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Sensor fault detection and isolation for smart irrigation wireless sensor network based on parity space

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ABSTRACT

In the recent years, wireless sensor network technology (WSN) has been widely adopted in precision agriculture for determining the needs of the soil in term of water by monitoring some environmental parameters. To do this, WSN is constructed using several sensor nodes; these small sensing devices are prone to failure and may produce erroneous measurements. To ensure good management of freshwater, the network service quality is necessary. To avoid the degradation of service, the detection of the faulty sensor in WSN is required. In this paper, a fault detection and isolation (FDI) algorithm derived from a parity space approach and based on direct redundancy is proposed toward detecting and isolating sensor fault in WSN. In laboratory experiments, the proposed FDI algorithm proved its effectiveness.

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1. INTRODUCTION

Nowadays, the world is experiencing a new technology which is the internet of things (IoT). In the upcoming years, IoT promises to make a revolution in the industrial world and a transformational change in our way of living. IoT is composed of electronic devices and sensors that communicate with each other via the internet to perform actions or provide services without human intervention [1]. With the emergence of the IoT technology, many domains start to adopt it and the agriculture sector is one of them. Smart irrigation is one of the applications that works with the IoT technology and aims on making a good management of freshwater and irrigates the farm automatically based on its needs. Much research is conducted on this topic proved the efficiency of smart irrigation in water saving and its good impact that has on the productivity of the crops compared to traditional irrigation [2]–[6]. Based on this, it is beneficial to adopt smart irrigation rather than a traditional one especially for the countries where their economy depends on agriculture. Among the components of smart irrigation is a wireless sensor network (WSN) technology which plays a great role in this application [7]. WSN is composed of many sensor nodes that have the role of sensing, processing, and transmitting the data. Through these sensors nodes, we can get much precise information in real time about the need of the crops in term of water requirement. This is done by monitoring and measuring some environmental parameters such as soil temperature and soil moisture and later forwarding this data periodically to the base station for calculating the amount of the water needed. To get the desired goals from this application, the WSN should operate correctly during agriculture season. The soil environment is considered a big challenge that can affect the accuracy of the sensors nodes over a long period of time. So, these small devices are prone to failure and require continuous monitoring and calibration to ensure the quality of the data issued by the WSN.

Calibrating manually a large scale of sensor nodes deployed in a farm is not practical and hard in the presence of large number of sensor nodes. To solve this issue, we opt for using the fault detection and isolation (FDI) approach for monitoring the quality of the data gathered from sensors and detecting if they are error free before they got used by the base station. This will ensure that we have accurate data and reliable image of our farm for making a suitable action [8]. In general, the concept of the FDI approach is to detect and determine the location of the possible fault in the engineering systems [9]. This approach has appeared with the increasing of automation processes in order to ensure a high level of the process performance without the presence of human operators. FDI methods can be categorized into two groups: the methods that require a mathematical model of the plant and the others that do not. The choice of the appropriate method depends on the application [10]. For technical process we can get its mathematical model with controlled or measured signals inputs. Whereas, when we have a WSN monitor natural phenomena like farmland, we cannot obtain a well pre-defined model of the soil characteristics and because of its variant nature we can modulate the ground based on some soil characteristics in real time through sensors and that makes not easy to detect and isolate sensor fault. For that, we will focus on the approach of the FDI that built its model in real time based on the measurement of the sensors as parity space approach with direct redundancy for detecting and isolating sensor fault in WSN and try to adapt this method on our case. This approach was used in our previous work in the theoretical framework [11], whereas in this paper, we developed it for a real implementation. We can classify sensor fault in WSN into hard fault and soft fault, in hard fault the sensor node cannot communicates and participates in the network activities anymore, while in soft fault, the sensor nodes still work but send erroneous data to the base station [12]. In this paper, we address the problem of the soft fault i.e. sensor measurement faults.

This paper is organized as: section 2 presents the prior and the related work. Section 3 describes the proposed node deployment. Then, the direct redundancy equations based on the parity space approach are provided in section 4. Section 5 presents our proposed FDI algorithm. In section 6, we present and discuss our laboratory experiments. Finally, conclusion is given in section 7.

