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AN ACC APPROACH AND TUNED SUPPORT VECTOR MACHINE FOR ENHANCING QUALITY OF SERVICE AND EFFICIENT FAULT DIAGNOSIS RESPECTIVELY IN IOT-ENABLED WSN APPLICATIONS

Lavina Balraj,
Assistant Professor,
Department of Computer Science and Engineering,
St. Joseph College of Engineering, Sriperumbudur.
(lavinabalraj2020@gmail.com)

S.Gowsalya,
Assistant Professor,
Department of Computer Science and Engineering,
St. Joseph College of Engineering, Sriperumbudur.
(gowsalyasub@gmail.com)

Abstract

The advancement of the Internet of Things (IoT) technologies will play a significant role in the growth of smart cities and industrial applications. Network sustainability is considered as a significant characteristic for IoT based applications. Wireless Sensor Network (WSN) is one of the emerging technologies utilized for sensing and data transferring processes in IoT-based applications offers such network sustainability where WSN is acted as the subnets in the IoT model. However, heterogeneous faults like hardware, software, and time-based faults are the major determinants that affect the network stability of IoT based WSN (IWSN) model and also the multi- objectives like coverage, connectivity and energy consumption are required to improve the quality of service in IoT based WSN (IWSN) model. In this paper, the Adaptive Coverage and Connectivity (ACC) scheme is proposed to attain the efficient IWSN model. It employs two underlying methodologies in which the first method provides the optimal coverage to all target objects and its mathematical model guarantees the coverage rate. The second method deals with connectivity and energy consumption of the network. The experimental results manifest that, unlike existing schemes, the proposed ACC scheme can sustain the network for a prolonged time. And at the same time, a novel Energy-Efficient Heterogeneous Fault Management scheme has been proposed to manage these heterogeneous faults in IWSN. Efficient heterogeneous fault detection in the proposed scheme can be achieved by using three novel diagnosis algorithms. The new Tuned Support Vector Machine classifier facilitates to classify the heterogeneous faults where the tuning parameters of the proposed classifier will be optimized through Hierarchy based Grasshopper Optimization Algorithm. Finally, the performance results evident that the diagnosis accuracy of the proposed scheme acquires 99% and the false alarm rate sustains below 1.5% during a higher fault probability rate. The diagnosis accuracy rate is enhanced up to 17% as compared with existing techniques.

***Keywords*:** Fault diagnosis, Heterogeneous Faults, Internet of Things, Network Stability, Wireless Sensor Network, Multi-objective, Quality of service, ACC.

1.1 INTRODUCTION

Internet of Things (IoT) has advanced as a new prototype that consists of changed smart grid, smart city and smart home applications. It interlocks the objects to develop new smart service area, value-added services and real-time applications. IoT allows combination of several enabling technologies with different abilities like sensing, computing, monitoring, managing, storage and connectivity [2]. Communication and interconnection are considered as major challenging concerns for the efficient development of IoT. In addition, the mobility of objects is permitted in the IoT model where the creation of rule for mobility and routing management is also addressed during the development of the IoT model [3–7].

Usually, identifying coverage, network connectivity and energy consumption are significant challenges in most of the above-mentioned applications of IWSN [10]. Sensing coverage of a WSN indicates how well the nodes supervise an area of interest where they are placed. Further, coverage is the slow measure of the network sensing ability. Network connectivity of a WSN implies how well the sensors can communicate where it states the performance measure of the network communication ability. Another critical challenge of WSN is energy consumption due to its rechargeable battery constraints [12–14]. Therefore, the description of these three performance measures facilitates the better improvement of WSNs for various IoT based applications [15].

IOT has been projected as one of the most dominant existing technologies that includes several smart objects assembled to provide reliable information. Typically, the IoT architecture can be categorized into three layers: sensor, communication, and application layer. Finally, the application layer accords with human-machine interaction and evaluating the information. Here, the data is supervised by several network systems and engrossed through different physical devices. Now, IoT-based WSN (IWSN) integration becomes smarter for several applications such as smart agriculture, smart grid, remote health monitoring, and disaster detection [7]. These smart applications necessitate real-time analytics for systematic decision making and consistent network process. IWSN offers unrestricted storage and computation capability for efficient data analysis in smart applications [8].

