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Fuzzy Logic Based Fault Diagnosis System for Wireless Sensor Networks

D. Deepika, Dr. S. Vasundra
Department of CSE, JNTU Anantapur,
Andhra Pradesh, India

Abstract— Fault diagnosis systems (FDSs) are tools designed to detect, isolate, identify, and, possibly, mitigate the occurrence of faults affecting complex systems. This paper aims to use fuzzy logic fault diagnosis for clustering the faults. Fuzzy logic system has an advantage of inbuilt cluster identification which doesn't supported by any other FDSs. By this inbuilt clustering the identification of faulty clusters can be done very quickly compared to the other systems by which the time taken to diagnose the faults will be reduced greatly. This paper focuses on router selection based on the energy problem, and identifying and localizing the fault nodes using the cluster groups. Further the system is tested for accuracy of fault localizations

Keywords— Fuzzy logic, cognitive FDS, Fault Dictionary, Evolving clustering, Adaptive learning

I. INTRODUCTION

Wireless sensor networks (WSNs) consist of a large number of distributed autonomous sensors developed to monitor physical and environmental conditions. Each sensor is capable of sensing, signal processing, and communicating wirelessly. WSNs can also be installed at low cost because wire installation is no longer necessary. This provides a great incentive for WSN adoption in large-scale systems in which monitoring is traditionally accomplished by wired sensors, such as in structural health monitoring and environmental monitoring systems.

For example, wire installation in structural health monitoring system accounts for about 25% of the total system cost and 75% of the installation time. The high mobility and random deployment ability of WSNs are opening a range of new applications that had been impractical in the past such as animal tracking and battle field surveillance. The ubiquitous computing paradigm adoption is accelerating with the help of wireless sensor technologies, whereby the physical world instrumented with pervasive networks of sensor-rich embedded systems. These systems will respond to our actions quickly and autonomously while blending into the background without people noticing them. This vision of the future has recently been termed the internet-of-things, or IoT.

To maintain small sizes and low costs, the electronics and enclosures of wireless sensors tend to be low cost thereby leaving them vulnerable to experiencing faults and failures. Moreover, the harsh environments in which WSN are usually deployed also increase the chances of abnormal sensor behavior. Therefore, wireless sensors in WSNs are more prone to error than traditional (wired) sensors. Incorrect measurements from malfunctioning sensors not only deteriorate the ability of the network to accurately take measurements but also can lead to wrong decisions which can be hazardous. Because WSNs consist of numerous sensors and these sensors are usually difficult to access after deployment, automated malfunction diagnosis capability would be an indispensable tool in maintaining the functionality and quality of the WSN.

System malfunction diagnosis has long been an important research topic in the field of control theory. The sensor malfunction diagnosis for WSNs, however, has unique challenges and thus requires further study. The two major new challenges of sensor malfunction diagnosis in WSNs are:

- A WSN usually contains a large number of sensors. These sensors can generate huge amounts of data that can be difficult for diagnosis algorithms to manage and process. Consequently, malfunction diagnosis algorithms must be both efficient and scalable for large WSNs.
- Each sensor usually has a limited amount of energy, which can constrain its operation. Aggregating data from wireless sensors and transmitting data sets to powerful base stations for malfunction diagnosis is not desired because of the significant communication energy required to do so. Therefore, diagnosis algorithms are required to be energy efficient by minimizing communications and distributing computing workload across the network.
- ***Energy efficiency*** – Generally batteries are used for providing power to sensors. When large numbers of networks of sensors are deployed, they are probable to run unattended for long periods of time. Designing energy-efficient methods that conserve the battery may well extend the lifetime of an application by months. Energy management techniques are to be implemented at all of the networking layers, from the application layer to the physical layer, and for variety of applications.
- ***Fault tolerance –*** In untimely generations of networked sensors, there are high failure and malfunction rates. In the majority sensor applications, it is not possible for a human to physically go over a region to repair and replace nodes. A considerable percentage of sensor nodes may stop working when deployed in hostile

environments. Therefore, algorithms must be provided by the system so that the application continues running without disruption when nodes become faulty or die.

