Distributed Clustering-based Sensor Fault Diagnosis for HVAC Systems ⋆

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Abstract: The paper presents a distributed Sensor Fault Diagnosis architecture for Industrial Wireless Sensor Networks monitoring HVAC systems, by exploiting a recently proposed distributed clustering method. The approach allows the detection and isolation of multiple sensor faults and considers the possible presence of modeling uncertainties and disturbances. Detectability and isolability conditions are provided. Simulation results show the effectiveness of the proposed method for an HVAC system.

Keywords: Sensor Networks, Distributed Fault Diagnosis, Building Automation, Clustering, Sensor Faults, HVAC Systems

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1. INTRODUCTION

In the last decade, the problem of energy management in buildings has become a prominent research area in the context of building automation (BA), both for monitoring and control. This interest is motivated by the fact that more than one third of the whole energy expenditure in modern cities is due to residential and commercial buildings and half of this consumption refers to heating, ventilation and air conditioning (HVAC) (see for example Pèrez-Lombard et al. (2008); Yuan et al. (2015), and references cited therein). Even if an increased efficiency of systems and materials and the adoption of green building policies has allowed to prevent a dramatic growth of such consumption in residential buildings, the design of control solutions remains of paramount importance in large commercial and industrial facilities to yield resource optimization while guaranteeing comfort of the occupants (Gupta et al. (2015); Sturzenegger et al. (2016)). From these premises, it clearly appears how the punctual, accurate, and robust monitoring of the environment thermal state is a key ingredient for such BA applications: the monitoring network appears as part of the HVAC system (Agarwal et al. (2011)), and Industrial Wireless Sensor Networks (IWSNs) are particularly suitable for this task, given the additional attention posed to robustness, reliability and maintainability features with respect to standard WSNs.

To meet these requirements, IWSNs usually adopt Fault Detection and Isolation (FDI) procedures (see Gungor and Hancke (2013); Reppa et al. (2016)) and it is agreed that a clustering approach is beneficial to improve efficiency and attain fault resilience (Zhang et al. (2015); Bianchin et al. (2015)). Indeed, the advantages of partitioning the sensors into clusters for sensor fault detection are mainly two. Firstly, by exploiting *network decomposition* (Abbasi and Younis (2007)), it allows to reduce communication, because each sensor can communicate for sensor fault detection purposes only with neighboring sensors, i.e. sensors belonging to the same cluster. Secondly, by adopting *data clustering* (Ma et al. (2011)), it allows to group sensors with similar modeling uncertainty and/or disturbances and it allows to reduce the conservativeness of the fault detection thresholds, by exploiting measurement locality.

Fault tolerant clustering approaches have been proposed in the literature (as in Gupta and Younis (2003); Zhang et al. (2015); Chen et al. (2015)), relying though on the presence of special cluster–head (CH) nodes to facilitate the clustering task and support the fault detection and anomaly recognition procedures. Conversely, considerable benefits in terms of scalability, robustness and reconfigurability of the network would be yielded by a solution that is completely distributed (see for example Boem et al. (2011); Shames et al. (2011); Stankovic et al. (2010); Boem et al. (2017) for an overview on distributed FDI).

Starting from the results in Bianchin et al. (2015); Cenedese et al. (2017), in this paper we address the problem of FDI in HVAC systems focusing on the monitoring IWSN. The main contribution we propose consists in:

(1) a methodology that considers heterogeneous sensors measuring different quantities and a procedure to tune the measurement model and properly design the clustering threshold bounds for estimation and FDI;
(2) a FDI algorithm that takes advantage of such clustering procedure and provides a model-based clustering reconfiguration strategy, able to cope with both single and multiple sensor faults;
(3) a numerical validation within the scenario of temperature monitoring for the smart management of an HVAC system.

