Recognition Of Faulty Node Detection Using Fuzzy Logic In IOT

D Ganesh Kumar, N.Insozhan,
Dr.V.Parthasarathy

Abstract: Internet of Things (IoT) is the expansion of connectivity to all the physical objects in our life. Wireless Sensor Network (WSN) is a group of nodes containing self-sustaining sensors, which senses surrounding conditions. Interconnection of these sensors into IoT will be a big revolution in growing sensor technology. The growth of sensor nodes, leads to the increase of faulty nodes count. This by default affects the Quality of Service (QoS) of WSN based IoT. Therefore by detecting the faulty nodes and reusing them enhances the quality of monitoring to a large extend. Due to the difficulty in identifying the internal status of sensor nodes, it is important to develop algorithms to find faulty nodes. The existing fault detection algorithm yields low accuracy. In this work, three input fuzzy inference system (FIS) is used, which identifies hardware faults like, transmitter circuit condition, receiver circuit condition and battery condition. The simulation results show that the proposed scheme increases the detection accuracy when compared to the conventional schemes.

Index Terms: Internet of Things (IoT), Receiver circuit condition, Transmitter circuit condition, Battery condition, Wireless Sensor Network (WSN).

I. INTRODUCTION

IoT is a system of interconnected computing devices, different types of machines, objects, creatures or persons that are equipped with individual identifiers, having the ability to communicate over a network without involving person-to-person or person-to-computer. While IoT does not infer a particular communication technology, wireless communication technologies will play a large role, and specifically WSNs. WSN is a network specially distributed with autonomous sensors which monitors the varying physical condition of environment. These sensors comparatively communicate the sensed information to another location. The small, inexpensive and low power nature of sensors make easy instalment in any kind of environment. Integration of these objects into IoT will be a big revolution of WSNs. Sensor nodes uses battery for power source. These sensor nodes with limited energy are mostly placed in harsh environment. The sensors which were subject to failure results in sensing data, processing and communicating it with errors. Thus, node failure ends up in network failure. Therefore, faulty node detection is a very important issue in WSN. Researches were conducted to study fault detection issue in WSNs. Majority of the fault analysis methods exhibit identical patterns. Conventional researches used the concept of mean, majority voting and median to identify faults in sensor nodes [1]. A fault detector for WSN is proposed in [2]. Based on rank the nodes were separated and the faulty nodes identified were disabled during the process and by doing so the QOS can get affected due to the loss of faulty Nodes. Therefore by reusing the faulty nodes we can improve the QOS greatly. This process uses Naïve Bayes [3] frame work. But this scheme faces problems in hotspots. In [4], a FIS is used to detect the faults in WSN. This strategy is based on modelling the sensor nodes by Takagi–Sugeno–Kang (TSK) FIS. Here, measurement of sensor node is approximated by a function of the measurement of the neighbouring sensor nodes. Due to lack of node details, this approach faces low detection accuracy. At the time of diagnosis, sizable numbers of non-faulty nodes are misinterpreted as faulty. In [5], a faulty node detection method based on RTD (Round Trip Delay) is proposed. This scheme is energy efficient and responsive. This scheme enhances the efficiency of fault detection. The idea behind this scheme is that each node informs its neighbors before their energy gets exhausted. Here, the fault condition of individual nodes is known to all nodes in the network. In [6], a new distributed Bayesian algorithm (DBA) is proposed for data fault detection. The probability of faults in sensor nodes are obtained using Bayesian network. Border nodes positioned in the network are utilized for adjusting the fault probability. This further enhances the correctness of fault probability by reducing the negative effect of sizable number of faulty nodes. An energy efficient distributed fault identification algorithm for WSN is proposed in [7]. The proposed scheme finds both hardware and software faults present in sensor nodes. This algorithm is distributed, self-detectable, also detects well known Byzantine faults like stick at 0 , stick at 1, and arbitrary data. Here, individual sensor node collects information from its neighbors and utilize the calculated mean to identify the faults in sensor nodes. In this algorithm, the detection accuracy and false alarm rate for lower degree and less fault probability are nearly one and zero, respectively. But the performancedegrades for higher fault probabilities. We can wrap up that the conventional methods points on distinct characteristics. In [8], a distributed faulty node detection and classification (FNDC) scheme for WSN is proposed, which identifies and reuses faulty sensor nodes based on the condition of hardware circuit. Fuzzy logic used, increases the detection accuracy and minimizes false alarm rate. The manuscript is arranged in the following order: Section II describes different hardware faults and section III describes fuzzy logic for faulty node detection. The algorithm is