In this paper, there are two underlying methods are implemented in the proposed scheme namely: Adaptive Coverage (AC) and Energy- Efficient Connectivity (EEC). The AC method is responsible for sensing coverage, whereas the network connectivity and energy consumption are managed by the EEC method. The primary features addressed in this work are prolonging the coverage rate, maintaining network connectivity, minimizing energy consumption and time complexity.

The E^2HFM scheme incorporates two methods: heterogeneous fault diagnosis and classification. Primarily, the heterogeneous fault diagnosis method employs three novel diagnosis algorithms to detect the different heterogeneous faults includes hardware, software, and time-based faults. Thereafter, these three diagnosis algorithms are formulated into a sequential process of the proposed E^2HFM scheme. Finally, the heterogeneous fault classification stage of the proposed scheme utilizes the Tuned Support Vector Machine (TSVM) to classify the faults according to the fault types.

The rest of the item is organized into several sections as follows. Section 2 considers the summary of the related work. Section 3 introduces the proposed Network model approach and E^2HFM scheme along with its underlying frameworks. The ACC scheme along with the mathematical model and performance evaluation is depicted in Section 4. Section 5 summarizes the simulation results and discussions. Finally, the conclusion and future work are described in Section 6.

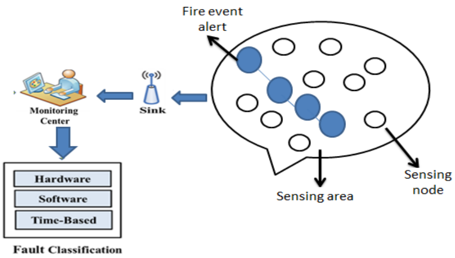


Fig. 1 Basic WSN architecture for forest fire detection and Heterogeneous Fault Management in IWSN

2. Related work

The following section offers a global review of the existing state-of-the-art schemes related to the connectivity, coverage and energy consumption problems of WSNs and at the same time heterogeneous fault diagnosis and classification issues of IWSNs. The sensing coverage problem can be considered as an optimization problem while sustaining network connectivity. Coverage is generally categorized into three main classes namely: target coverage, barrier coverage and area coverage [28, 29]. A comparison of several fault management approaches is summarized in Table 1.

In [17], the authors present a Monte-Carlo Markov Chain (MCMC) scheme to determine the sensing coverage of WSN. MCMC is stated to be the probability that the sensor network with multi-state nodes can effectively convey the coverage oriented sensed data to the mobile sink within a specified time. To save the battery energy and extend the lifetime of the network, nodes follow a random duty-cycling method. To minimize the coverage problem, the authors aim to establish a minimum number of nodes in the sensing area to satisfy the coverage requirements of the target objects [20]. Here, Sink and sensor Placement, Scheduling, Routing with Connected coverage (SPSRC) scheme has proposed. The scheme combines the decision for the position of sink and nodes, operating schedules of the distributed nodes and sensed information flow routes from every alive node to its allocated central sink for connecting the sensed coverage. Constructive Heuristic and Disjunctive Heuristic algorithms are employed to generate feasible solutions of the SPSRC scheme. The ma- jor problem with these two algorithms is that they allocate the responsibility of choosing alive nodes to the lower energy sensor nodes. This increases the number of dead node and the connectivity of the entire network iscollapsed.

The sensor nodes provide unpredicted responses owing to the extensive range of real-time applications and resource restrictions. This makes a variety of node and link failures in IWSN. A Node-Link Failure Fault Tolerance (NLFFT) scheme is presented to manage the faults caused either by sensor node or link failure during data communication [18]. The NLFFT scheme comprises two mechanisms: improved-handoff and quadratic minimum spanning tree mechanism. The improved-handoff mechanism establishes a way to identify the failure node caused by poor battery power. Then, the faulty node is replaced with appropriate neighbor nodes. The second mechanism deals with link failure and replaces the damaged edge with an alternative edge in the communication link. These two mechanisms facilitate the NLFFT scheme to achieve better accuracy and throughput. However, the selection of alternate edge develops the additional communication overhead and affects the network stability of IWSN.