2. PRIOR AND RELATED WORK

With the increased use of the WSN in many applications, the research for ensuring the reliability of the data issued by the WSN became fundamental. In this section, we will give a review of the existing work in the area of sensor fault detection in WSN. A survey on fault diagnosis in WSN can be found in [12]. In [13] the authors made studies on soil sensors that are distributed in different regions in order to measure some soil parameters for scientific purposes. In their experiment, they observed that not all information captured by sensors are reliable. So, they proposed to use an operational range of the sensors for detecting faulty data, the data that are fully within operational range of the sensor are usable data otherwise, they are faulty. This method succeeded to discard some faulty data. However, not all of data that are within the operational range are reliable. In [14] a list of common faults in sensor network is proposed for checking the gathered data against it. The authors provide also a list of some features of data and the monitored environment that can help in fault detecting process. In [15], the time correlation of the sensor is proposed to detect certain fault and determine the initial state of the node and then for taking the final decision if the node is defective or not, they used the spatial correlation. A distributed Bayesian approach used in [16], each node calculates its fault probability using its reading and the reading of its neighbors' nodes. This method requires enough number neighbors for obtaining correct diagnosed probability of nodes. Voting scheme in [17]–[19] proposed for detecting faulty sensors in WSN with distributed architecture; each node exchanges its measured values with its neighbors for executing sensor fault detection algorithm. This method requires at least four neighbors for achieving high detection accuracy. Trend correlation and the median are adopted in [20] for detecting sensor fault in WSN. Each sensor node detects its faults by calculating the trend correlation between its data series and those of its neighboring nodes. For supporting the fault detection, the sensor nodes calculate also the median value of the sensed data received from their neighboring nodes. To trigger the fault detection process toward improving the fault response time, there is a self-starting mechanism based on the cubic exponential smoothing prediction method implemented in each sensor node. All calculations done at the level of each sensor node. Although, these calculations are low in terms of complexity, they consume the low and limited energy of the nodes during the communication and calculation process for executing fault detection algorithm. This energy consumption makes the mechanism not efficient. Yarinezhad and Hashemi [21] considers that a sensor node is composed of five components which are: battery, sensor, receiver, transmitter, and microcontroller circuits. The failure of one of these components does not mean that the node cannot be reused in network activities. Based on hardware conditions, a cellular learning automaton that is implemented within each node assign a status to it. This status can be normal, traffic, end or dead. Based on the status, the nodes are used in the network. This approach succeeds to reuse faulty sensor node. However, implementing machine learning in sensor nodes is not recommended for these devices with limited energy and computation capacity. Table 1 presents a summary and comparison of the previous discussed works. Most of the approaches used in the previously mentioned works require a hardware redundancy which mean, each node should have more than one neighbor and need to communicate with their neighbors for performing a correct fault diagnosed. It is known that the critical problem of the sensor nodes is their limited energy source and should consume it wisely [22]. The sensor nodes consume their energy during their monitoring of the events, communication, and in data processing [23]. Adopting these approaches will drain early the batteries of the nodes. Our main contribution in this paper is to develop an approach for sensor FDI in a WSN that is easy to implement and needs less hardware redundancy compared to the above approaches cited, and also does not require a lot of communication between nodes to execute a FDI algorithm, as result saves the energy of the nodes.

Table 1. Summary of the previous works

Reference	Approach	Require multiple sensor nodes neighbors	The communication between sensor nodes is required
Ramanathan *et al.* [13]	Operational range	No	No
Jia *et al.*[15]	Temporal- Spatial correlation	Yes	Yes
Yuan *et al.*[16]	Bayesian	Yes	Yes
Chen *et al.* [17]	Majority voting	Yes	Yes
Jiang [18]	Majority voting	Yes	Yes
Marzat *et al.* [19]	Majority voting	Yes	Yes
Fu *et al.* [20]	Trend Correlation	Yes	Yes
Yarinezhad and Hashemi [21]	Cellular learning automata	Yes	Yes
This paper	Parity space	No	No

3. PROPOSED NODE DEPLOYMENT

The soil is a complex system characterized by the spatial heterogeneity of soil properties. Before distributing the sensor nodes in a farm, we propose to make a study of the farm that we want to cultivate and to divide it into equivalence zones where every zone has almost the same soil conditions [24]. In each zone we plant two sensor nodes measuring the same quantity in soil with the same depth as depicted in Figure 1, to get redundant measurements. The measurement of each sensor node writing as the following expression:

$$y_j(k) = c_j x(k) + f_j(k) \tag{1}$$

where $y_j(k)$ is the measurement vector at node j, $x(k)$ is a vector that represents the target quantities, c_j is the measurement matrix at node j that indicates which quantities are measured at node j and $f_j(k)$ is the fault vector.