- *D.Ganesh Kumar, Asst.Prof., Velt ech Multi Tech is currently pursuing Ph.d in Information Technology in Anna University, Chennai,India, PH-9894433922. E-mail: ganeshprivate@gmail.com,*
- *N.Insozhan Asst.Prof., Velt ech Multi Tech is currently pursuing Ph.d in Information Technology in Anna University, Chennai,India, E-mail: sozhan.me@gmail.com,*
- *Dr.V.Parthasarathy is working as Professor .Email- sarathy.vp@gmail.com*

proposed in section IV and results are discussed in section V. The manuscript is concluded in section VI.

II. FAULT DIAGNOSIS

Faults are classified into hardware and software, which occurs due to dense physical environment. Some of the sensor nodes may transmit some incorrect messages at a particular time while they sense the environment correctly. These types of sensor nodes are software faulty nodes. Hardware faults are permanent or static. Distinct parts of node's hardware get damaged due to hardware faults. Because of this, the transmitted data cannot reach cluster heads (CHs) and base stations (BSs). The major hardware circuit faults are transmitter circuit fault, receiver circuit fault, sensor circuit fault and battery fault.

A. Transmitter circuit fault

The status of transmitter circuit of each node is monitored by CH. All the member nodes of cluster send 200 bits of lifeline message to CH in the particular time duration. After receiving lifeline message from member nodes, CH acknowledges member nodes with lifeline-ok message of the same size. Transmitter circuit efficiency is expressed by

$$g(\phi) = \frac{\omega}{S_t} \qquad (1)$$

where ω is the lifeline message count collected by the CH and S_t is total time expend by the WSN. Based on the value of function, CH decides about the member node's transmitter condition. If the value is less, CH identifies node has transmitter circuit fault. Else the condition is fine.

B. Battery fault

Every node itself can detect the battery fault based on remaining energy of individual node. Energy consumed by i^{th} sensor node for transmitting one message is defined by the expression:

$$\nu_i = \begin{cases} \left(\tau_t + \tau_{d1}\rho^2\right)L_i & ;\rho < d_0 \\ \left(\tau_t + \tau_{d2}\rho^4\right)L_i & ;\rho \geq d_0 \end{cases} \qquad (2)$$

Where τ_t [J/bit] is per bit energy consumed to run transmitter electronics. The $\tau_{d1}\left[J/bit/m^2\right]$ and $\tau_{d2}\left[J/bit/m^4\right]$ denotes energy utilized for the amplifier in free space and multipath model where $d_0 = \sqrt{\frac{\tau_{d1}}{\tau_{d2}}}$. ρ is the average transmission distance from CH to sensor nodes and L_i is the size of message send by each node. The energy consumed by i^{th} sensor node for one message reception is defined by the following expression:

$$\Lambda_i = (\varepsilon_r L_i) \qquad (3)$$

Where $\varepsilon_r\left[J/bit\right]$ denotes the per bit energy consumption by
the receiver electronics.

C. Receiver circuit fault

Node itself can detect the faults in receiver circuit. The efficiency of receiver circuit is defined as

$$g(\phi) = \frac{\mu}{S_t} \qquad (4)$$

Where μ is the total number of lifeline-ok messages received
by sensor nodes.