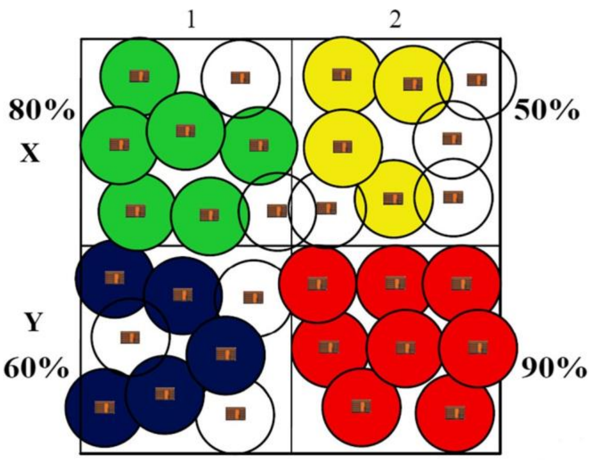
3 proposed ACC and faulty management scheme

A novel Adaptive Coverage and Connectivity (ACC) scheme is proposed to reduce the coverage, connectivity and energy consumption problems of WSN. It involves two efficient underlying methodologies namely: Adaptive Coverage (AC) method and Energy-Efficient Connectivity (EEC) method. The AC method focuses on offering optimum coverage rates to the entire sensing area which will increase the network lifetime of WSN. At the same time, the EEC method offers network connectivity among multiple sensor nodes that reduces the energy consumption and maximizes the network sustainability of WSN and also the proposed E^2HFM scheme involves two stages: heterogeneous fault diagnosis and heterogeneous fault classification. A detailed description of these two stages is demonstrated in the following sections. The framework of the proposed method is exposed in Figure 2. The framework incorporates the multiple heterogeneous fault diagnosis approaches into a sequential process of the proposed E^2HFM method in the IWSNs.

3.1 Adaptive coverage method

As discussed earlier, the area coverage can be categorized as full coverage and partial coverage. The full coverage refers to every point of sensing area is covered by at least one node and there arise overlapping among sensor nodes whereas some points are not covered in partial coverage. In the proposed work, dense coverage mode and sparse coverage mode are considered as full coverage and partial coverage respectively. Since dense coverage is stringent condition and costly, it should be utilized only if required.

Figure 3 states a generic model for adaptive coverage. The figure depicts an area of interest fragmented into four regions (X1, X2, Y1, Y2) to acquire different levels of sensing coverage. For example, Y2 has a 90% coverage necessity being a crucial sensing area. Instead, supervising 50% of X2 is sufficient. Thus, IWSN applications may need network configurations with different modes of coverage.



	Health Status		Location			
F_{ID}	S_{ID}	D_{ID}	N_{CR}	N_{BR}	X_n	Y_n

F_{ID} : Frame Identification ID
S_{ID} : Source ID
D_{ID} : Destination ID
N_{CR} : Sensor Current Reading
N_{BR} : Sensor Battery Reading
X_n : X position of Source
Y_n : Y position of Source

battery energy whereas the node kept a large amount of energy in sparse mode. The proposed AC method figures out the information and pays more consideration to both modes. Based on inter-node distance, the AC method automatically switched to any one of the nodes. This category of switching technique can extend the battery energy of sensor nodes for a prolonged time.

3.2 Heterogeneous Fault Diagnosis

The proposed heterogeneous fault diagnosis approach detects the hardware failure includes transceiver unit, microcontroller unit, battery unit, and sensor unit faults of the deployed nodes. Primarily, the sink node forwards a Hardware Fault Diagnosis Information to the 1 hop neighbors nodes set within the radius of *2R* and initiates the timer. In this work, the battery of the sink is assumed to be more powerful compared to the normal nodes. Figure 3 shows the message format in which the first field holds the frame identification ID and the next two fields denote source and destination IDs. The fourth and fifth fields indicate the health status and the last two fields designate the geographical location of the sensor node.