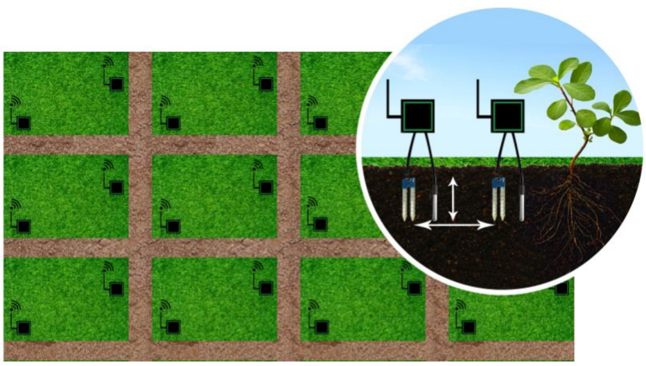


Figure 1. Sensors nodes distribution

4. PARITY EQUATION APPROACH

Parity space approach enables the detection and isolation of faults in a system by exploiting all useful redundant information that is available in the plant. We can classify redundancy into two steps: direct redundancy and analytical redundancy [25]. In this paper, we are focusing on direct redundancy.

We have direct redundancy when there are two or more sensors that measure the same quantity. Based on the instantaneous redundant measurement of the sensors we formulate a mathematical model as model as in (2):

$$y(k) = \begin{bmatrix} y_1(k) \\ y_2(k) \\ \vdots \\ y_j(k) \end{bmatrix} \tag{2}$$

FDI process can be divided in two categories: residual generation and decision making [26].

In the first step, we generate a residual (parity vector) based on mathematical model by multiplying the model (2) on the left by w:

$$r(k) = wy(k) \tag{3}$$

where w is a projection matrix that makes the residual independent of $x(k)$ and sensitive just to the occurrence of the fault in sensors and it defined based on measurement matrix (c) of the mathematical model and should satisfy the following relation:

$$wc = 0 \tag{4}$$

4.1. Fault detection

The residual signal is a fault indicator and through it, we can detect the presence of the fault in the WSN; when there is no fault in the WSN a residual equal to zero or near to zero and deviates from zero in the occurrence of the fault in sensors.

$$if \qquad f_j = 0 \qquad r = 0 \tag{5}$$

$$if \qquad f_j \neq 0 \qquad r \neq 0 \tag{6}$$

According to (3) and (4) the residual can be expressed as (7):

$$r(k) = wf(k) \tag{7}$$

4.2. Fault isolation

In the case of fault detection in WSN, we need to locate the presence of the fault i.e. locate the faulty sensor. To isolate the faulty sensor we multiply the transpose of each column of the parity matrix (w) by the generated residual as in (8):

$$FI_k = w_k^T r \qquad k = 1, 2, ...n. \tag{8}$$

This function measures the correlation of the residual vector with fault signature directions. If the fault is detected, the largest value of FI_k corresponds to the faulty sensor [27].

5. PROPOSED FDI ALGORITHM

For each zone (i) we calculate its residual. We have two sensor nodes measure the same quantity $x(k)$. The outputs of the sensors are the state variable; then, the measurement matrix c equal $[1 \quad 1]^T$. And the mathematical model of each zone (i) writes as (9):

$$y_i(k) = \begin{bmatrix} y_i^1(k) \\ y_i^2(k) \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} x(k) + \begin{bmatrix} f_i^1 \\ f_i^2 \end{bmatrix} \tag{9}$$

y_i^1, y_i^2 are the measurement of sensor 1 and 2 respectively in a zone (i) and f_i^1, f_i^2 is the fault that can affect sensor node 1 and 2 respectively. So according to relation 4, the parity vector w which is orthogonal to c equal $w = [1 \quad -1]$ and the residual equal:

$$r_i = y_i^1 - y_i^2 \tag{10}$$

To avoid false alarm, we made some modifications on our residual. In the real implementation, the residual value will be not null during healthy sensor operating mode, so we define the fault detection threshold by a test, which means; the threshold is the maximum residual value in healthy sensors operating mode.