- ***Localization*** – By means of wireless sensor networks to track or locate things is an application that is gaining much attention lately. There are various sensor network protocols and applications that imagine every node knows its location. How is this possible? If every node were prepared with a GPS component, both the energy and financial of a large sensor network would become very expensive. If a minute fraction of the nodes are aware of their location, is it possible for the left over nodes to discover their location?

II. EXISTING FDSs

In the past decade, many studies have developed sensor fault diagnosis methods. However, only a few of them are tailor-made for WSNs and take WSN energy constraints into account. Sensor fault diagnosis contains three main stages.

- The first stage, malfunction detection, refers to the detection of whether malfunctioning sensors exist in the network. This stage may not necessarily point out which sensors are abnormal.
- The second stage, malfunction isolation and malfunction type identification, refers to the isolation of abnormal sensors and the identification of the malfunction type that is occurring in the identified sensor.
- The third stage, malfunction recovery, refers to the automatic correction of the detected errors. Each stage is increasingly difficult to achieve. Hence, not all malfunction diagnosis methods achieve all three stages of analysis.

Most of the model-based methods require a complete observation of the system; thereby they are usually implemented as a centralized method. On the other hand, the simple assumptions used in model-free methods can be easily implemented distributive. As a result, most of the existing methods are either centralized model-based methods (e.g., Li et al. [1]); Dunia et al. [2]; Jiang [3]).

Kobayashi et al. [4] proposed a centralized sensor fault diagnosis method that uses a bank of Kalman filters. Both methods assume that the system model is linear, and they formulate the model as a state space model. For a network of N sensors, an N-Kalman filter system is established such that the i^{th} Kalman filter is based on all but the i^{th} sensor. Assuming that there is only one faulty sensor in the network, exactly one Kalman filter (out of the N Kalman filters) behaves differently from the others. Therefore, the faulty sensor can be detected and isolated. The difference between Da's method and Kobayashi's method is the way they measure the discrepancies between the Kalman filters. When the state space model is accurate, both methods give accurate detection results.

Li et al. [5] relaxes the at-most-one-faulty-sensor constraint by introducing reference sensors. Reference sensors refer to sensors that are known to be functioning normally during the fault detection process. Li's method requires the number of reference sensors to be more than the number of uncertain sensors (i.e., those in unknown fault state). A relationship between each uncertain sensor and the reference sensors can be found based on the state-space-model of the underlying system. (In order for the relationships to be existing, the method also has a special restriction on the feed-through matrix D in the state-space model.) With measurements of reference sensors, the output of an uncertain sensor can be predicted. If the observed measurements of the uncertain sensor do not agree with the predicted value, the uncertain sensor will be diagnosed as faulty. Although this method allows more than one faulty sensors exist in the system, it also increases the operation cost as reference sensors are expensive to maintain.

Jiang et al. [6] suggested a model-based method which distinguishes sensor faults from monitored system faults and detect abnormal changes in system time constants (Liptak [7]) and gains in both sensor system and monitored system. This method assumes the normal state-space model of the system and sensor dynamics is known and the monitored system has much smaller time constant than the sensor systems. During the fault detection process, a window of the sensor measurements and system inputs are used to identify system dynamics by subspace method. If the identified model shows discrepancies from the normal model in slow dynamics, a degradation of the monitored system is concluded. Similarly, if the identified model shows discrepancies in fast dynamics region, a degradation of the sensor is concluded. The identified system model is also used to calculate the changes in the gains of the system and the sensor such that the correct gain of the sensor measurements can be corrected.

III. PROPOSED FDSs

This paper uses a fuzzy logic based FDSs where the detection of faults is automatic. Means there will be no user intervention in any manner. The process of FDSs in the proposed method is followed by finding and rectifying the following faults:

- Best Router Selection
- Best Cluster Node Selection
- Fault cluster node localization

Any Sensor Network basically encounters three types of faults:

- Router failures
- Node Failures
- Malicious Nodes

The first two categories of the faults are occurred due to lack of energy at that particular transmission or the router or the node will not be available at that present time. So any FDSs must ensure the appropriate verification of the router current status and the energy level of that router and cluster nodes.