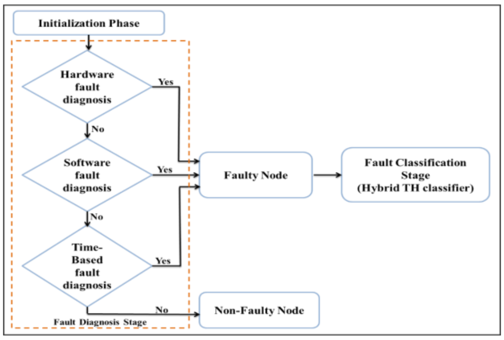


Figure 2. The framework of proposed E[2]HFM method

Figure 3. The $Info_{HFD}$ message format

If a single-hop node set gets the $Info_{HFD}$ frame from the sink, every sensor node formulates a health status and then sends back its status to the sink. If the sink node receives the $Info_{HFD}$ from a node (n_i) within ∂ time, then it takes a decision that the microcontroller and transceiver units of the corresponding n_i are operating normally. Next, the battery unit fault of n_i is identified

on the basis of the current N_{BR} value. If the residual battery (RB_i) of n_i is lesser than a threshold (T_2) value, then it deduces that the battery unit of n_i is faulty. Finally, the detection of a sensor unit fault of a node can be achieved based on S_{CR} of the sensor unit. If an $Info_{HFD}$ frame contains the N_{CR} value of n_i, then it takes a decision that the sensor unit of a node n_i is non-faulty otherwise it is recognized as faulty. Similarly, all sensor nodes broadcast the $Info_{HFD}$ message to complete the mechanism of hardware fault detection which is illustrated in Algorithm 1.

Algorithm 1 – Hardware Fault Diagnosis Algorithm

Begin

$N = \{n1, n2, ..., nk\}$

*/*set of deployed nodes*/*

$Nhf = \{nhf1, nhf2, ..., nhfq\}$

*/*set of hardware faulty nodes*/*

1 Initially, sink broadcasts a $Info_{HFD}$ in the range *2R*
/ Fault diagnosis process*/*

2 Initiate ∂ timer

3 **if**($\partial \leq T_1$)**then**
/ Hardware fault diagnosis*/*

```
Receive Info_HFD frame for node n_i;
Microcontroller and Transceiver units of n_i is non-faulty;
if (RB_i ≤ T_2) then
    Battery unit fault has appeared in n_i;
    Node n_i is inserted into N_hf;
end if
else
    Microcontroller and Transceiver units of n_i is faulty;
    Node n_i is inserted into N_hf;
end if
if Info_HFD content N_CR then
    Sensor unit of n_i is non-faulty;
else
    Sensor unit of n_i is faulty;
    Node n_i is inserted into N_hf;
end if
end
```

In case of software failures, the proposed approach detects the gain, offset, and stuck-at faults of the deployed nodes. The key objective of Algorithm 2 is to assess the sensor reading variations as a software fault. In this work, an optimal threshold value has been computed to diagnose the software fault as exposed. $\sum 2$

According to the T_3 value, the software faulty node has been detected during subsequent rounds. If $|N_{RR} - n_i(N_{CR})|$ is less than or equal to the T_3 value, then it decides that the software unit of n_i is non-faulty, otherwise, it is recognized as software faulty. Once the software fault is detected, it is necessary to find out the type of software fault.

The fault diagnosis process receives sensor information at time $_i t$ can be defined as follows 10 $z^j(t)$ represents the i^{th} type of data gathered in the j^{th} node at time t. It is difficult to employ the attained data directly to classify the fault category. Hence, the corresponding optimal features in the sensor data should be formulated. The software fault type formulation of the node at time t is depicted as follows:

Algorithm 2 – Software Fault Diagnosis Algorithm

```
Begin
    N = {n1,n2,....,nk}
    /*set of deployed nodes*/
    Nsf = {nsf1,nsf2,....., nsfq}
    /*set of software faulty nodes*/
    if (∂ ≤ T1) then
        Receive Info_HFD frame for node n_i;
        Compute T3 using Eq.1;
        if (|N_RR − n_i(N_CR)| ≤ T3) then
            Software unit of n_i is non-faulty;
        else
            Software unit of n_i is faulty;
            Node n_i is inserted into N_sf;
            Determine software fault type using Eq.;
        end if
    end if
end
```

The proposed scheme detects the major types of time-based failures such as permanent, intermittent, and transient faults of the deployed nodes.

