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Distributed Self Intermittent Fault Diagnosis in Dense Wireless Sensor Network

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Abstract – A distributed sensor network (DSN) is a grouping of low-power and low-cost sensor nodes (SNs) that are stochastically placed in a large-scale area for monitoring regions and enabling various applications. The quality of service in DSN is impacted by the sporadic appearance of defective sensor nodes, especially over the dense wireless network. Due to that, sensor nodes are affected, which reduces network performance during communication. In recent years, the majority of the fault detection techniques in use rely on the neighbor's sensing data over the dense sensor network to determine the fault state of SNs, and based on these, the self-diagnosis is done by receiving information on statistics, thresholds, majority voting, hypothetical testing, comparison, or machine learning. As a result, the false data positive rate (FDPR), detection data accuracy (DDA), and false data alarm rate (FDAR) of these defect detection algorithms are low. Due to high energy expenditure and long detection delay these approaches are not suitable for large scale. In this paper, an enhanced three-sigma edit test-based distributed self-fault dense diagnosis (DSFDD3SET) algorithm is proposed. The performance of the proposed DSFDD3SET has been evaluated using Python, and MATLAB. The experimental results of the DSFDD3SET have been compared with the existing distributed self-fault diagnosis algorithm. The experimental results efficacy outperforms the existing algorithms.

Index Terms – Distributed Sensor Network, Fault Diagnosis, Statistical Method, Intermittent Fault, KNN, Three Sigma Edit Test, Self-Intermittent.

1. INTRODUCTION

Distributed network(DSN) contains thousand number of tiny small sensor nodes that have low processing power, limited memory, and battery constraints and are deployed in a large environment, dense area for different applications like communication, monitoring of the environment, industries, monitoring, and landslide operations [1, 2, 3]. Sensor nodes are communicating with each other through their sensing and capability of limited processing within the environment using a medium of wireless. The distributed sensor nodes make an ad-hoc network without any specific network infrastructure and establish peer-to-peer communication between two sensor nodes.

In order to provide accurate sensor information based on the distributed environment and its variables. Determining all types of sensor irregularities and detecting the fault conditions in distributed sensor networks requires quick diagnosis, sometimes even becoming crucial. A faulty distributed sensor node is created when one or more predictors produce incorrect results. Based on these incorrect results sensor nodes are divided into many categories that depend upon the actions. Some of the sensor nodes behave faulty temporarily and produces defective reading at various time instants [4], as opposed to the transiently faulty sensor node [5], which gives faulty data only once throughout the course of its whole life cycle. Such form of error identified as an intermittent error identifies the defective nodes in a dynamic topology in a specific time interval in the literature [6,7], It adheres to a repeated diagnosis process for detecting the incidence of a number of defects repeatedly in output analysis [8, 9]. In DSNs, topology is made up of numerous nodes spread out in numerous configurations. Its deployment might be arbitrary, targeted, dense, or sparse. Due to the rapid development of this industry, DSNs have many potential applications. In added sectors, like big data and data analytics where there is a vast amount of data to be analyzed, WSN is playing a significant role.

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A threshold is selected to obtain precise local sensor detections and the comparison of the detections to the threshold results in the choice. The most effective decision for the distance-based static method is used to address the problem of data fault in cooperative DSNs [10]. This best distance-based approach is derived from the Neyman-Pearson concept. Many works of literature have been earlier put forth to address the process of channel decoding and the forwarding process of relay fusion is the best option, and By using IFS construction and fuzzy algorithms distribution of data decisions has been taken due to their similarity of weightage TOPSIS of data are used to build the multi-attribute verdict the intermittent structure is used for fuzzy based on the set of IFS. A lot of people use machine learning to find problems with WSNs. The research community has encountered a variety of faults, and they may be classified into the following sensed data as offset Out of bounds, fault, and stuck-at-fault. Such as a result, the distance-based intermittent technique is adopted in the literature review because it works with all classifiers. The data accuracy of the distance-based statistical approach is increased with the use of machine learning algorithms [11, 12].

In the context of distributed sensor nodes, their deployment typically occurs in dense, hostile, and hard-to-reach network environments, which are lying to various errors. These faulty nodes can cause inaccuracies and undesirable outcomes even during normal operations. To mitigate and prevent the impact of these faults on sensor node activities, the research addressing to the distributed self-fault method has been carried out [13, 14, 6]. Normal circumstances result in sensor nodes producing accurate results during data transmission, whereas softly malfunctioning sensor nodes produce inaccurate data that deviates from the original readings because of the network environment. Regardless of whether the data is accurate or inaccurate, it is handled as a typical random variable that varies between various sensor network nodes [9, 15]. The significance of dense fault detection in DSNs is paramount, given their crucial applications in various environmental domains. To meet the demands of DSNs, there is a pressing need to develop an effective self-fault diagnosis algorithm, ensuring the network's resilience and prolonged operation even in the occurrence of errors.

The effectiveness of distributed self-fault diagnosis methods, such as those relying on sample median, mean, variance, correlations, or co-variance, is compromised due to the significant variation in network data when dealing with faulty nodes in a distributed process. This becomes especially problematic in dense network environments where multiple sensor nodes may be faulty within a specific region. To address this issue, the paper proposes an enhanced K-nearest neighbor (KNN) based enhanced sigma edit test method for diagnosing faulty information in Distributed Sensor Networks (DSNs). In this algorithm, the dense network's diagnostic performance relies on the nearby sensor nodes, with each node's communicating its base node and engaging in self-fault diagnosis to determine whether it is fault-free or faulty. Accurate identification of each node's status hinges on the behavior of its neighboring nodes. The presented self-fault diagnosis algorithms demonstrate superior performance in dense networks, particularly when predicting the likelihood of multiple neighboring sensor nodes being faulty.

From the existing literature, it is evident that all current methods result in a higher number of data transmissions across the dense network and continuous exchange of data status. This process leads to a rapid depletion of the sensor node energy in Distributed Sensor Networks (DSNs). Due to this sensor node behaves in reduced concert and produces bigger overhead of network in the existing, so for reducing the energy overhead need to develop and design an effective distributed self-fault diagnosis approach for dense DSNs.