The proposed system utilized a fuzzy logic scheme so that the automation process will be speeded up and the faulty nodes are localized very efficiently.

A. Router Diagnosis:

This paper tests the condition of the router weather the router has enough energy or not and then the status (ON/OFF) of the router is verified. The status verification is important as the router is in OFF state then the data will not be transmitted further and if the router has less energy than data loss occurs. The process of router diagnosis is depicted below.

Step 1. The Service provider sends a data to some destination through the main terminal.

Step 2. The router diagnosis verifies two conditions weather the status is ON/OFF. If the status is OFF then the test terminal verifies the next router sequentially.

Step 3. If the router status is ON then the terminal verifies the energy state if the energy of that router is sufficient then that router is selected for data transmission.

Then the router diagnosis terminates and then the transmission control is forwarded to the cluster group of nodes for further diagnosis. The process of router selection is depicted in figure 1.

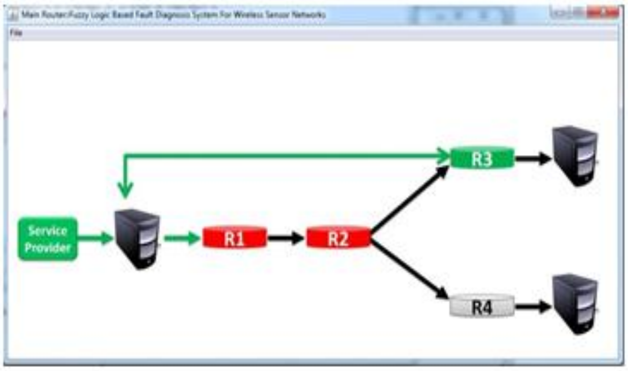
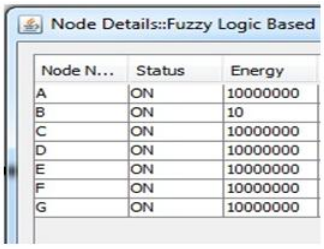


Fig 1: Router Selection Process

As the figure clearly depicts that the router R1 and router R2 are not selected and R3 has been selected due the status and energy levels which are depicted in figure 2.



Node Details::Fuzzy Logic Based

Node N...	Status	Energy
A	ON	10000000
B	ON	10
C	ON	10000000
D	ON	10000000
E	ON	10000000
F	ON	10000000
G	ON	10000000

Fig 2: Router Details

The routers R1 and R2 status are in OFF so the two routers are not considered for transmission.

B. Cluster Node Diagnosis

The process of router diagnosis is applied to select the best path between the cluster nodes. The nodes are also diagnosed for status and energy levels. If the particular node is in OFF state or the energy of the node is less than the threshold then that node will be considered as fault node and eliminated as outlier. The outlier node is represented in red color and the outlier process is depicted in figure 3.

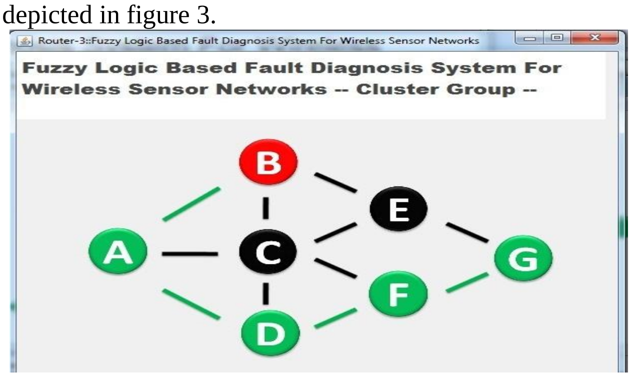
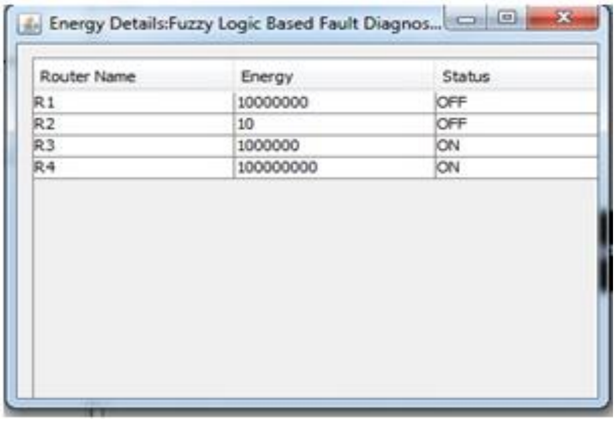


Fig 3: Node Selection

As the figure clearly depicts that the node B is represented as outlier due to that the node energy capacity is less than the threshold value and the values are depicted in figure 4.