III. FUZZY LOGIC FOR FAULTY NODE DETECTION

In this work, the sensor node's hardware status is evaluated by fuzzy logic rules. Three input FIS for faulty node detection is displayed in Fig. 1. Fuzzy logic system has four parts namely fuzzifier, FIS, fuzzy rule base and defuzzifier. Battery, transmitter and receiver conditions of each sensor nodes are given as the inputs for FIS. The output of FIS shows the condition of individual sensor nodes. The output of FIS may be a normal node, end node or dead node.

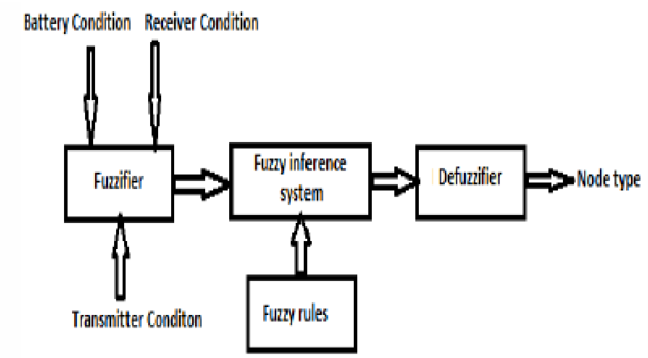

Fig. 1. Three input FIS for faulty node detection

If a node has not any fault in hardware circuit and its hardware circuit behaving properly, then that node is classified as normal node. So any type of job can done by normal node. If a node has fault in its receiver circuit, then it is classified as end node. Using sensor circuit, the end node can sense data and transmit it to neighbouring nodes. But it cannot obtain any data from others. If node's battery power and/or transmitter is faulty then is classified as dead node. We define three linguistic variables for each fuzzy input. The linguistic variables defined for input and output are as follows: Transmitter Condition = {Less, Moderate, High}
Battery Condition = {Poor, Normal, Good}
Receiver Condition = {Less, Moderate, High}
Node Decision = {Normal node, End node, Dead node}
The membership functions developed for the transmitter condition are given by

$$\beta_{TL}(a)=\begin{cases}1 & ;a<0.16\\ \dfrac{0.33-a}{0.17} & ;0.16\le a\le 0.33\\ 0 & ;a>0.33\end{cases} \tag{5}$$

$$\beta_{TM}(a)=\begin{cases}0 & ;a<0.16\\ \dfrac{a-0.16}{0.17} & ;0.16\le a\le 0.33\\ 1 & ;0.33\le a\le 0.5\\ \dfrac{0.66-a}{0.16} & ;0.33\le a\le 0.5\\ 0 & ;a>0.66\end{cases} \tag{6}$$

$$\beta_{TH}(a)=\begin{cases}0 & ;a<0.5\\ \dfrac{a-0.5}{0.16} & ;0.5\le a\le 0.66\\ 1 & ;a>0.66\end{cases} \tag{7}$$

Here $a\in[0,1]$ The corresponding membership plot is displayed in Fig. 2.

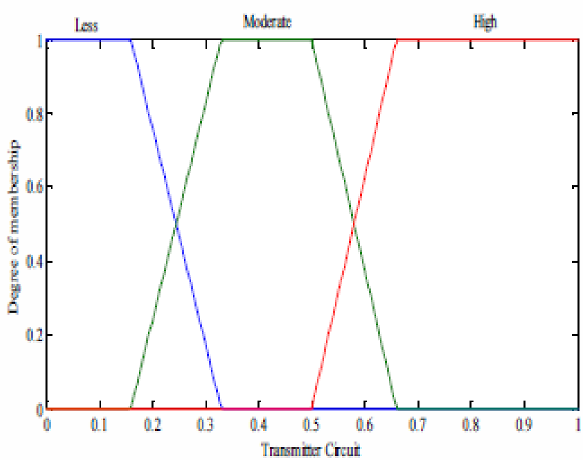

Fig. 2. Membership plot for Transmitter Condition

The membership functions developed for the battery condition are given by

$$\beta_{BP}(b)=\begin{cases}1 & ;b\le 0.0976\\ \dfrac{0.3232-b}{0.2256} & ;0.0976<b<0.3232\\ 0 & ;b\ge 0.3232\end{cases} \tag{8}$$