Following is a summary of this paper's main contribution:

a) The upgraded edit test algorithm for self-fault diagnosis in DSNs is introduced in the study and is based on K-nearest neighbours (KNN).

b) The proposed method presents the KNN-based enhanced edit test for comparison with traditional and comparison models.

c) Each sensor node can accurately diagnose itself using the Distributed Self-Fault Dense Diagnosis (DSFDD3SET) algorithm with detection of high accuracy, a low false alarm rate, and a low false positive rate.

d) Using Python and MATLAB, the DSFDD3SET algorithm's performance is assessed, and the results are contrasted with those of earlier studies in the literature by Panda et al. [16] and Panda et al. [17].

The remaining portion of the manuscript is presented as it follows. A thorough literature assessment of the presented work is provided in Section 2. System, network, and failure models are discussed in Section 3. Section 4 provides more information on the proposed DSFDD3SET algorithm. The simulation results are presented in Section 5 along with remarks. Finally, the conclusion is provided in Section 6.

2. RELATED WORK

In a distributed dense sensor network, intermittent faulty nodes often produce noisy data from neighbouring nodes, causing fluctuations in the median and variance compared to the statistics of actual data. Some good nodes may also share real data with minimal noise, depend on channel and their conditions, within acceptable limits. However, if a significant portion of the data becomes suspicious and contains excessive noise, it leads to changes in the median and variance that surpass the tolerance limits.

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Distributed defect detection in dense sensor networks is becoming more prevalent [16]. A typical distributed fault detection (DFD) method was proposed in reference [17], which was compared with the DIFD and DSFD3SET methods. Recent academic works have proposed several improved distributed intermittent that identify the fault in the distributed environment built on DFD, DIFD, and DSFD3SET algorithms, DIFD, and DSFD3SET algorithms. However, these algorithms' performance may decline significantly when a small number of neighboring sensor nodes and the failure of probability is high, as they tend to judge large-scale sensors too harshly when the node is actually in a normal condition. Intermittent sensor node defects are suggested to occur with an estimated number of faults during a given period [8] [9]. In [18], the different cutting-edge test cases, configurations, and developments for communication within the specified sensing range are suggested. In [19], it is suggested for EELRP to improve the lifetime of the network, increase the energy and delivery rate based on their path hops, and secure replicas over the dynamic environment in [20]. The author [21] suggested GBK for enhanced network lifetime and increased stability based on the K-mean; on the other hand, dynamically detect the fault within a certain coverage area for the determination of transient and intermittent faults [22] and [23]. In [24], it is suggested to use a supervised method to classify the sensor node by analyzing the data transmission duration from start to finish that was gathered at the washbasin. The authors suggested in [25], a broadened technique that is based on the conditional random field of the neighborhood (NHCRF), a broadened process that the authors suggest in [25], is used to model the network as a graph. To identify the damaged or faulty nodes in WSNs are examined the strength of received signal, delay, and frequency and ability of these fault detection methods to distinguish between various WSN issues is constrained by their probabilistic methodology.

To identify flawed nodes in WSNs, a centralized strategy utilizing fuzzy logic and majority voting is suggested in [26] and [27] for classifying the fault identification reactive, efficient, and k-coverage to enhance the network lifetime presented in [28] [29]. To calculate the proportion of broken sensing nodes in the static and dynamic network, authors employ fuzzy logic [30]. The next step is to detect defective nodes using the majority voting method that is based on prediction of fault. To enhance the quality and performance of large-scale WSNs, another strategy is offered in [16] and presents a fuzzy rule-based technique for categorizing and managing problematic nodes. Since information gathered from all neighbor sensors is taken decisions, this centralized solution, despite needing additional connectivity to share data with the fusion centre, offers good accuracy. The author suggested the supervised methods for finding faults and diagnosis of the node behavior to identify the types of fault [31] within the classified range to optimize the memetic concepts for different modes [32] and [33]. Enhancing the energy of sensor nodes to increase network connectivity and life time in the proposed routing algorithm [34] to detect fault identification is presented in [35]. The author [36] suggested a different application for reducing faults over the fault tolerance routing methodologies. A distributed method, on the other hand, is described in [37] and [8], in which every node communicates with its nearby sensors to determine its failure state. In order to cut down on transmission overhead, the nodes are regularly diagnosed for a certain time interval. The self-diagnosis algorithm is generally based on the modified three sigma edit test when it calculates the statistics that is mean and variance. Intermittent problems are identified by comparing the mean difference of the observed value and standard fault with a pre-specified threshold, according to a failure diagnosis technique based on majority neighbor cooperation suggested in [22]. To overcome limitations, machine learning techniques are employed for defect diagnostics. In WSNs, neural networks are used to diagnose composite types of failures [23, 7]. Deep learning-based defect diagnosis, known for its powerful feature representation capabilities, has been proposed in recent years. While machine learning is utilized for detecting sensor drift faults in cyber-physical structures, it might not be appropriate for WSN scenarios [38]. Support vector machines (SVM) have been employed in WSNs to categorize problematic sensor nodes [7]. Additionally, [38] suggests that highly random trees can be used in wireless sensor networks for diagnosing faults.

Table 1 Summary of Taxonomy Based Related Works

Sl, No	Author	Taxonomy	Contribution
1	Ju Y et al. [1]	Fault detection	Survey of different fault detection techniques and its future.
2	Cao L et al.[2]	Kernel extreme learning machine (KELM)	Artificial bee colony algorithm used to find the diagnosis issues.
3	Sumathi J et al.[3]	Cluster based routing	The approaches of the decentralized technique determine the selection of path and forwarding eliminated data over a single point