2. PROBLEM FORMULATION

We consider an IWSN composed of N sensors, which communicate according to an undirected graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V}$ is the set of the nodes (the sensors) and $\mathcal{E}$ is the set of the edges connecting the nodes. We define the set of neighbours of node i: $\mathcal{N}_i = \{l \in \mathcal{V} : (l, i) \in \mathcal{E}\}$. The sensors $\mathcal{V}$ monitor the indoor temperature in different rooms of a building. In each area the heat diffusion is modeled as

$$T_i(k+1) = h(T_i(k), u(k), P_i) + \eta_i(T_i(k), u(k), P_i, u_e(k)), \tag{1}$$

where $T_i(k)$ is the temperature at a point P_i at time k; h is a field modeling the nominal heat diffusion depending on the past temperature, the local inputs u (including the HVAC input and possibly the outdoor temperature if known) and the position P_i; η_i considers modeling uncertainty and disturbances u_e, including the unknown/unmodeled influence of neighboring rooms' temperature or unknown/unmodeled inputs or phenomena, such as the effects of windows, lights or electrical appliances, or the presence of people in the environment.

Thus, each i-th node provides a noisy measurement y_i of temperature T_i:

$$y_i(k) = T_i(k) + d_i(k) + f_i(k), \tag{2}$$

where $d_i(k)$ is the measurement noise at time k and $f_i(k)$ explicitly models the effect of possible faults affecting sensor i at time k (clearly, $f_i(k) = 0$ in healthy conditions).

Hypothesis 1. The measurement noise at each node is assumed to be bounded, i.e. $|d_i(k)| \leq \bar{d}_i$, $i = 1, \ldots, N$, where $\bar{d}_i$ is a known constant positive value.

For notation simplicity we assume in the following that all the sensors are characterized by the same constant noise bound $\bar{d}$. This case can be trivially extended to account for more heterogeneous sensors and to consider time-varying or state-dependent measurement noise.

With the aim of performing fault detection on the sensor network, we build on the clustering method proposed in Cenedese et al. (2017) in order to group sensors in each room into clusters having similar uncertainty conditions. Clustering results and a novel model-based sensor fault diagnosis strategy are used to detect the presence of faults and isolate faulty sensors in the clusters.

3. DISTRIBUTED CLUSTERING

The distributed clustering technique introduced in Cenedese et al. (2017) is briefly recalled. Each node i is associated with the corresponding measurement y_i at the time when we perform the clustering, which has to satisfy the following criteria:

(1) connectivity;
(2) measurements similarity, such that the difference between two measurements in the same cluster is lower than a given clustering bound b;
(3) maximality, minimizing the number of clusters.

We replace the measurements similarity criterion with a consistency criterion, allowing sensors to measure different quantities, and designing the bound b based on the model of the system. This allows to obtain clusters that have similar modeling uncertainty or disturbances. In the following section we explain how each sensor can compute the bound b in a distributed way using only local communication with neighbours.

3.1 The consistency criterion

Each sensor i communicates its own measurement y_i to the neighbouring sensors and compares it with the measurements y_j taken by neighbouring nodes $j \in \mathcal{N}_i$. For each pair (i, j) in healthy conditions:

$$|y_i - y_j| = |T_i - T_j + d_i - d_j| \,. \tag{3}$$

Since the actual temperature at each point is unknown, and temperatures at different spatial points may be quite different simply due to the physics of the problem and not due to the presence of anomalies, each node can compute an estimate of the temperature based on the nominal model, past measurements, known inputs and position:

$$\hat{T}_i(k) = h(y_i(k-1), u(k-1), P_i). \tag{4}$$

Similarly, each node can compute the estimate also for the neighbouring sensors, assuming that the positions P_j, $j \in \mathcal{N}_i$ are known to node i. In the case that the positions P_j, $j \in \mathcal{N}_i$ are unknown to node i, the estimates $\hat{T}_j$ can be communicated to the neighbours together with the measurements y_j reducing the computation cost at each node, but increasing the communication cost. By substituting (1) in (3) and using (4), we have that

$$|y_i - y_j| \leq \left|\hat{T}_i - \hat{T}_j\right| + |-\Delta h_i + \Delta h_j| + |\eta_j - \eta_i| + 2\bar{d}, \tag{5}$$

where $\Delta h_i(k) = h(y_i(k), u(k), P_i) - h(x_i(k), u(k), P_i)$. Given Hypothesis 1, it is possible to compute a bound $\bar{\Delta} h_i(k)$ for $|\Delta h_i(k)|$:

$$\bar{\Delta} h_i := \max_{|d_i| \leq \bar{d}} |h(y_i, u, P_i) - h(y_i - d_i, u, P_i)| \,.$$