$$\beta_{BN}(b)=\begin{cases}0 & ;b\le 0.0976\\ \dfrac{b-0.0976}{0.2256} & ;0.0976\le b\le 0.3232\\ 1 & ;0.3232\le b\le 0.5488\\ \dfrac{0.7744-b}{0.4512} & ;0.5488\le b\le 0.7744\\ 0 & ;b\ge 0.7744\end{cases} \tag{9}$$

$$\beta_{BG}(b)=\begin{cases}0 & ;b\le 0.5488\\ \dfrac{b-0.5488}{0.2256} & ;0.5488<b<0.7744\\ 1 & ;b\ge 0.7744\end{cases} \tag{10}$$

Here b belongs to [0,1]. The corresponding membership plot is displayed in Fig. 3.

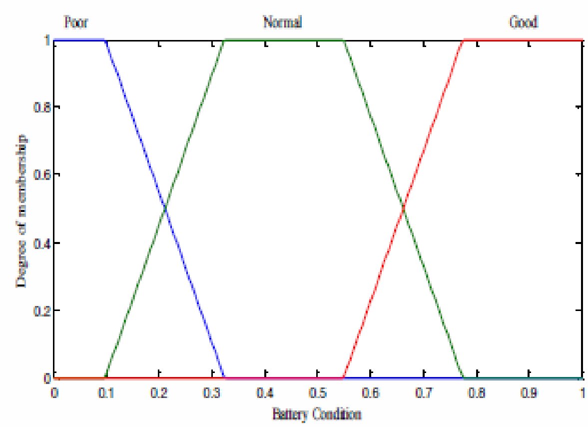

Fig. 3. Membership plot for Battery Condition

The membership functions developed for the receiver circuit are given by

$$\beta_{RL}(c)=\begin{cases}1 & ;c<0.16\\ \dfrac{0.33-c}{0.17} & ;0.16\le c\le 0.33\\ 0 & ;c>0.33\end{cases} \tag{11}$$

$$\beta_{RM}(c)=\begin{cases}0 & ;c<0.16\\ \dfrac{c-0.16}{0.17} & ;0.16\le c\le 0.33\\ 1 & ;0.33\le c\le 0.5\\ \dfrac{0.66-c}{0.16} & ;0.33\le c\le 0.5\\ 0 & ;c>0.66\end{cases} \tag{12}$$

$$\beta_{RH}(c)=\begin{cases}0 & ;c<0.5\\ \dfrac{c-0.5}{0.16} & ;0.5\le c\le 0.66\\ 1 & ;c>0.66\end{cases} \tag{13}$$

Here c belongs to [0,1]. The corresponding membership plot is displayed in Fig. 4.

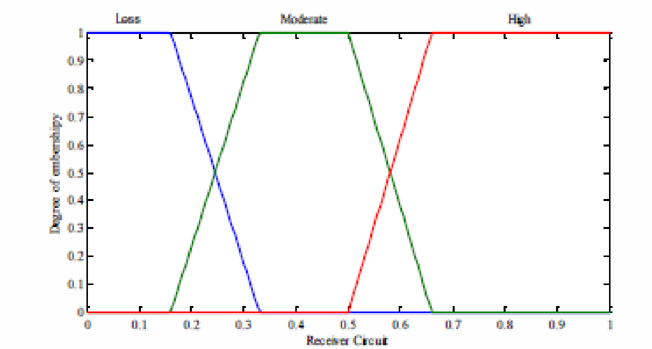

Fig. 4. Membership plot for Receiver Condition

The defuzzifier is based on the centroid method [9-11]. The defuzzifier output is node decision. The decision includes normal node, end node and dead node. The membership function developed for the node decision are given by