			of failure which provides the guarantee precise routing decisions.
4	Narayan V et al.[5]	Region-based clustering	The study employs schemes to ensure complete coverage of the entire network area for sending data to their Base stations (BS's) using a hybrid scheme.
5	Sarmasti Z et al.[6]	Common mode failures (CMFs)	Centralized and distributed fault detection techniques used for identifying Critical Manufacturing Features (CMFs).
6	Loganathan S et al.[7]	Self-diagnosis fault detection	The cluster head algorithms (LEACH) predict filtered data.
7	Kumar D et al.[8]	Traversal-based diagnosis	To predict the fault based on the FFNN (Feed-forward neural network) model implemented with GS (Gravitational search) learning algorithms.
8	Niu Y et al.[9]	cooperative decision-making	A new residual generator is developed using the moving-horizon estimator to achieve distributed detection of intermittent faults (IFs) in sensor networks.
9	Huang DW et al.[11]	Hybrid diagnosis	By using multi voting algorithm and sensed neighbour information.
10	Rafeh R,[12]	Trust-based fault detection	Network life time, data accuracy.
11	Sharma S et al.[13]	Data transmission issues	Survey of methods of last decades.
12	Babu N et al.[14]	Limitation of node failure and recover	Survey of existing approaches.
13	Haq MZ et al.[15]	To manage the fault tolerance and connectivity of network.	Using the three types of disjoint path vectors include fault-tolerant techniques which are based on PINC, DPV, and ADPV.
14	Panda M et al.[16]	Self-fault diagnosis	More effective in challenging environments where traditional methods struggle to detect faults.
15	Panda M et al.[17]	Predicting the faulty behavior of nodes in the network	To determine the final fault status using the voting technique where each node to detect its own status.
16	Bala I et al.[18]	Resource allocation schemes	Dynamic heterogeneous networks.
17	Hajipour Z et al.[19]	Energy efficient	By using EELRP to detect the fault.
18	Sujihelen L et al.[20]	Detecting replica nodes	To identify the dynamic and static faults in distributed networks using Strategic Security System (SSS).
19	Ben Gouissem B et al.[21]	Grid-based k-means clustering	In each grid cell, the k-means algorithm is run to create a cluster head, with the node closest to the grid cell centroid being elected as the cluster head.
20	Khalifa B et al.[22]	Distributed hole detection and repair	Real-time detection of coverage holes, along with precise estimation of their location and size as they occur.

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21	Swain RR et al.[23]	Majority neighbors coordination	Multiple fault kinds, such as fail-and-stop, crashes, omissions, timing issues, and inaccurate computations are all detected using Gaussian function techniques.
22	Panda M et al.[24]	Distributed fault diagnosis	By employing robust statistical methods to find out the fault
23	Ju Y et al.[25]	Fault detection in NDSs	Detection of faults using Network Intrusion Prevention (NIP) under different communication arranging outlines.
24	Ahmadi SH et al.[26]	Fuzzy logic methods	Automation of fault diagnosis in DCS
25	Choudhary A et al.[27]	Cluster algorithm	Whenever the sensor node behaves in suspicious activity and transmits the data to its base station then cluster heads trigger the identification of fault.
26	Sahu S et al.[28]	Scheduling process of fault-tolerant.	Multilevel K-coverage analysis demonstrates that in a certain given network lifetime it conserves more energy compared with its flat K-coverage distribution.
27	Yasir Abdullah R et al.[29]	Fuzzy-based anomaly detection model	The real data is used to identify instances based on semi-supervised anomaly detection that deviates from the commonly observed data pattern.
28	Sahu S et al.[30]	distributed clustered fault tolerance scheduling	Based on a sweep-line redundancy check algorithm to deployed sensor or cluster head (CH) can be active, redundant, or dead/faulty for the same target region of interest (R)
29	Saeed U et al.[31]	Supervised machine learning-based technique	The detection scheme based on Extra-Trees demonstrates robustness against signal noise and effectively reduces both bias and variance errors.
30	De Brito JA et al.[32]	Sensor Allocation Problem (SAP)	The concepts of memetic algorithms are utilized to discover high-quality solutions.
31	Chen X, [33]	Clustering algorithm	In order to filter and evaluate the dependability of supportive facts nodes, a stable neighbour screening model is created based on the DSNs. The spatiotemporal correlation of the data nodes is then taken into account while creating a detection data stability evaluation model.
32	Mittal M et al.[34]	Low-Energy Adaptive Clustering	An intrusion detection system (IDS) is suggested for anomaly detection, utilizing the support vector machine (SVM) approach for selecting optimal features.
33	Prasad R et al.[35]	DBN based self-detection	Fault detection based on the distance
34	Katkar P et al.[36]	Fault tolerant approach	Comparing and analysis of existing approaches

Statistical methods including computing mean, z-score, variance, robust median, and MAD have been utilized in earlier studies to detect problematic nodes in WSNs by comparing the findings with a threshold. A majority vote and regular testing are crucial elements in identifying intermittent issues. However, the classification of malfunctioning nodes in WSNs that requires increased computational complexity is achieved using centralized machine learning (ML) algorithms. In this research, we propose a straightforward distributed dense fault diagnostic method using K-nearest neighbors (KNN) to identify intermittent faults with minimal computing complexity. The proposed method combines the advantages of centralized and distributed algorithms, making it possible

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to identify changes in median and variance, or either of them, when a failure occurs in a single step.

3. SYSTEM MODEL

The system model encompasses sensor failure models and distributed dense network models. Within the network model, it includes the deployment positions and communication strategies among cluster sensor nodes and their interactions cluster heads are given. To describe the prediction error that happens during data transmission between the cluster and its nearby nodes, an error model is used.

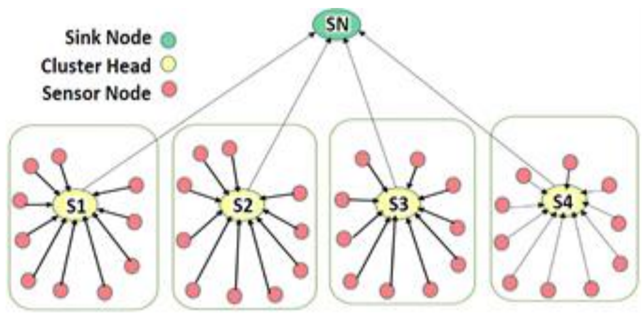

Figure1 Random Structure of Dense Network

Figure 1 illustrates the arbitrary distribution of a dense topology based on the unit disk model. Sensor nodes, represented as s_n1, s_n2, s_n3 ……………..s_n40, are randomly deployed in the distributed environment. Clusters, denoted as S1, S2, S3, and S4, facilitate communication between the sensor nodes. Each distributed sensor node, for example, s_n1 to s_n10, can communicate with its neighboring Cluster Head S1, as long as the specific radius of the cluster head nodes s_n1 to s_n10 falls within Tr. Likewise, the remaining sensor nodes are associated with their respective neighbors. For instance, s_n1 to s_n10 communicate with S1, s_n11 to s_n20 with S2, s_n21 to s_n30 with S3, and s_n31 to s_n40 with S4. All nodes can interconnect with their cluster head, and S1 can connect with S2, S3, and S4 through the Sink node, involving multi-hop communication. In the event that a sensor node cannot establish communication with its neighboring cluster node or cluster-to-cluster communication, it may be expected as a soft fault. Table 2 presents the list of symbols used throughout the problem formulation and algorithms.