Router Name	Energy	Status
R1	10000000	OFF
R2	10	OFF
R3	1000000	ON
R4	100000000	ON

Fig 4: Node Details

Even the node B is in ON condition due to less energy level the node is eliminated as outlier.

C. Fault Localization

The process of fault diagnosis has to detect the faulty nodes which is either been attacked or the node is under adversary observation. The fuzzy logic algorithm uses a signature comparison scheme where the nodes are signed with a pre-defined signature and if any adversary tries to access that particular node then the signature will be modified and then the node will be detected as malicious. The nodes with status of ON and the energy levels satisfying the threshold value are also be localized the localization is depicted in figure5.

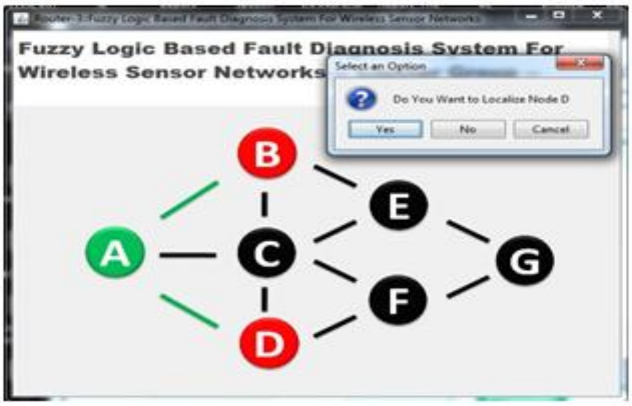


Fig 5: Node Localization

The figure 4 has the details of the nodes see that the node D is in ON state and the energy is also good but in figure 5 the node is represented as faulty. The user then decides whether to localize that node or not.

IV. ANALYSIS

This paper introduced the concept of fuzzy logic into the FDSs with effective capabilities for detecting as well as eliminating the possible occurrences of nodes. The only metric that has to be considered is that how the system detects and eliminates the faults i.e., the accuracy of fault localization.

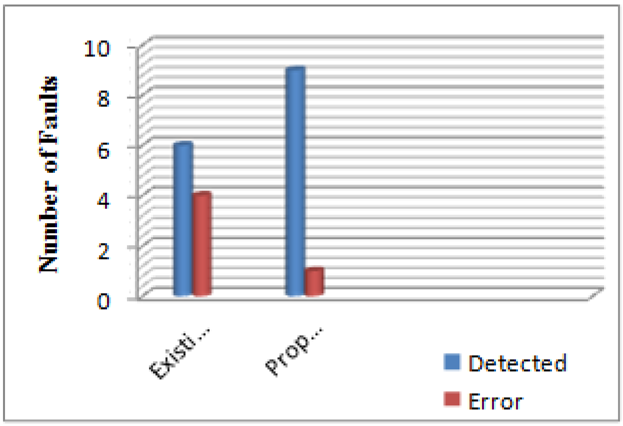


Fig 6: Accuracy Comparison

This paper is an extension of work in [1] so for comparison the results in [1] are taken and depicted in the figure 6. As the results clearly depict that the faults detected by the proposed system are more accurate than the existing system.

V. CONCLUSION

This paper aims to implement and self building fault diagnosis system based on fuzzy logic. The fuzzy logic is a basic clustering technique used to verify the cluster groups with the signatures. The proposed method diagnosis the basic WSNs fault occurrences like the router failures, node failures and the faulty nodes. Further this paper provides the user with the flexibility for changing the energy and status of the routers and nodes dynamically. The analysis results are also promising compared to the FDSs proposed in the existing approach.

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