An assumption has been made for the following threshold range that would fix for a different type of time-based faults. In the case of a permanent fault, the lower bound threshold value is $LT_p = 0.8$ and the higher bound threshold value is $HT_p = 1.0$. The lower and higher bound threshold values of intermittent fault are $LT_i = 0.3$ and $HT_i = 0.79$ respectively. Finally, the fault rate of transient fault is considered as $LT_t = 0.01$ and $HT_t = 0.29$. The FC_i value for sensor n_i will be compared with various fault rates to identify the real fault condition of the node. The real fault condition $RF(n_i)$ of node n_i can be computed as follows:

Every sensor can be determined as faulty by N_M neighbors in the sensing field. If a node n_i inclined towards a healthy node is identified by the diagnosis algorithm, then the surrounding neighbors are designated as healthy neighbors in the network.

Performance Evaluation

In the section, the proposed ACC scheme is compared and assessed with related existing coverage and connectivity schemes like DS [21] and GA [23]. To execute these two schemes, their existing parameters are employed except for the node's energy parameters defined and compared with similar simulation arrangement.

5.1 *Simulation setup*

The simulation experiment was implemented in the MATLAB environment and its simulation setup is shown in Table 4. It was conducted in the sensing area of *100 m* × *100 m* in which the sensor nodes are randomly deployed. All sensors know their geographical location of the sensing region where they have been deployed. The sensing and con- nectivity range of each node will be in the range of *10 m* and *20 m* respectively.

Each node begins its operation with the initial battery en- ergy of *2 J*. The control and data packet sizes are considered as 20 bytes and 50 bytes respectively. Each simulation experi- ment has been executed ten times and thus the average value was computed. All the experiments were implemented in a stationary field, i.e., the sink and sensors were fixed. The communication and sensing ranges of all sensor nodes are assumed to be the same. There are two types of networks examined in the proposed work such as a smaller network (50 nodes) and a larger network (300 nodes).

The efficiency of the proposed and existing methodologies are assessed through carrying out two different simulation experiments namely: WSN#1 and WSN#2. In WSN#1, the sink was located at (50, 50) whereas, the sink was located at (100, 50) in WSN#2. In Fig. 6, the red and blue nodes repre- sent the randomly deployed nodes and target objects respectively.

The sink node is denoted by the yellow triangle. Finally, the green circle intends the coverage area of nodes with a radius of S_R. In most of the existing works, simulation exper- iments are executed in WSN#1 setup only. To overcome this, the proposed work performed in a new simulation setup

Table 4 Simulation setup properties

Type	Parameters	Value
Network topology	Network size	100 m × 100 m
	No. of nodes	50,100,150,200,250,300
	Channel	Wireless
	Channel type	Bidirectional
	Node deployment	Random
	Sink position (X,Y)	(50 m, 50 m), (100 m, 50 m)
	Data packet size	50 bytes
	Control packet size	20 bytes
	Initial energy	2 J
	Sensing range	10 m
	Connectivity range	20 m

(WSN#2) for analyzing the performance of IWSN. The key role of analyzing WSN#2 setup is to test the performance of proposed as well as existing schemes under different sink position.

The performance of the proposed E^2HFM scheme was assessed and compared with three candidate schemes such as HFD [26], INSA [17], and FDRFC [23]. To ensure that the comparisons were fair, all the above schemes employed the same distributed methodology to identify the fault diagnosis of scattered sensor nodes.