3.1. Assumptions

- The energy level of each cluster sensor node stays constant during installation, and the cluster nodes are homogeneous by nature, as anticipated.
- Every sensor node in a cluster transmits information across the network from one cluster to the next while also collecting information from nodes close by.
- Any cluster node or cluster head that gets a data value and forecasts that some data is missing should be viewed as faulty, either in terms of the node or the data.
- Each cluster sensor node in the network is kept active and coordinated by the supervised learning process.
- The battery source that powers each cluster sensor node in the network has a specific threshold, and each cluster sensor node has the same energy loss during each transmission.
- We can forecast the communication link's faultlessness during transmission or get information from the clusters nearby nodes.

The cluster head interacts with its neighbors while each sensor node in the cluster periodically gathers data.

Table 2 List of Notations with Description

Symbols	Description
S	A collection of each cluster sensor node
s_i	Sensor node in the ith cluster
k	Data sample from the K^{TH} cluster
CN_{egi}	Set of s_i's neighbouring sensor nodes in a cluster
d_i (t)	Data from s_i's cluster sensed at time.
Nd_i	Data detected by cluster neighbours
CNT_i	Storage of the Cluster Neighboring at s_i
TFS_i	Overall number of cluster sensor nodes Si's fault status
θ1	Minimal criterion or threshold value
θ2	Greatest threshold value
$TFSN_{egi,m}$	Cluster neighbor node total final fault status
CAD_i	Absolute deviations in clusters around the median
$cmed_i$	Nd_i statistics for the cluster median over nearby nodes
α	Probability that a malfunctioning sensor node will occasionally give inaccurate data
Na	degree of the cluster network's sensor nodes
T	Observational time interval to identify the sporadic malfunctioning cluster sensing data.
δT	Period of time after which a new test will be

	conducted to examine the sensor nodes' intermittent behavior.
Ni	Si degree of the sensor cluster node.
TI	The moment the self-fault diagnosing process is initiated

3.2. Network Model

The cluster nodes s_i and s_j in the cluster sensor network are close to one another within the cluster transmission range of s_i , which represents the distance between them at time instant t. Any two sensor nodes, s_i ands_j, can communicate with one another in a single hop to calculate this distance. Communication between each sensor node, s_i , and its nearby nodes, CN_{egi} (t) ⊂ S is possible. The sensor network can communicate with them as well because it is tightly connected to its neighbouring nodes, CN_{egi} (t). Sensor node s_i collects data and stores it locally in its memory before sending it to neighbouring sensor nodes for testing. As a result, as the transmission range expands, Na likewise does, and vice versa, affecting the degree Cluster node Na of the sensor nodes. In Dense Sensor Networks (DSNs), wireless communication serves as the main way of communication for all sensor nodes. Each node in synchronous WSNs periodically broadcasts & receives signals from its neighbours. In order to allow communication between the nodes, physical layer protocol (IEEE 802.15.4) is used.

3.3. Fault Model

Hard and soft faults can affect sensor nodes. Let PR be the likelihood that a sensor node will experience intermittent failure. The set of fault-free sensor nodes is referred to as FF, and the conventional of arbitrarily selected cluster sensor nodes (⌈pCNT faulty nodes in cluster network) that are susceptible to soft or self-fault (intermittent fault) stands marked by way of FS. FS is further divided into the clusters S1 and S2.

In WSNs, the clusters S1 and S2 stand for the set of self-faulty (stuck at zero) cluster nodes and gathered cluster intermittent (FS= S1 ⊂ S2) nodes, respectively. The collection of fault-free sensor nodes |CNT = |S| = |FF + FS| and FF = S - FS. This demonstrates that set S contains both the faulted and non-faulty nodes in WSNs. Additionally, it is presumable that |FS |<< |FF|, or that there are much fewer faulty nodes in DSNs than FF.

Each cluster node has the ability to sense, send, receive, process, forward, and decide how to handle a defect based on the sensor nodes around it. In reality, these types of cluster nodes are categorized such intelligent or smart cluster sensor. Based on the observed data from its neighbours throughout time period T, each sensor node reports the results. A series of results for a sensor node si are recognized at that time under the following presumptions:

B1) Each time instant t, the data from a sensor node si can either be fault-free or intermittently flawed.

B2) The likelihood that a sensor node si would occasionally malfunction, failing to give accurate cluster sensed data value, α is. The likelihood that a cluster nodes data will deliver accurate, or data that is free of errors, is 1−α. This is portrayed as a sensor node's intermittently flawed behavior in a Cluster Network.

B3) Here test results exist self-determining, i.e., result of test considering one time instantaneous has no bearing on result at a different time of interval instant.

The expectations B1 through B3 are used for identifying the intermittently faulty in the cluster network. The above model is based on the trials process of Bernoulli which is based on discrete behavior and distribution process having 2 faulty cluster sensor node and probable consequences considered by d = 0 and d = 1. Intended for d = 1, the cluster sensor fault nodes arise with likelihood α and for d = 0, the likelihood of letdown of cluster sensor node represent 1 − α. Expectations B1 through B3 stay jumble-sale to diagnose cluster intermittently defective nodes based on the Bernoulli trials process in a specified cluster network, which has a distinct sharing and 2 possible predict consequences denoted by d = 0 and d = 1, is used to simulate this process. On behalf of d = 1, the cluster fault nodes with specific likelihood, while intended for d = 0, the sensor node will fail with probability of 1 − α. The following Equation (1) presents the probability density function.

K (d) = α d (1 − α) d−1 ………………………………………………………………………………………. (1)

The Bernoulli distribution of intermittent defects is used to describe the each node have collect the data from each cluster head and communicate with its neighbors node s_i at time interval instant t, abbreviated as Nd_i (t).

4. DISTRIBUTED SELF-FAULTING DISTANCE-BASED DENSE ALGORITHMS FOR IDENTIFYING INTERMITTENT FAULTS

Each cluster node s_i in the defined network or within the range is connected to the cluster head, and K numbers of information are continuously collected from its adjacent sensor nodes at regular intervals of time δT. This is known as distributed density, making many small cluster networks. It is initially anticipated that, as time allows, the defective cluster node will create a αK amount of inaccurate value at unintentional intervals when the data are compared with the gathered data and genuine data of the sensing node in order to detect its faulty or fault-free sensor node. Locating any potentially malfunctioning sensor nodes in the network requires performing a distributed analysis of the data from the various sensor nodes.