Since the goal of the clustering is to partition the sensors into groups with similar uncertainty, we neglect the term $\eta_j - \eta_i$ for the definition of the local clustering bound b_i:

$$b_i = \min_j \left[\left|\hat{T}_i - \hat{T}_j\right| + \bar{\Delta} h_i + \bar{\Delta} h_j + 2\bar{d} \right].$$

We then apply Algorithm 2 in Cenedese et al. (2017) to partition the sensor network in clusters.

4. SENSOR FAULT DIAGNOSIS

Once the IWSN is partitioned into clusters, the distributed fault detection and isolation method is implemented at each sensor i. We assume that the initial clustering is performed in healthy conditions. At each time step, each node communicates its measurements (and estimates) only to neighbouring nodes belonging to the same cluster $\mathcal{C}_i$: $\mathcal{N}_i^* = \mathcal{N}_i \cap \mathcal{C}_i$. At each time step, sensor i computes two different residual signals r_1^{ij} and r_2^i for sensor fault detection:

$$r_1^{ij}(k) = y_i(k) - y_j(k),$$
$$r_2^i(k) = y_i(k) - \hat{y}_i(k),$$

where

$$\hat{y}_i(k) = h(y_i(k-1), u(k-1), P_i) + \lambda(y_i(k-1) - \hat{y}_i(k-1))$$

is the model-based observer estimate (with $0 < \lambda < 1$ to guarantee the convergence).
Then, it firstly checks the coherence with neighbouring sensors. In fact, in healthy conditions, $\forall j \in \mathcal{N}_i^*$,

$$\left|r_1^{ij}(k)\right| \leq \left|\hat{T}_i(k) - \hat{T}_j(k)\right| + \bar{\Delta} h_i + \bar{\Delta} h_j + 2\bar{d} := \bar{r}_1^{ij}(k). \tag{6}$$

Secondly, it checks the coherence with respect to its own past measurements and the model. In healthy conditions,

$$\begin{aligned}\left|r_2^i(k)\right| &= \left|\lambda r_2^i(k-1) + \Delta h_i(k-1) + \eta_i(k-1) + d_i(k)\right| \\ &\leq \left|\lambda r_2^i(k-1)\right| + \bar{\Delta} h_i(k) + \bar{\eta}_i(k-1) + \bar{d} := \bar{r}_2^i(k), \end{aligned} \tag{7}$$

where $\bar{\eta}_i$ satisfies the following

Hypothesis 2. The modeling uncertainty at each node is assumed to be bounded, i.e. $|\eta_i(k)| \leq \bar{\eta}_i(k)$, $\forall k$, $i = 1, \ldots, N$, where $\bar{\eta}_i(k)$ is a known positive value.

In healthy conditions the residual signals (r_1^{ij}, r_2^i) are lower than the corresponding thresholds ($\bar{r}_1^{ij}$, $\bar{r}_2^i$). When at least one of the two residual signals crosses the corresponding threshold in at least one of the sensors of the cluster, then it is possible to conclude that a fault has occurred in one or more sensors of the cluster. It is important to note that the proposed thresholds guarantee the absence of false-alarms thanks to the way they are defined in (6)-(7). It is also worth noting, as it will be deeply explained in Section 5, that residual r_1^{ij} is sensitive both to faults in sensor i and sensor j. On the other hand, residual r_2^i is sensitive only on faults on sensor i. This double redundancy allows the isolation of the faulty sensor(s) in each cluster.

After fault isolation, the faulty sensors are removed from the sensor network. The clustering algorithm can be performed to reconfigure the clusters.