Table 2. Simulation setting parameters

	Parameters	Value
Network Topology	Network size	1000 m x 1000 m
	Number of nodes	100, 200, 300, 400, 500
	Node deployment	Random
	Transmission range	150 m
	Antenna model	Omni-directional antenna
	Propagation model	Two-Ray Ground
	Traffic Range	Constant Bit Rate
	No. of Heterogeneous Faults	3
	Sink position (X,Y)	(500 m , 500 m), (1000 m , 500 m)
	Sensing range	5 m
	Simulation time	200 s
	Channel	Wireless
	Channel type	Bidirectional
	Initial energy	5 J
Hybrid TH classifier	a_{max}	1
	a_{min}	0.00001
	Number of search agents	50
	Number of iterations	100
	σ	0.001

Each existing schemes have unique characteristics to identify the occurrence of one or two faults in the network. Further, these schemes are employed under the condition of the selection of the same training parameter and utilization of the same generated fault dataset. Among them, the common parameters of every scheme are set based on the corresponding literature. To validate the robustness of the performance results and minimize their randomness, under the same conditions, the simulation scenario can be run 50 times and thus, the average value is taken for different performance metrics. Moreover, the HFD scheme was manipulated with hardware and time-based faults whereas the INSA and FDRFC schemes addressed the time-based and software faults respectively. Nevertheless, most of the existing schemes do not focus on simulating these three faults simultaneously. The best fault detection scheme for each fault has been anticipated for the comparison process. Therefore, the proposed scheme was compared with HFD, INSA, and FDRFC schemes.

Experimental Result and Analysis

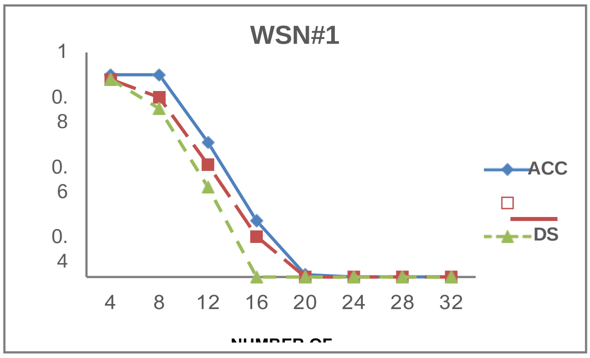
The performance of the proposed scheme will be assessed according to the coverage rate, Number of Coverage and Connectivity Nodes

(NCCN), average energy consumption, network lifetime, redundancy rate, connection cost and cover- age efficiency. Here, NCCN is the novel metric to validate the connectivity performance of the proposed scheme.

The proposed E^2HFM scheme is assessed as well as compared with other existing state-of- art schemes through several performance metrics. These metrics include *Detection Accuracy Rate, False Alarm Rate, Network Stability Rate (NSR), Network Coverage Ratio, Diagnosis Latency Rate, Network Lifetime, and Average Energy Consumption*. Here, NSR is the novel metric to demonstrate the stability and reliability of the proposed scheme.

5.2 *Impact of coveragerate*

Coverage Rate (CR) is a significant metric for computing the coverage consistency of IWSN and is the region covered by nodes in an area of interest. This CR metric is likely to be a maximum (almost 100%) range as long as possible. Typically, the CR for coverage control schemes begins in an extreme of almost 100% range however a scheme is considered more effective if it maintains the CR value as maximum for a prolonged time. Figure 7 depicts the attained experiment re- sults of the CR value in WSN#1 environment. As it can be noted in Fig. 7, ACC remains maximum values in CR for a prolonged time.



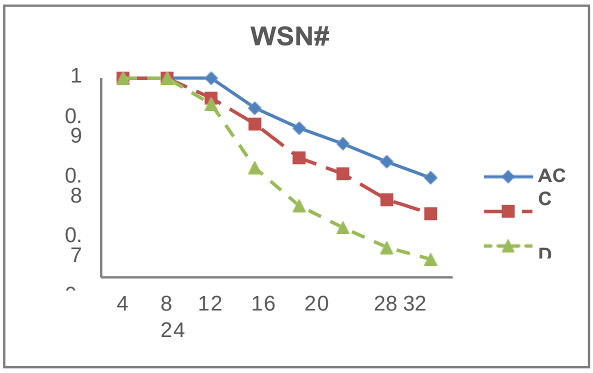
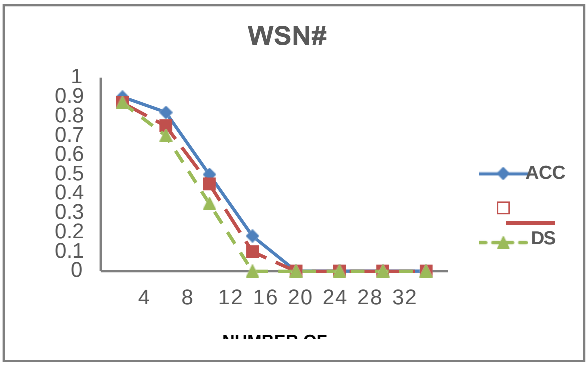