Algorithm 1 The proposed FDI algorithm

Data: y_i^1, y_i^2 are the data received from sensor 1 and 2 respectively at an instant t to calculate the residual according to (10)
$r_i \leftarrow y_i^1 - y_i^2$;
if $|r_i| > h_d$ **then**
  /* if the residual higher than a threshold there is a fault detected and r_i stills in its value
  $r_i \leftarrow y_i^1 - y_i^2$
else
  /* if the residual lower than a threshold, r_i will take the value 0 $r_i \leftarrow 0$
end
/* if a fault is detected, fault isolation executed according to (8), The index of w_k that give the largest value in this multiplication $w_k^T r$, corresponds to the index of the faulty sensor. Where w_k is the k^{th} column of parity space matrix.

6. LABORATORY EXPERIMENTS

The performance of the FDI algorithm is confirmed by the experimental prototype shown in Figure 2. Soil temperature and soil moisture are the two variables required to be monitored for controlling the amount of the water needed in the irrigation system [28]. In this experiment, within an iron frame containing soil, we plant two soil temperature sensors (DS18B20) and two soil moisture sensors (YL69) in the same depth. These sensors are connected to Arduino microcontroller board and communicate via XBee module with the main central calculator placed near the iron frame.

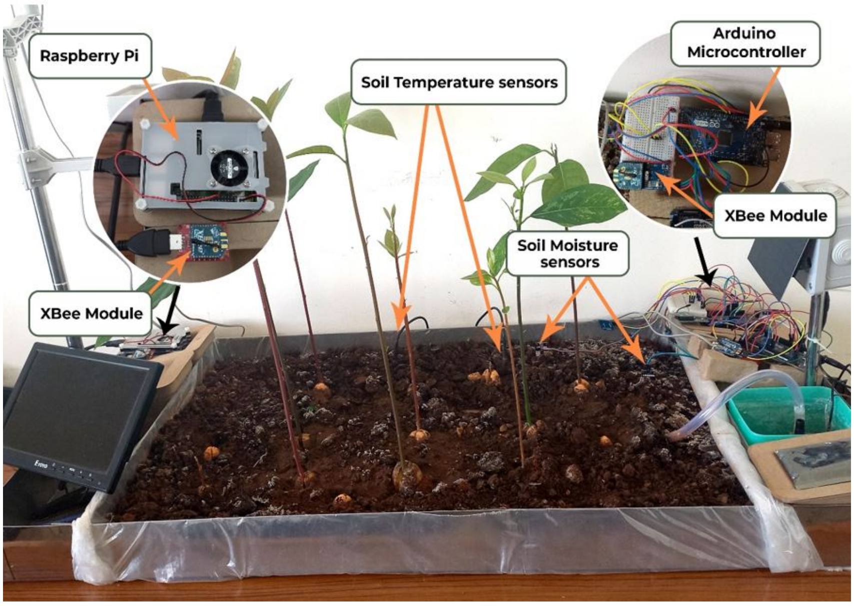
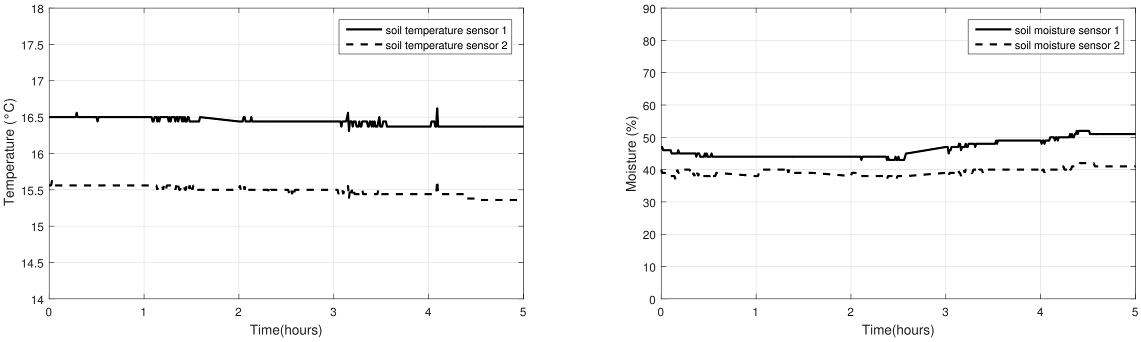


Figure 2. Experimental prototype of the wireless sensor network deployed in soil for measuring soil temperature and soil moisture