If each cluster node shares its K number of interpretations with its neighbouring nodes, each sensor node in the network holds CN_{egi} amount of node value, where Na is the network's sensor nodes' collective cluster degree. Instead of recording these enormous amounts of observed data and running into storage problems, each cluster sensor node now shares data or values Nd_i (t) with his adjacent information of sensing data CN_{egi} (t) in each sequence. This method also forecasts the fault state at that instant t. This technique will be done K times to determine the fault status independently.

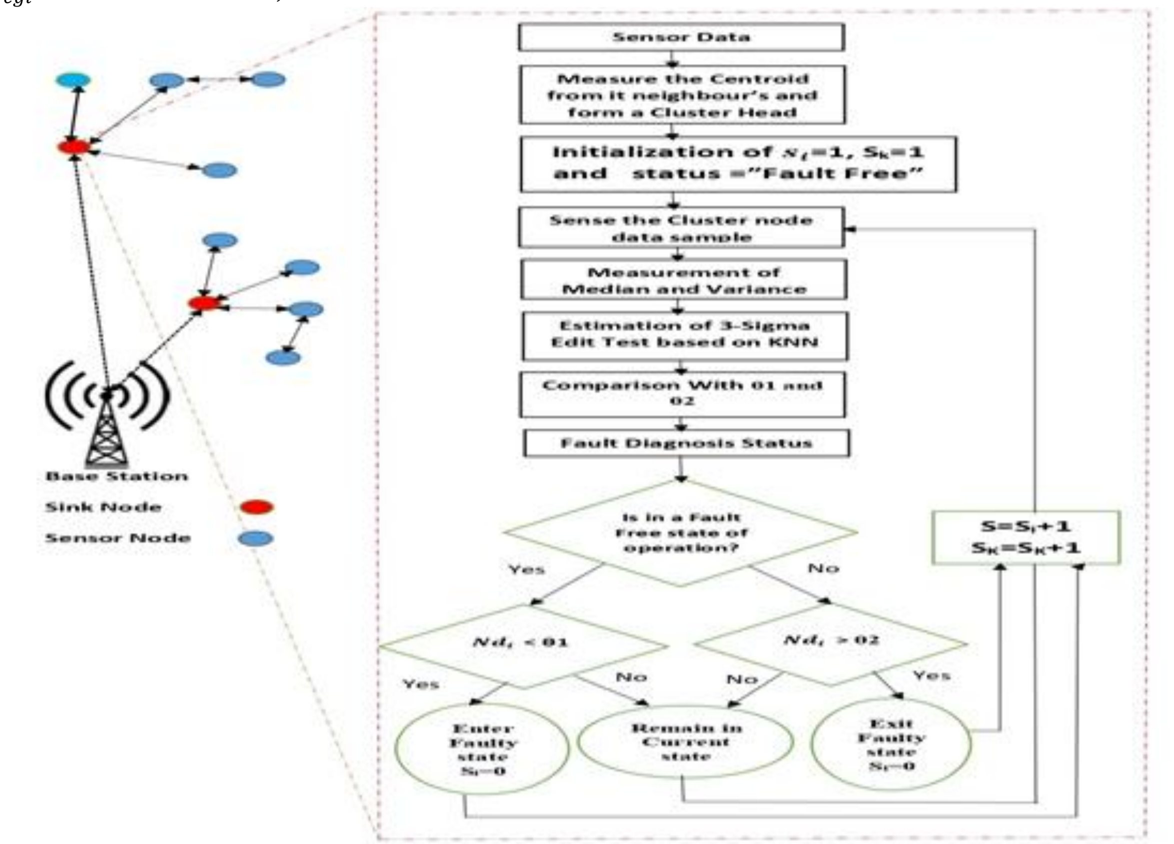

Figure 2 Basic Architecture of Distributed Dense Wireless Sensor Network

In the distributed dense wireless sensor nodes, figure 2 shows the basic architecture of the distributed dense wireless sensor network in block diagram form, making it obvious that the sensor nodes are made up of many components. Node information sensing, cluster creation, distance measurement with variance, and problem diagnosis based on various models The sensor unit comprises various sensors, including microscopic ones for pressure, temperature, and humidity, among others, and it also gathers data from its neighbours. Following this, sensor nodes locate their closest neighbors and create a cluster head to facilitate communication with other nodes and the base station. In order to ascertain changes and confirm the node's behaviour after the cluster has formed, it measures the distance with its variance. To assess the node's fault status, the sensor node's final component compares the real value with the observed value. Failures of an item for a brief period of time in any context are described as intermittent faults in general.

4.1. Proposed SFD Algorithm

Input: Total Fault status (TFS_i) of s_i

Output: Cluster Data: d_i (1), d_i (2) …., d_i (k)

Transmission Range (T_C)

Initialization: S= s_i , where i $\in$ [1, N], is the set of all cluster nodes and CN_{egi} is ith sensor node neighbours.

/* Time Coordination with KNN*/

Begin

1. For $s_i \in$ S do

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2. $D_i \leftarrow d_i$ (1) , d_i (2) ,… d_i (k)
3. If d_i (1) && d_i (2) &&…&& d_i (k) ≤ θ1 or ≥ θ2 then
   i. Collect cluster kth sample from cluster neighbours nodes (CN_{egi})
   ii. Construct cluster neighborhood CNT_i
   iii. $Nd_i = d_j$ (k)$_{j\in CN_{egi}}$
   iv. $Nd_i = d_i$ (k) ∪ Nd_i
   v. Binary Sort (Nd_i)
4. /* Step-1 : Dense network is calculated using the median ($cmed_i$) of Nd_i * /
   i. If [|CN_{egi}| + 1]% 2 = = 0 then
   ii. $cmed_i$ = { Nd_i [(|CN_{egi}|+1)/2] + Nd_i [(|CN_{egi}|+1)/2+1]}/2
   iii. Else
   iv. $cmed_i = Nd_i$ [(|CN_{egi}|+1)/2]
   v. End
5. /* Step-2 : Calculation of each dense cluster node's absolute standard deviation CAD_j * /
   i. For j ← 1 to (| CN_{egi}|+1) do
   ii. CAD_j =(Nd_i [j] - $cmed_i$)
   iii. End
6. /* Step-3: Using the connected cluster network to calculate the Z_n scale estimator (c * | d_i - d_j ; i < j |) */
   i. For j ← 1 to | CN_{egi} | do
      i. For m ← j + 1 to (CN_{egi} + 1) do
      ii. $Zn_{j,m} = c_n$ * | Nd_i [j] - Nd_i [j] |
      iii. End
   ii. End
   iii. Convert $Zn_{j,m}$ into one-dimensional array
   iv. Binary Sort ($Zn_{j,m}$)
7. /* Step-4: Kth-order statistics calculation from a dense network */
   i. W= [CN_{egi}/2] +1
   ii. K= w * (w-1)/2
   iii. $\sigma_{Z_n} = Zn_{j,m}$ [k]
8. /* Step-5: Calculation of cluster head nodes' fault status along with accompanying sensor nodes in a distributed, dense network (s_i) * /
   i. a_i = (d_i (k) - cmd_i / σ_{Z_n}
   ii. If a_i < c * σ_{Z_n} then
   iii. TFS_i =0 (Fault free node)
   iv. Else
   v. TFS_i =1 (Faulty Sensor node)
   vi. End
9. /* Step-6: calculation of a distributed dense network's cluster sensor neighbours' final failure status. (CN_{egi}) */
   i. For j ← 1 to | CN_{egi}| +1 do
   ii. a_j = CAD_j / σ_{Z_n}
   iii. If a_j < c * σ_{Z_n} then
      i. $TFSN_{egi,j}$ = 0 (Fault free sensor node)
   iv. Else
      i. $TFSN_{egi,j}$ = 1 (Faulty sensor node)
   v. End
   vi. End
10. Else
   i. /* don't take any action (an intermittent error has occurred).* /
   ii. End