Fig. 7 Analysis of CR in WSN#1 (a) 50 nodes, (b) 300 nodes

In particular, the ACC scheme maintains the higher CR value as a maximum of 16th round for larger networks where- as the existing schemes like DS and GA schemes maintain until 12th round only. It clearly shows the better network sustainability of the proposed ACC scheme. This is due to optimal network coverage and connectivity methodologies are incorporated in the ACC scheme. In the proposed scheme, the sensing area is fully covered which is guaranteed by the AC method and necessary information is conveyed to the sink node with the aid of the EEC method.

On the contrary, only partial coverage is provided by DS and GA schemes which leads to attaining lesser CR values than the ACC scheme. The lower CR values in existing schemes clearly indicate that they are not adopted for IoT based applications where those applications require coverage reliability and periodical sensing information. The obtained results of CR value for the WSN#2 environment are shown in Fig. 8.

The results clearly evident that the proposed scheme main- tains higher CR values compared to the existing schemes. At the same time, the CR values of WSN#1 environment is higher than WSN#2 due to center position of sink that covers all sensing area in the network. This center position ensures the sensing target objects are properly sensed and report to the sink node.



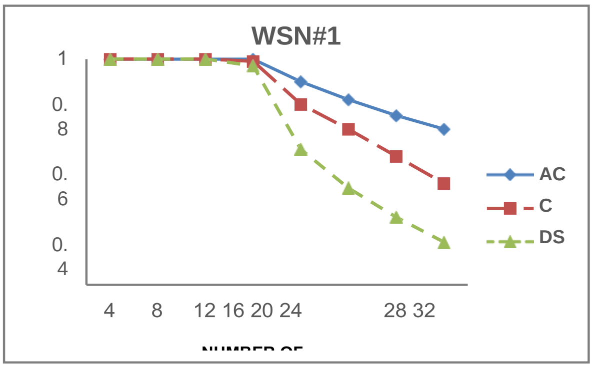


Fig. 8 Analysis of CR in WSN#2 (a) 50 nodes, (b) 300 nodes

Impact of Detection Accuracy Rate

The Detection Accuracy Rate (DAR) [38] is computed by

$$DAR(\%) = \frac{N_D}{N_A} x100 \quad (26)$$

where N_D indicates a set of faulty sensor nodes diagnosed through implemented schemes and N_A signifies a set of original failure nodes.

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Figure 6a and 6b expose the DAR value for case 1 and case 2 respectively. These results manifest that the DAR of the proposed E^{2}HFM is better as compared with existing schemes for both IWSN#1 and IWSN#2 cases. Especially, when the fault probability rate exceeds 35%, the DAR of the FDRFC, INSA, and HFD schemes reduces linearly, while the DAR of the proposed E^{2}HFM scheme still exceeds above 99%. This can be attributed to monitoring the hardware, software, and time-based fault status simultaneously of the deployed nodes in IWSN. These different types of faults are classified using the multi-class TSVM method. The detection algorithm in the proposed E^{2}HFM scheme assists in identifying the heterogeneous faults rapidly. It stimulates the proposed E^{2}HFM to detect all types of faulty nodes significantly in the network. In contrast, the DAR of the FDRFC scheme attains lower DAR because it entirely depends on the training dataset. It does not detect the faults induced in real-time readings.