5. DETECTABILITY AND ISOLABILITY ANALYSIS

In this section, we analyse some sufficient conditions on the faults, with respect to noises and uncertainties, to allow the detection by the proposed distributed method. The proofs are omitted due to space constraints.

5.1 Detectability of a single fault

Let us consider a general fault f_i occurring on sensor i, that is, for $k \geq k_f$, the i-th output equation is

$$y_i(k) = T_i(k) + d_i(k) + f_i(k), \tag{8}$$

where $f_i(k)$ could even be zero at some time after k_f in the case of intermittent faults. We are not assuming a specific type of sensor fault (persistent, intermittent, bias, drift,..).

Proposition 3. Let us consider that sensor i is affected by a fault f_i for $k \geq k_f$. It is sufficient that the fault effect satisfies the following condition to guarantee fault detection by means of residual r_2^i:

$$\left|\sum_{h=k_f}^{k-1} \lambda^{k-h-1} f_i(h+1)\right| > 2\bar{r}_2^i(k).$$

The condition in the previous proposition gives a characterization of the cumulative fault effect needed to guarantee fault detection by the proposed architecture by means of residual r_2^i in the worst case scenario, despite the presence of uncertainties and disturbances that may hide its effect. We now provide a sufficient condition regarding the instantaneous effect of the fault.

Proposition 4. Let us consider that sensor i is affected by a fault f_i at time $\bar{k}$. It is sufficient that the fault satisfies the following condition to guarantee fault detection at time $\bar{k}$:

$$\left|f_i(\bar{k})\right| > 2\bar{r}_2^i(\bar{k}).$$

Furthermore, we provide the following sufficient condition for a fault f_i to be detected at time $k_d \geq k_f$ by means of the residual r_1^{ij}.

Proposition 5. Let us consider the case that sensor i is affected by a fault f_i. It is sufficient that at time k_d the fault satisfies the following condition to guarantee fault detection:

$$|f_i(k_d)| > 2\bar{r}_1^{ij}(k_d).$$

In a similar way, it is possible to prove the following.

Proposition 6. If a fault f_j is occurring in sensor j, $j \in \mathcal{N}_i^*$,

- it will not be detected by residual r_2^i in sensor i;
- the following condition is sufficient for sensor i to detect the fault by means of residual r_1^{ij} at time k_d:

$$|f_j(k_d)| > 2\bar{r}_1^{ij}(k_d).$$

5.2 Detectability of multiple faults

We have the following theoretical result.

Proposition 7. Let us consider the case that sensor i is affected by a fault f_i and simultaneously a fault f_j is occurring in sensor j, $j \in \mathcal{N}_i^*$. The following condition is sufficient to guarantee the fault detection at time k_d by the proposed distributed sensor fault detection scheme:

$$|f_i(k_d) - f_j(k_d)| > 2\bar{r}_1^{ij}(k_d).$$

It is worth noting that, depending on the sign of the faults, the presence of multiple faults may either improve or compromise the fault detection.

By analyzing the results in the previous propositions, it is important to note that the use of two different residual signals may possibly increase the detectability performance of the proposed distributed architecture and, as we will see in the following section, allows to isolate faults distinguishing between local and neighbouring faults.

5.3 Isolability analysis

After fault detection, node i communicates the alarm to neighbouring sensors j, $j \in \mathcal{N}_i^*$, according to the following:

$$d_1^{ij}(k) = \begin{cases} 0 & \text{if } \left|r_1^{ij}(k)\right| \leq \bar{r}_1^{ij}(k) \\ 1 & \text{if } \left|r_1^{ij}(k)\right| > \bar{r}_1^{ij}(k) \end{cases}$$

$$d_2^{i} = \begin{cases} 0 & \text{if } \left|r_2^{i}\right| \leq \bar{r}_2^{i} \\ 1 & \text{if } \left|r_2^{i}\right| > \bar{r}_2^{i} \end{cases}$$

and receives analogous information from the neighbours.