End.

Algorithm 1 Self-Fault Diagnosis Algorithm for Distributed Dense WSN

The DSFDD3SET algorithm1 aims to detect faulty sensor nodes in distributed sensor networks using network prediction and fault models. Each sensor node's data s_i at time instant k is represented as s_i (k). The algorithm1 distinguishes between actual sensed data and erroneous data, where A represents the actual data measured by each cluster with associated sensor nodes s_i ands_j. The erroneous data is predicted to be temporally and spatially independent from each other.

In a dense network, it is assumed that the variance is the same for all fault-free sensor nodes and is denoted as σ^2. On the other hand, the measurement data from faulty sensor nodes have a very high variance, which is denoted as σ_f^2. The degree of a sensor node s_i is represented by the number of

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neighboring sensor nodes it has. In the distributed approach, each sensor node gathers a set of neighboring nodes from one cluster, denoted as CN_{egi}, and this set is defined as CNT_i.To determine the distance within the dense network, the median value **(**$cmed_i$**)** of the distances Nd_i is considered. Each sensor node then becomes a cluster head based on the nearest distance with its absolute standard deviationCAD_j. To establish the connected cluster network, each sensor node calculates the Z_n scale estimator (c * | d_i - d_j ; i < j |) and uses it to determine the estimation of distance. The sensor nodes based on his statistics of distance and cluster head to communicate with neighbor sensor nodes. It gather the information from its neighbors of all the cluster and determine the status of the node, if sensor node s_i observed value is less than or greater than the specified threshold value it present the behaviour the node. The status of the senor node depends of the status sensor neighbor CN_{egi} nodes.

According to the suggested method, the initial step entails confirming whether any of the nearby sensor nodes are defective. By keeping an eye on the estimated median or standard deviation, this verification is carried out. The standard deviation shows the deviation or spread of the data, whereas the median offers us a notion of where the data is most centrally located. However, the existence of false data from flawed sensor nodes has a significant impact on these statistical forecasts. Even a single erroneous data point can significantly impact these statistical estimates, causing them to be unreliable. In DSN applications, it is essential to consider the statistics of the observations. If the measured median and standard deviation fall outside the specified interval, it indicates the presence of an outlier or faulty sensor node.

Traditional methods use a comparison model where each sensor node compares its own data with the data from its neighbours to identify the fault state of the sensor nodes. Figure 3 depicts an Illustrative example of the deployed sensor nodes in the aforementioned environment. Depending on how little the data varies between two defective nodes, the algorithms can falsely think they are fault-free. As a result, both nodes detect their own fault-free states inaccurately. The outlyingness of an observation from a sensor node Si in relation to an estimated median is to be evaluated using a statistical measure, according to a novel approach that is suggested to address this problem. With the aid of this approach, defective nodes can be more accurately identified, hence reducing the chance of inaccurate fault-free detection in such circumstances.

The sensor node s_i 's dispersion between distances is represented by the quantity Nd_i . The value of a_j must be bigger than c times the standard deviation of the c * σ_{Z_n} scale estimator σ_{Z_n} in order to rule out problematic nodes. The node is thought to be defective if this criterion is satisfied; otherwise, it is thought to be fault-free. The thresholds θ 1 and θ 2 can be defined in terms of the variance in the false data as it is assumed that the observed data values follow a normal distribution. For instance, there is a 99.78% chance that the observation falls between Nd_i -3σ and Nd_i +3σ if θ1=3σ where σ is the standard deviation of the incorrect data. If one node's data considerably deviates from the actual data, either above or above the stated range, the median utilized here may differ from the true number. This method can also be used to determine whether any of Si's nearby sensor nodes are malfunctioning.

4.2. Illustrative Example

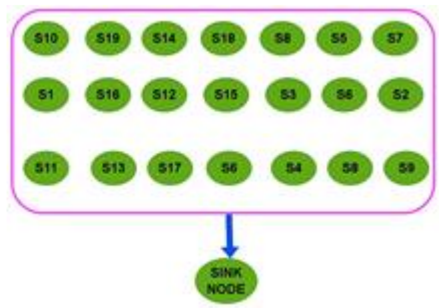

Figure 3 Deployment of Sensor Node

Step-1: Deployed the sensor node in dense wireless sensor network

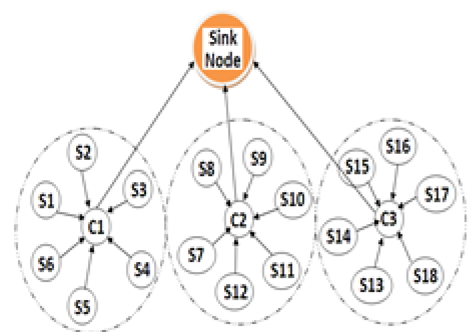

Figure 4 Cluster Generation

Step-2: After completing step-1, the formation of clusters takes place. Figure 4 depicts an example of cluster generation. /* generating clusters based on the data or nodes processed in the previous step */