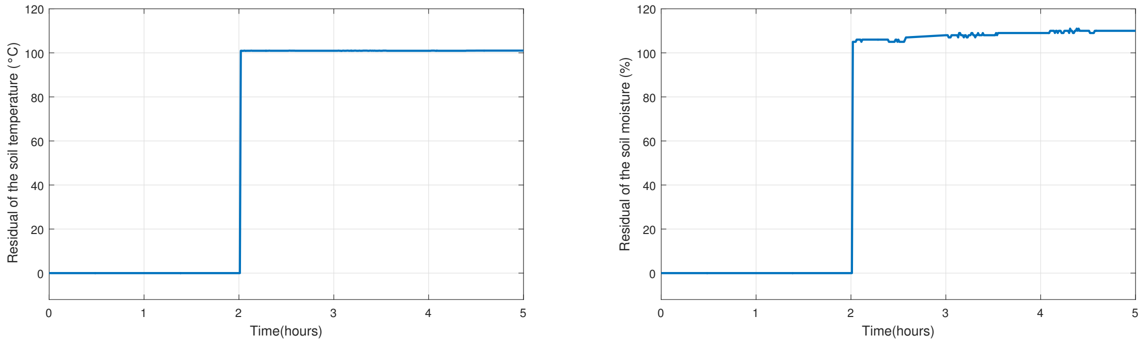
The sensors data will be sent directly to the main calculator for analysis. To analysis the gathered data, we implement our FDI algorithm on it. Before executing the FDI algorithm, we store the data sent by the sensors in their healthy mode for 5 hours with sampling time equals ts=60 s as it is shown in Figure 3(a) for soil temperature and in Figure 3(b) for soil moisture, in order to define the fault detection thresholds.



(a) (b)

Figure 3. Soil temperature and moisture recorded by the wireless sensor network in its healthy mode (a) soil temperature, (b) soil moisture

For each quantity $x(k)$, we generate a residual in healthy sensors operating cases, and the maximum level reached by the residual is the fault detection threshold. In our case, the fault detection threshold for soil temperature and soil moisture are respectively 1°c and 11%. After defining the fault detection thresholds, we inject a sensor fault of type 'abrupt' in each sensor and the FDI algorithm is used to detect and isolate the different faults. In the first experiment, we inject a sensor fault into the soil temperature sensor 1 and in the soil moisture sensor 1 at t= 2 h. Figure 4 shows the residual evolution of the soil temperature in Figure 4(a) and the soil moisture in Figure 4(b). We can see the impact of the sensor fault on the two generated residuals; the two residuals deviate from zero after fault injection. Our FDI algorithm succeeded to detect sensors faults immediately after their injection.

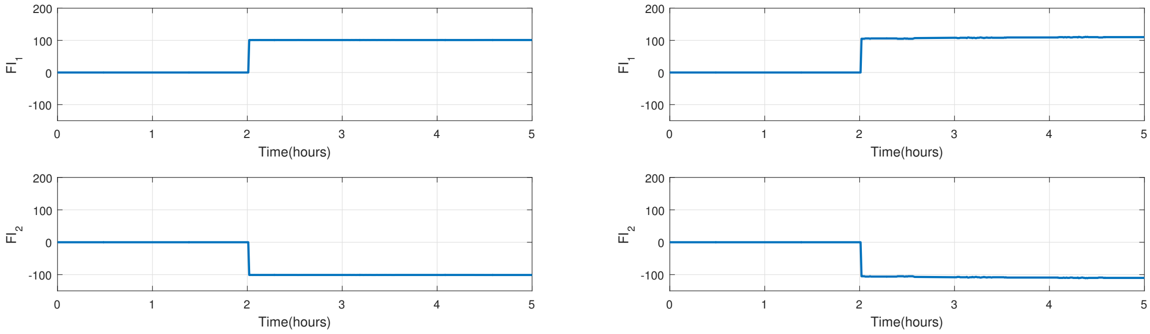


(a) (b)