In order to reduce the communication cost, the communication is required only after fault detection. If not received, the quantities d_1^j are assumed to be null. By exploiting the fact that, as shown in the previous sections, residual r_2^i is sensitive only on local faults f_i, while residual r_1^{ij} is sensitive both to local faults affecting sensor i, and faults occurring in the neighbouring sensor j, it is possible to develop a fault isolation logic. In Table 1, we provide the Fault Isolation (FI) decisions for each couple (i,j) depending on the values of the signals $d_1^{ij} = d_1^{ji}$, d_2^i, d_2^j.

d_1^{ij}	d_2^i	d_2^j	FI Decision
1	0	0	f_i OR f_j
1	1	0	f_i
1	0	1	f_j
1	1	1	f_i AND f_j
0	1	0	f_i
0	0	1	f_j
0	1	1	f_i AND f_j

Table 1.

Due to the way the detection thresholds are designed, if the residual crosses the corresponding threshold, the presence of a fault is guaranteed. Viceversa, as long as the residual is lower than the corresponding threshold, the absence of the fault cannot be guaranteed, since it could be 'hidden' by the noise, disturbances or other faults presence. The communication with other neighbouring sensors $l \in \mathcal{N}_i^*$, $l \neq j$, may support the isolation decision when it is not possible to distinguish between the presence of f_i or f_j (see the first row of Table 1) only considering the signals of the couple (i,j). It is interesting to note the scenario described by the last row of Table 1. The simultaneous presence of f_i and f_j may be not detected by d_1^{ij} for two different reasons: in the specific application threshold $\bar{r}_1^{ij}$ could be slightly more conservative than $\bar{r}_2^i$ or the two faults may have the same sign and similar magnitude (see Prop. 7).

6. SIMULATION RESULTS

In this section, we illustrate the application of the distributed clustering-based sensor fault detection method to an IWSN monitoring the performance of an HVAC system, composed of the electromechanical part and a single zone, i.e. a room. We simulate the HVAC system presented in Reppa et al. (2015), using the same parameters except for the dimension of the room, chosen as $4.5\,\text{m} \times 1.75\,\text{m} \times 4.5\,\text{m}$. The system is controlled by 2 feedback linearization controllers whose gains are selected as $K = 1$. The desired values of the temperature of the cooling coil and the room are set up as follows: $T^e = 10°C$ and $T = 22°C$. The diffusion of the heating in the room at time k is modelled according to the heat equation (Guenther and Lee (1996), Myint-U and Debnath (2007)) solution for a room of length L:

$$T_i(P_i,k)=T_f(k)+\sum_{n=1}^{\infty}B_n(k)\sin\left(\frac{2n-1}{L}\frac{\pi}{2}P_i\right)e^{-\left(\frac{2n-1}{L}\frac{\pi}{2}\right)^2 k} \tag{9}$$

where T_f is the temperature of the air introduced in the room by the fan and

$$B_n(k)=\frac{2}{L}\int_0^L [T_i(P_i,k-1)-T_f(k)]\sin\left(\frac{2n-1}{L}\frac{\pi}{2}P_i\right)dP_i. \tag{10}$$

The room temperature is characterized by some uncertainty modelled everywhere as the sum of a noise $\eta^{(1)} \sim \mathcal{N}(0,10^{-4})$ and a term computed at each position P_i as $\eta^{(2)} = -2.3e^{-l}$, being $l = |P_i - P_s|$ the distance between P_i and the source of an unmodelled phenomenon, such as the presence of a window or a door, located in $P_s = (4\,\text{m}, 4.5\,\text{m})$. This phenomenon, not considered in the nominal model for estimation, causes a reduction of the temperature in the top-right corner of the room that decays from -2.3 in P_s to 0 going towards the centre of the room. The bound on the uncertainty is set to $\bar{\eta}_i = 2.006$ at each point. In the room, $N = 20$ sensors are randomly deployed such that the resulting graph is connected (see Figure 1 for a network example).