Step:-3: The Euclidean distance of K number of neighboring sensor nodes is calculated /* to determine the distance of each node from its K nearest neighbors */

Step-4: The K-nearest neighbors (KNN) algorithm is employed to compute distances based on the calculated Euclidean distance. / * Finding the actual distance using the KNN algorithm */

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Step-5: Observed value and real value are compared based on the data points /* to assess the similarity or discrepancy between the received and transmitted data values */

Step-6: Identifying potential faults in the sensor nodes by applying a statistical test that considers deviations beyond three standard deviations from the median, as determined by the KNN approach. /* The fault status of the sensor node is determined using a 3 sigma edit test based on the K-nearest neighbors (KNN) algorithm */

5. RESULTS AND DISCUSSIONS

MATLAB and Python [34] are used to simulate the performance and assess the proposed DSFDD3SET. To verify the suggested outcome, the DSFDD3SET's performance study is contrasted with the DFD and DIFD algorithms that are currently in use [5]. The accuracy of the diagnosis, the rate of false alarms, and the rate of false positives are the metrics used to assess the performance of the suggested algorithm.

In steps of 0.05, the DSFDD3SET method is tested for various fault prediction probabilities ranging from data values of 0.05 to 0.3. Since the cluster size of the network affects the distance-based performance, the suggested approach is tested for various node cluster degrees, which is represented as a graph with a set of vertices and a set of edges.

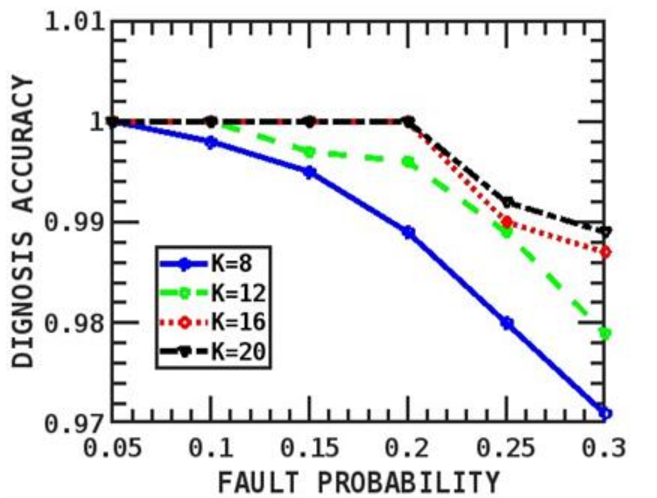
The transmission ranges are set to 58, 63, 78, and 84 in order to achieve a sensor node's cluster degree in steps of 5 from 10 to 25. For each point in the graph, we ran 100 experiments, and the degree of the cluster node. The model consequences demonstrate that suggested technique performs better than DIFD and DFD, and it is also noted that detecting a cluster node's fault status is dependable even when it has intermittent faults for an extended period of time.

5.1. Text Calculation of the Minimum Testing Quantity Needed to Diagnose the Intermittent

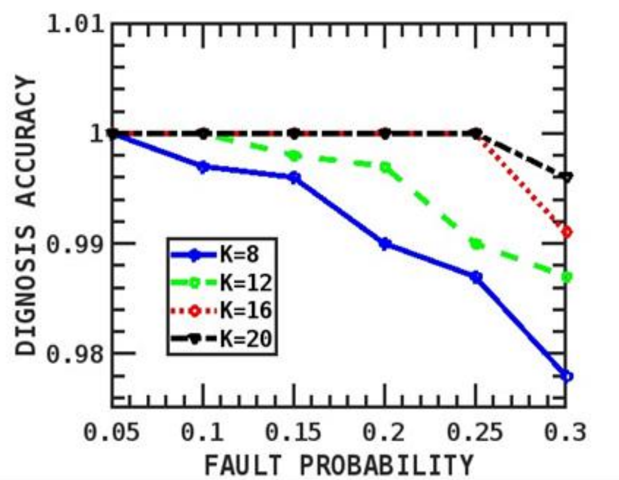
Initial estimates are made on the bare minimum of tests needed to locate the sensor node that experiences intermittent failure. The DSFDD3SET algorithm is run for a minimal number of iterations (K) to obtain diagnosis as the clustering performance of the temporary and intermittently defective cluster node varies from one time-interval instantaneous to the next. Here the no. of interactions based on the testing of data or K sensor value, is 20 with esteem to the 95% time interval, the cluster result demonstrates that the analysis of fault and produce the correctness is 100%.

For a network of 2048 sensors and 30% damaged sensor nodes, figure 5 displays the accuracy of diagnosis performance for different K values based on the clustering degree Na=10,15,20,25 where K = 8,12,16, and 20. It displays the performance diagnosis accuracy with regard to the defective nodes, as demonstrated by the values of 0.05, 0.1, 0.15, 0.2, 0.25, and 0.3 for each individual sensor in each cluster region under various cluster neighbour counts. Randomly selected nodes with degrees of 10, 15, 20, and 25 make up the cluster's neighbour nodes. Figures demonstrate how the DSFDD3SET method works better than the current approaches and offers a higher degree of diagnostic accuracy. It has been demonstrated that when neighbouring nodes grow, diagnosis accuracy grows relative to every other approach now in use with regard to k values.

Performance increases as the number of nodes with regard to k values increases, but message transmission also goes up at the same time. When the neighbors values are 30 or higher, the DSFDD3SET algorithm performs better than other algorithms in this situation with K = 8, 12, 16, and 20, as shown by the findings in figures 5 (a), (b), (c), and (d).