Figure 4. Residual evolution (a) soil temperature and (b) soil moisture

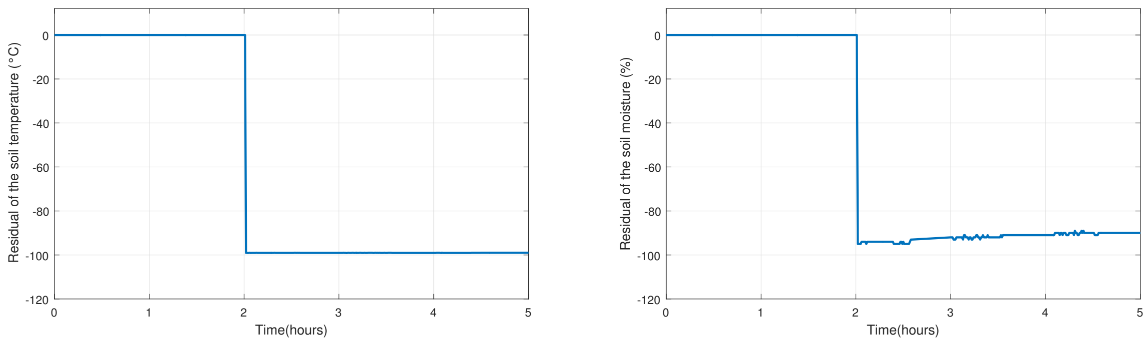
After fault detection, our algorithm calculates the correlation of the two residuals with each column of its parity matrix in order to isolate faulty sensor as explained in section 4.2. In Figure 5(a) , FI_1 is the correlation of the soil temperature residual with the first column of the parity matrix while FI_2 is the correlation of the soil temperature residual with the second column. And as can be seen, after fault detection (t= 2 h), FI_1 has the largest magnitude compared to FI_2; which means the faulty sensor is the soil temperature sensor 1. The same analysis for soil moisture sensors in Figure 5(b), after fault detection, FI_1 has the largest magnitude compared to FI_2; which means the faulty sensor is the soil moisture sensor 1.

In the second experiment, we inject a sensor fault into the soil temperature sensor 2 and in the soil moisture sensor 2 at t= 2 h. Figure 6 shows the residual evolution of the soil temperature in Figure 6(a) and the soil moisture in Figure 6(b). The two residuals deviate from zero after fault injection, which means there is a fault detected. In Figure 7(a), FI_2 has the largest magnitude compared to FI_1, which means the faulty sensor is the soil temperature sensor 2. The same analysis for soil moisture sensors in Figure 7(b), after fault detection, FI_2 has the largest magnitude compared to FI_1, which means the faulty sensor is the soil moisture sensor 2.



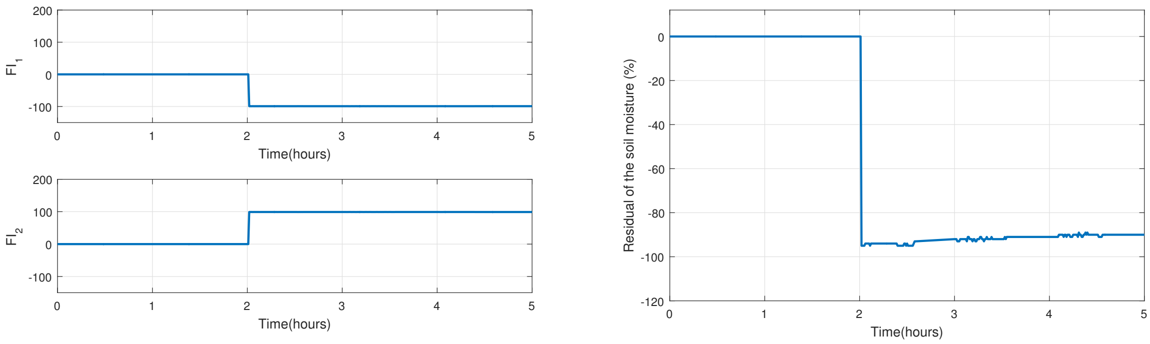
(a) (b)

Figure 5. Fault isolation process (a) soil temperature and (b) soil moisture



(a) (b)

Figure 6. Residual evolution (a) soil temperature and (b) soil moisture



(a) (b)

Figure 7. Fault isolation process (a) soil temperature and (b) soil moisture

7. CONCLUSION

In this work, we propose a sensor FDI algorithm for detecting and isolating sensor fault in WSN for smart irrigation. Our method aims at using less hardware redundancy. Each sensor node does not require a lot of communication between its neighbors for executing sensor FDI algorithm, as result saving the energy of the nodes and extending the life of the network. Our algorithm easy and fast in implementation and does not require model of the monitored system and depend only on instantaneous measurement of the sensors that measure the same quantity in the same zone. In our laboratory experiment, we planted two soil temperature and two soil moisture sensors in the soil to measure and send their data wirelessly to the main central calculator for analysis. First we define the fault detection threshold by a test for each quantity and after that we inject abrupt fault into each sensor for testing the effectiveness of our algorithm. Experimental results proved the effectiveness of our algorithm, each time we inject sensor fault, our algorithm immediately detect and isolate it.

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