $\overline{\Delta H}_3 = 0$ for calculating the adaptive thresholds. Regarding the noise in the sensor measurements, we assume bounded noise of magnitude $\overline{w}_I^{(k)} = 0.05$.

The detection results for the three agents are portrayed in Fig. 2. From the figure it becomes evident that the sources are detected by $\mathscr{D}_1$ and $\mathscr{D}_3$, since the magnitude of the residual has crossed the threshold. Note that although Σ_2 is interconnected with the other 2 subsystems, its detection agent $\mathscr{D}_2$ is not triggered by the presence of the sources in the other subsystems. Following detection, the isolators $\mathscr{I}_1$ and $\mathscr{I}_3$ are activated by the respective agents. The isolation results for $\mathscr{I}_{1,j}, j \in \{1,\ldots,5\}$ are portrayed in Fig. 3. Following the proposed decision logic, the source is correctly isolated in Z3 (Fig. 3(c)) since this is the only instance for which residuals remain below the thresholds at all times. Similarly, the second source is also correctly isolated in Z7 by the third agent.What is particularly interesting in the above scenario is that both sources are correctly detected and localized, even though for one of the two sources, there is no sensor in the room with the contamination (note that Z3 has no sensor).

V. CONCLUSIONS

In this paper, we presented a model-based, distributed architecture for detecting and isolating multiple contaminant events that may occur in a multi-zone building. By modeling the monolithic building system as a set of interconnected subsystems based on structural decomposition, we design distributed contaminant event monitoring agents, with each one dedicated to a corresponding interconnected, subsystem. Each agent consists of a contaminant event detector and a bank of contaminant event isolators, while it may exchange information with its neighboring subsystems. The detectors of the contaminant event monitoring agents pursuit first-level of diagnosis, at which one or more contaminated building subsystems are isolated. The bank of isolators in contaminant event monitoring agent conducts second-level diagnosis by isolating the zone where the contaminant source is located in the building subsystem. Simulation results showed the effectiveness of the distributed diagnostic technique in isolating multiple contaminants in a 14-zone building case study.