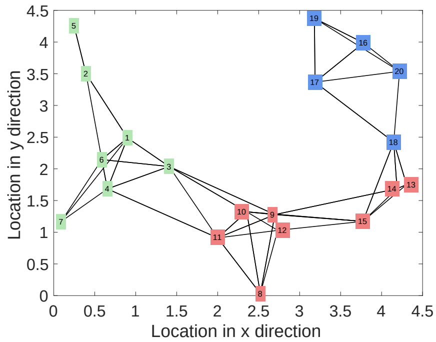


Fig. 1. IWSN with 20 sensors. The green nodes belong to $\mathcal{C}_1$, the red nodes belong to $\mathcal{C}_2$ and the blue ones belong to $\mathcal{C}_3$.

Other parameters used for the simulations are the filter gain $\lambda = 0.7$ and the measurement noise bound $\bar{d} = 0.4$. Moreover, since we are considering a sensor network, a discretization of the system has been performed using Euler's explicit method, with sampling rate equal to 1 min. In the simulations, we consider both single and multiple sensor faults scenarios for three different kind of faults:

- *constant sudden faults*: $f(k) = c \cdot u(k - k_f)$,
- *temporary faults*: $f(k) = c \cdot [u(k - k_{f_1}) - u(k - k_{f_2})]$, $k_{f_2} > k_{f_1}$,
- *linear degrading faults*: $f(k) = c \cdot k \cdot u(k - k_f)$,

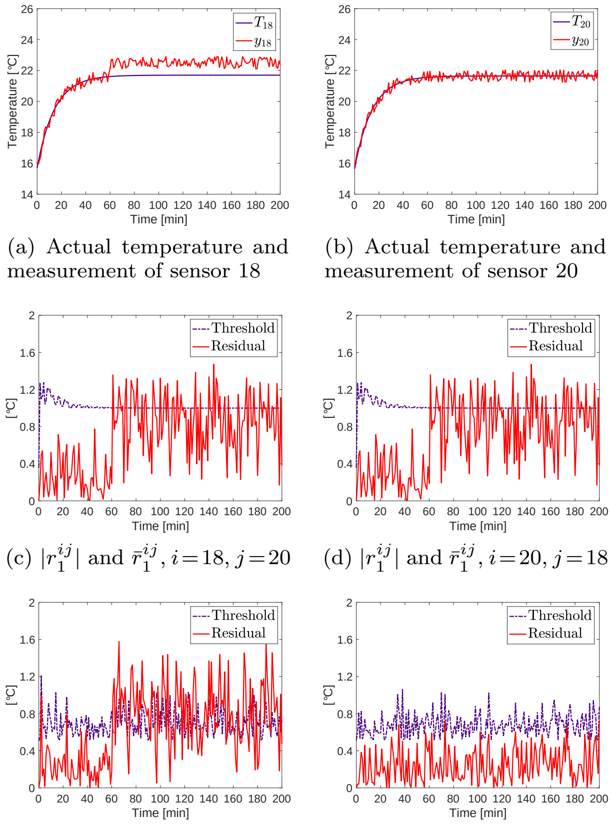
where c is a positive random constant representing the amplitude of the fault and $u(\cdot)$ is the unit step.
At the first time step, the proposed distributed clustering algorithm is performed, assuming that no faults are affecting the sensors. The result of the clustering (see Figure 1) is the set of clusters $\mathcal{C}^* = \{\mathcal{C}_1, \mathcal{C}_2, \mathcal{C}_3\}$, with $\mathcal{C}_1 = \{1,2,3,4,5,6,7\}$, $\mathcal{C}_2 = \{8,9,10,11,12,13,14,15\}$ and $\mathcal{C}_3 = \{16,17,18,19,20\}$, which satisfies both the conditions on connectivity and on measurement similarity. Moreover, as expected, the sensors in the top-right corner, namely the area with higher uncertainty, are grouped together.