$$\beta_{Dead}(d)=\begin{cases}1 & ;d<1\\ \dfrac{d-1}{3} & ;1\le d\le 4\\ 0 & ;d>4\end{cases} \tag{14}$$

$$\beta_{End}(d)=\begin{cases}0 & ;d<1\\ \dfrac{d-1}{3} & ;1\le d\le 4\\ 1 & ;4\le d\le 6\\ \dfrac{8-d}{2} & ;6\le d\le 8\\ 0 & ;d>8\end{cases} \tag{15}$$

$$\beta_{Normal}(d)=\begin{cases}0 & ;d<8\\ \dfrac{d-8}{10-8} & ;8\le d\le 10\\ 1 & ;d>10\end{cases} \tag{16}$$

Here d belongs to [0,1]. The corresponding membership plot is displayed in fig.5

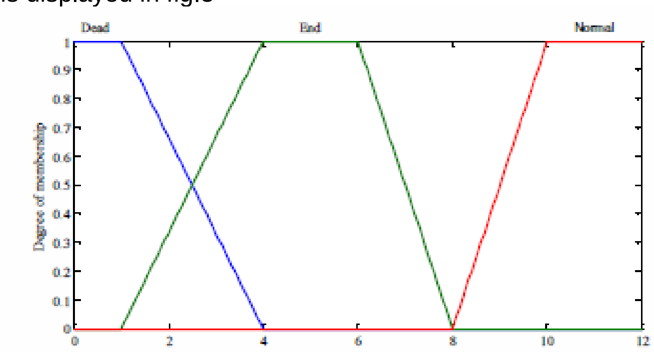

Fig. 5. Membership plot for node decision

IV. PROPOSED ALGORITHM

Based on three membership functions, 27 fuzzy rules are developed. These are displayed in Table 1. These rules help in decision making process.

TABLE I
FUZZY RULE BASED DECISION MAKING

Rule No	Transmitter Condition	Battery Condition	Receiver Condition	Node decision
0	Less	Poor	Less	Dead
1	Less	Poor	Moderate	Dead
2	Less	Poor	High	Dead
3	Less	Normal	Less	Dead
4	Less	Normal	Moderate	Dead
5	Less	Normal	High	Dead
6	Less	Good	Less	Dead
7	Less	Good	Moderate	Dead
8	Less	Good	High	Dead
9	Moderate	Poor	Less	Dead
10	Moderate	Poor	Moderate	Dead
11	Moderate	Poor	High	Dead
12	Moderate	Normal	Less	End
13	Moderate	Normal	Moderate	Normal
14	Moderate	Normal	High	Normal
15	Moderate	Good	Less	End
16	Moderate	Good	Moderate	Normal
17	Moderate	Good	High	Normal
18	High	Poor	Less	Dead
19	High	Poor	Moderate	Dead
20	High	Poor	High	Dead
21	High	Normal	Less	End
22	High	Normal	Moderate	Normal
23	High	Normal	High	Normal
24	High	Good	Less	End
25	High	Good	Moderate	Normal
26	High	Good	High	Normal

The following steps are executed to identify the status of each sensor node.
1. The transmitter, receiver and battery conditions of each sensor node are measured.
2. These are given as the input for FIS.
3. The FIS decides about each node based on Table I.

V. SIMULATION RESULTS AND DISCUSSION

The settings considered for the simulation study are listed in Table II.