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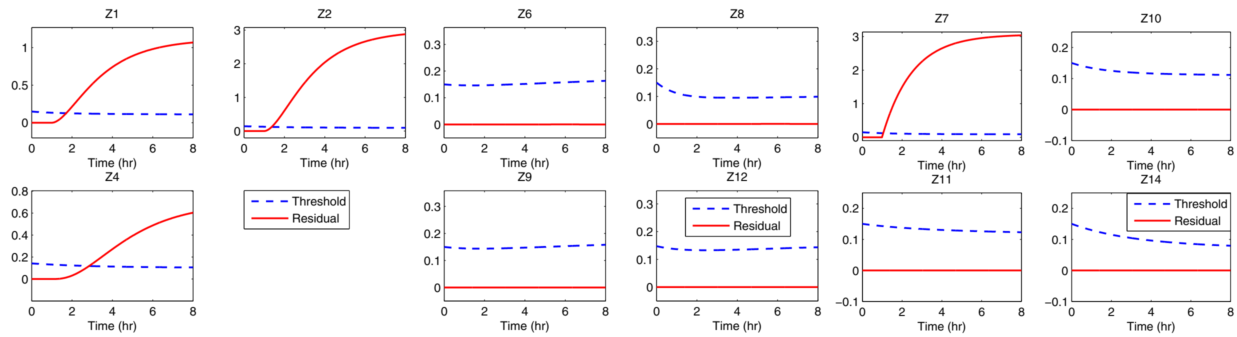
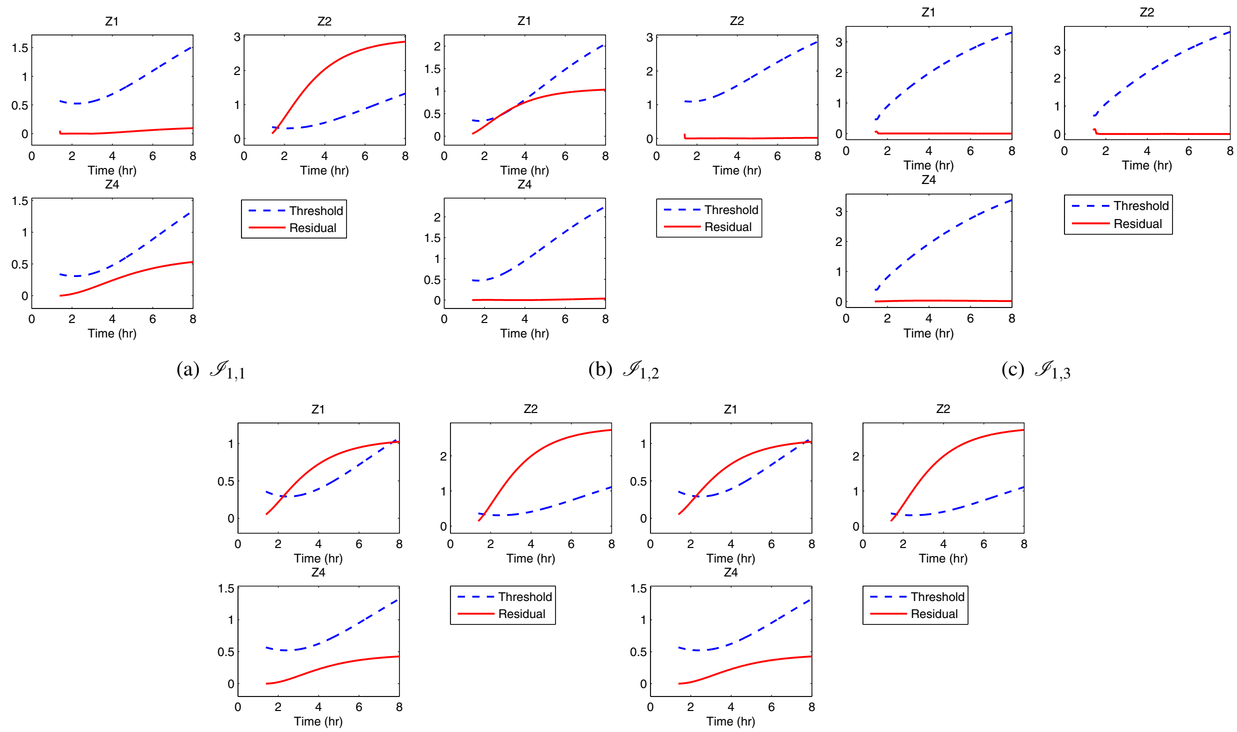


(a) $\mathscr{D}_1$ (b) $\mathscr{D}_2$ (c) $\mathscr{D}_3$

Fig. 2. Contaminant Detectors for the 3 Subsystems. The residual $\varepsilon_{y_I}^{(k)}(t)$, is displayed using solid lines while the corresponding adaptive thresholds $\overline{\varepsilon}_{y_I}^{(k)}(t)$ are displayed using dashed lines. Note that for $\Sigma_1: \ k \in \{1,2,3\} = M_{y_1}(\{1,2,4\})$, for $\Sigma_2: \ k \in \{1,2,3,4\} = M_{y_2}(\{6,8,9,12\})$ and for $\Sigma_3: \ k \in \{1,2,3,4\} = M_{y_3}(\{7,10,11,14\})$.



(a) $\mathscr{I}_{1,1}$ (b) $\mathscr{I}_{1,2}$ (c) $\mathscr{I}_{1,3}$

(d) $\mathscr{I}_{1,4}$ (e) $\mathscr{I}_{1,5}$

Fig. 3. Contaminant Isolators for the first subsystem (Σ_1). The residual $\varepsilon_{y_{1,j}}^{(k)}(t)$ is displayed using solid lines while the corresponding adaptive thresholds $\overline{\varepsilon}_{y_{1,j}}^{(k)}(t)$ are displayed using dashed lines. Note that for $\Sigma_1: \ j \in \{1,2,3,4,5\} = M_{x_1}(\{1,2,3,4,5\}), \ k \in \{1,2,3\} = M_{y_1}(\{1,2,4\})$.

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