Let us consider a first scenario where a single abrupt fault $f_{18}(k) = 0.8 \cdot u(k - k_{f_{18}})$ occurs in the 18-th sensor at time $k_{f_{18}} = 60$ min. The results of the distributed sensor fault detection and isolation method are shown in Figure 2, where the performances of the faulty sensor 18 are compared with those of the healthy sensor 20 belonging to the same cluster $\mathcal{C}_3$. Due to space constraints, we show the results only for a couple of sensors, but similar and coherent behaviours are obtained for the other sensors. By analyzing r_1^{ij} (Figure 2, (c) and (d)), both sensors can detect the presence of a fault at $k = 61$ min. At the same time, by observing the residuals $|r_2^i|$ (Figure 2, (e) and (f), detection for $|r_2^{18}|$ and no detection for $|r_2^{20}|$), the correct fault is isolated.

We can observe similar results in Figure 3 for the case of a temporary fault $f_{(18)}(k) = 1.5 \cdot [u(k - k_{f_{18,1}}) - u(k - k_{f_{18,2}})]$, $k_{f_{18,1}} = 60$ min, $k_{f_{18,2}} = 70$ min. The detection and isolation method is successful from the very beginning of the fault where the residuals cross the related thresholds in correspondence of the faulty values.

In Figure 4 we illustrate the relationship between the detection time and the amplitude of the fault, represented by the rate c in the case of linear degrading faults occurring at $k_f = 60$ min. The parameter c is chosen in the interval $[0.02, 1]$. As expected, as the amplitude of the fault increases, the detection delay $(k_d - k_f)$ becomes smaller.

Let us now consider the case that multiple faults may simultaneously affect the sensors in the sensor network. In Figure 5 we can see the case of multiple linear degrading faults occurring in sensors 18 and 20 belonging to the same cluster. The considered faults are $f_{(18)}(k) = 0.06 \cdot u(k - k_{f_{18}})$ occurring at $k_{f_{18}} = 60$ min and $f_{(20)}(k) = 0.02 \cdot u(k - k_{f_{20}})$ occurring at time $k_{f_{20}} = 61$ min.



(a) Actual temperature and measurement of sensor 18

(b) Actual temperature and measurement of sensor 20

(c) $|r_1^{ij}|$ and $\bar{r}_1^{ij}$, $i=18$, $j=20$

(d) $|r_1^{ij}|$ and $\bar{r}_1^{ij}$, $i=20$, $j=18$

(e) $|r_2^{i}|$ and $\bar{r}_2^{i}$, $i=18$

(f) $|r_2^{i}|$ and $\bar{r}_2^{i}$, $i=20$

Fig. 2. Comparison between sensor 18, affected by a single sudden fault $f_{(18)}(k) = 0.8 \cdot u(k - k_{f_{18}})$ at $k_{f_{18}} = 60$ min, and the healthy sensor 20.

Other scenarios have been considered in simulation showing the effectiveness of the proposed method. They are omitted due to space constraints.

7. CONCLUSIONS

In this paper, a distributed sensor fault diagnosis architecture based on a clustering approach is proposed for IWSN monitoring HVAC systems. Detectability and isolability properties are analyzed. Simulation results showing the effectiveness of the proposed method are provided. As a future work, we are going to consider the possible simultaneous presence of process and sensor faults.

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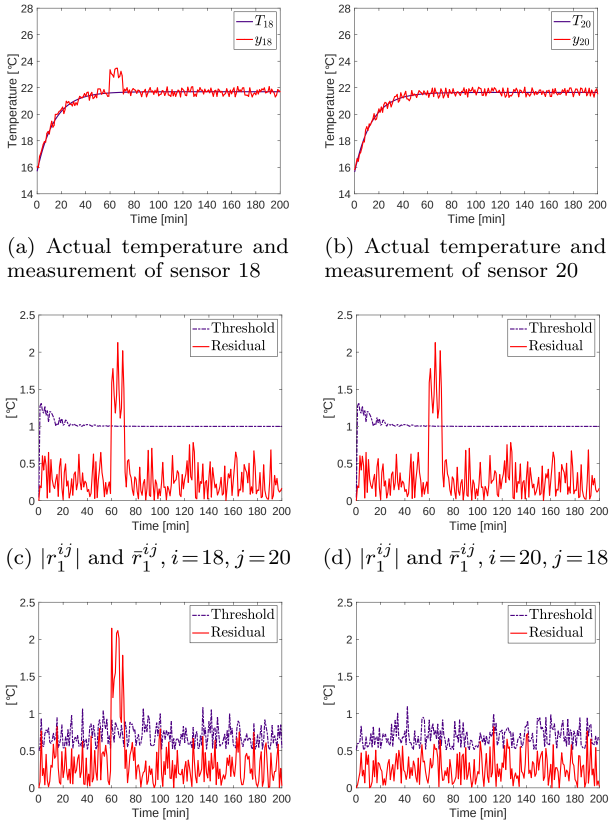