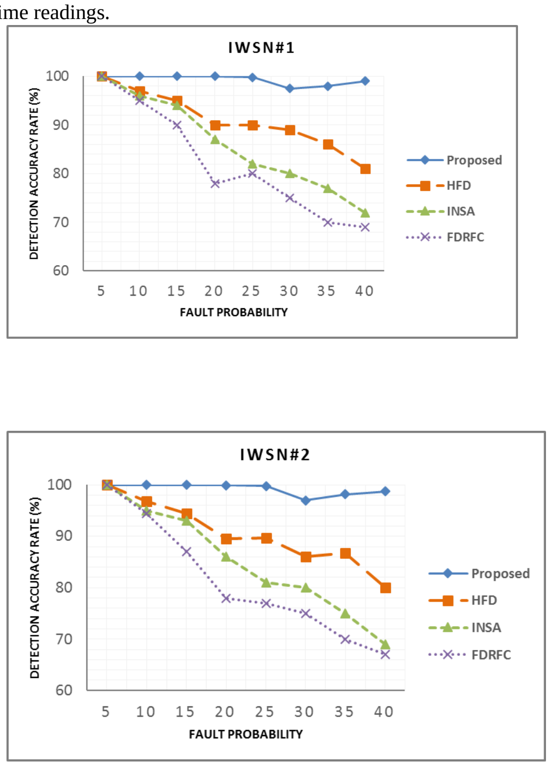

Figure 6 Comparison of DAR under different fault probability rates in (a) IWSN#1 (b) IWSN#2

Conclusion

In IWSN, there will be a sink node which gathers sensing information from all the sensor nodes. Nevertheless, coverage, connectivity and energy consumption are the three most sig- nificant objectives for guaranteed the data forwarding from each node to a sink. In this work, the ACC scheme has been proposed that tries to consider three objectives simultaneously for problem formulation. The primary step of the proposed scheme aims to build adaptive coverage among the sensor nodes. Thereafter, it maintains the network connectivity as long as possible, while covering a sensing area as large as possible.

The experiment results are simulated in the MATLAB en- vironment. A set of simulations are executed in two different WSN environments and a comparison with the related works are accomplished. The performance results have shown that the proposed scheme outperforms all existing schemes like DS and GA schemes for smaller as well as larger networks. In particular, CR results validated that the proposed scheme maintains the sensing coverage as long as possible, whereas the AEC results confirmed that it consumes lesser energy for coverage and connectivity process. Finally, the higher connec- tivity performance has been proven by the NCCN results. Therefore, it can conclude that the proposed ACC scheme improves the quality of service of the IWSN model through appropriate coverage, connectivity, and energy management methods.

The proposed scheme has a wide range of IWSN based applications in large scale industries to supervise some speified target events such as possible fire region, gas leakages, animal tracking, etc. However, it does not address the secure forwarding mechanism during data transmission.

Owing to the limited battery resources of sensor nodes and diverse deployment environments, fault diagnosis in IWSN has become a more challenging task. Almost no existing fault management scheme has been established to identify and classify the different types of heterogeneous faults in the IWSN. But, the proposed E^{2}HFM scheme considered all the heterogeneous faults (hardware, software, and time-based faults) during the fault diagnosis stage itself. The initial step of the proposed E^{2}HFM scheme is to identify the heterogeneous faults of the deployed sensor nodes in IWSN. Subsequently, the Hybrid TH classifier has been exploited to classify the faults into their corresponding types. The HGOA in Hybrid TH classifier balances the exploitation and exploration in searching space which stimulates the HGOA to obtain the optimal values for TSVM parameters (s, δ) during the training process.

The simulation results are assessed in the MATLAB platform where a set of experiments are evaluated under two different IWSN scenarios. The obtained results manifest that the proposed E^{2}HFM scheme outperforms the FDRFC, INSA, and HFD schemes for large-scale IWSN. Particularly, the results of the NSR metric proven that the proposed E^{2}HFM scheme perpetuates the network for an extensive period. The NL of E^{2}HFM has enhanced by 37%, 23%, and 12% when compared with FDRFC, INSA, and HFD schemes respectively. Furthermore, the E^{2}HFM still sustains with *0.1 J* AEC, 96% NCR, and 99% DAR for dense IWSN circumstances. The AEC results validate that it depletes lesser battery energy for the diagnosis as well as classification stages. Henceforth, it can be concluded that the proposed E^{2}HFM scheme prolonging the network stability by the implementation of an effective fault management strategy in IWSN.

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