TABLE II
VALUES USED IN SIMULATIONS

Symbol	Parameter	Value
	network area	$500\times500\text{m}^2$
	node size	$50-300$
	base station location	$(50,175)$
	sensing range	10 m
τ_t	energy spent by transmitter electronics	50 nJ/bit
ε_r	energy spent by receiver electronics	50 nJ/bit
τ_{d1}	required energy for the amplifier in free space	10 pJ/bit/m^2
τ_{d2}	required energy for the amplifier in multipath	0.0013 pJ/bit/m^4

In Fig. 6, False alarm rate vs. number of faulty nodes are compared for two different faulty detection schemes. False alarm rate is the proportion of number of non faulty nodes detected as faulty nodes to the number of non faulty nodes in the WSN. It is noted that, increase in the count of faulty nodes, increases the false alarm rate irrespective of detection scheme. For 300 faulty nodes, the proposed scheme shows an improvement of 12.5% in false alarm rate over faulty detection in WSN (FDWSN) scheme [12].

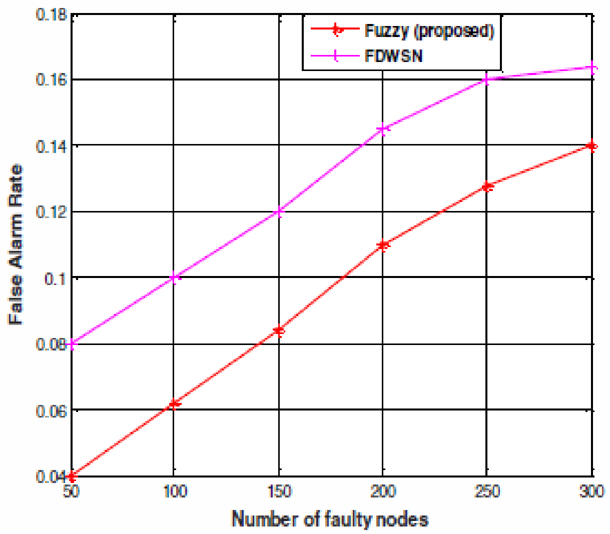

Fig. 6. False alarm rate vs. number of faulty nodes

In Fig. 7, detection accuracy vs. number of faulty nodes are compared for two different faulty detection schemes. Detection accuracy is the proportion of count of faulty sensor nodes identified to the count of faulty nodes within WSN. It is noted that, increase in the count of faulty nodes, decrease the detection accuracy. For 300 nodes, the proposed scheme shows an improvement of 9.5% over the FDWSN scheme.

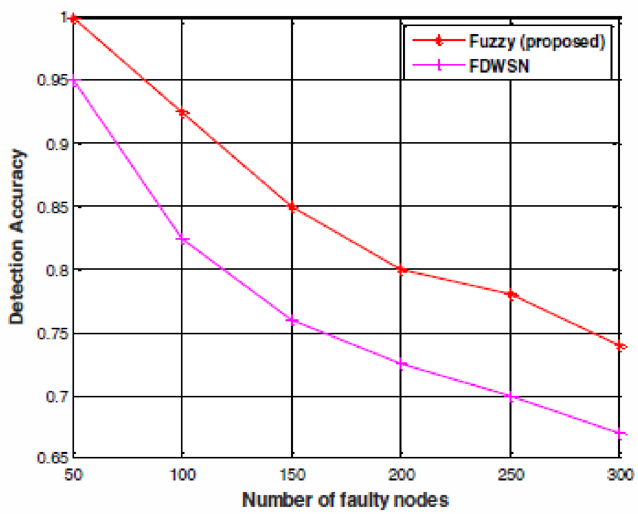

Fig. 7. Detection accuracy vs. number of faulty nodes

VI. CONCLUSION

A three input, fuzzy logic based faulty node detection scheme for WSN based IoT is proposed in this work. Through simulations, it is demonstrated that proposed scheme offers improved false alarm rate and detection accuracy performances over the conventional FDWSN scheme. In this work, we have considered smaller monitoring area and smaller number of nodes. As a future study, this work can be tested for large monitoring area with large nodes. The proposed scheme can also be tested for software faults in WSN.

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