(a) Actual temperature and measurement of sensor 18

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(c) $|r_1^{ij}|$ and $\bar{r}_1^{ij}$, $i=18$, $j=20$

(d) $|r_1^{ij}|$ and $\bar{r}_1^{ij}$, $i=20$, $j=18$

(e) $|r_2^i|$ and $\bar{r}_2^i$, $i=18$

(f) $|r_2^i|$ and $\bar{r}_2^i$, $i=20$

Fig. 3. Comparison between sensor 18, affected by an intermittent fault $f_{(18)}(t) = 1.5 \cdot [u(k - k_{f_{18,1}}) - u(k - k_{f_{18,2}})]$, $k_{f_{18,1}} = 60$ min, $k_{f_{18,2}} = 70$ min, and the healthy sensor 20.

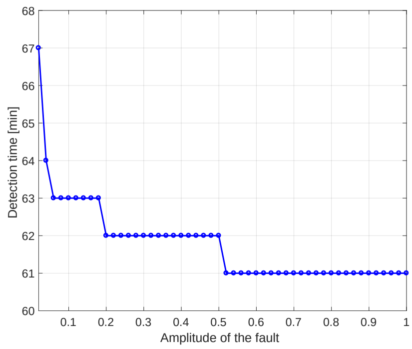

Fig. 4. Detection time vs. fault amplitude (c parameter) for single linear degrading faults, $k_f = 60$ min.

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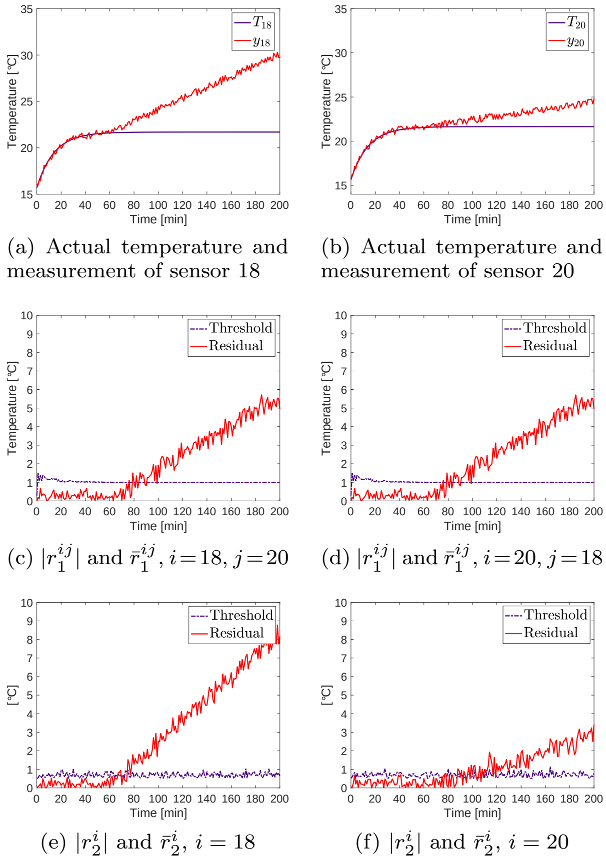

Fig. 5. Comparison between sensor 18, affected by fault $f_{(18)}(k) = 0.06 \cdot u(k - k_{f_{18}})$ at $k_{f_{18}} = 60$ min and sensor 20 affected by $f_{(20)}(k) = 0.02 \cdot u(k - k_{f_{20}})$.

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