(a) Dense N_a =10



(b) Dense N_a =15

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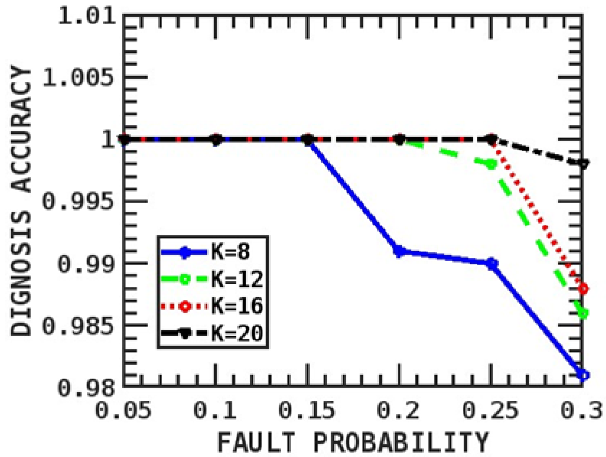
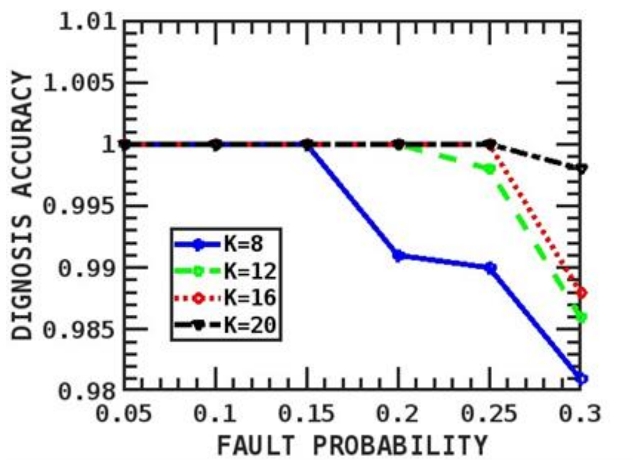
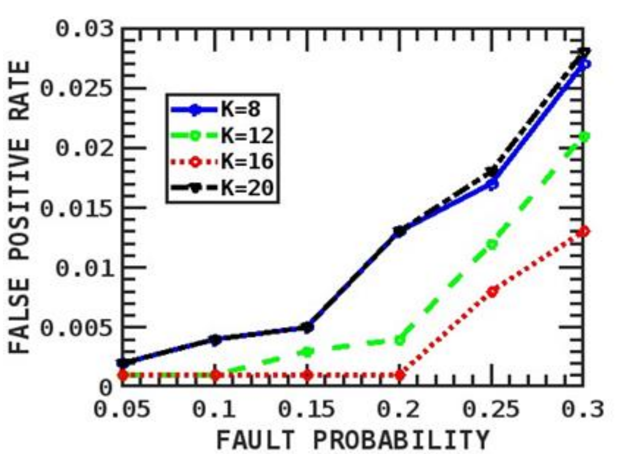


(c) Dense N_a =20

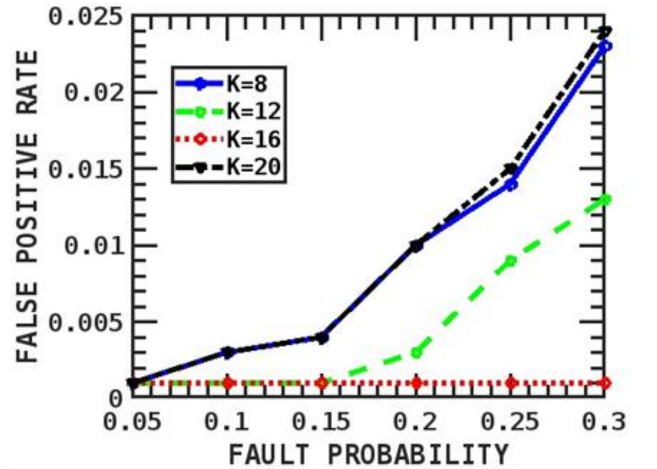


(d) Dense N_a =25

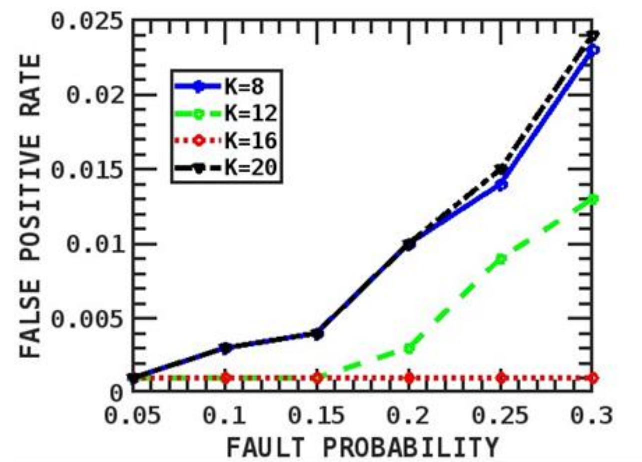
Figure 5 Accuracy of Diagnosis vs Likelihood of Fault for the DSFDD3SET Algorithm for Different Degree of Nodes (N_a= 10, 15, 20, 25)



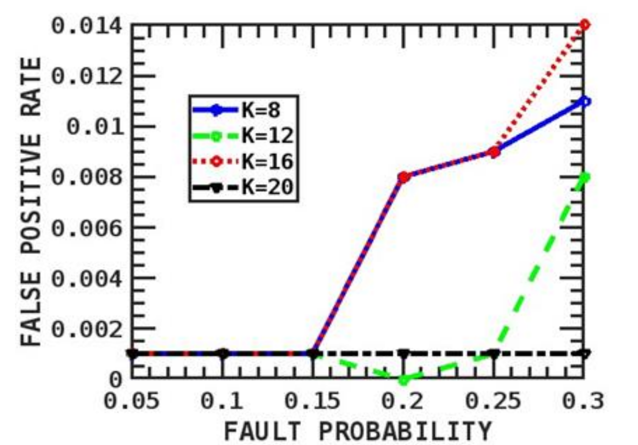
(a) Dense N_a =10



(b) Dense N_a =15



(c) Dense N_a =20



(d) Dense N_a =25

Figure 6 False Positive Rate vs Likelihood of Fault for the DSFDD3SET Algorithm for Different Degree of Nodes (N_a= 10, 15, 20, 25)

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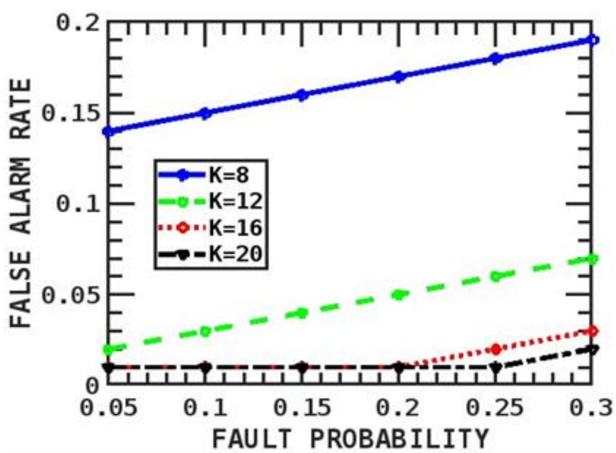
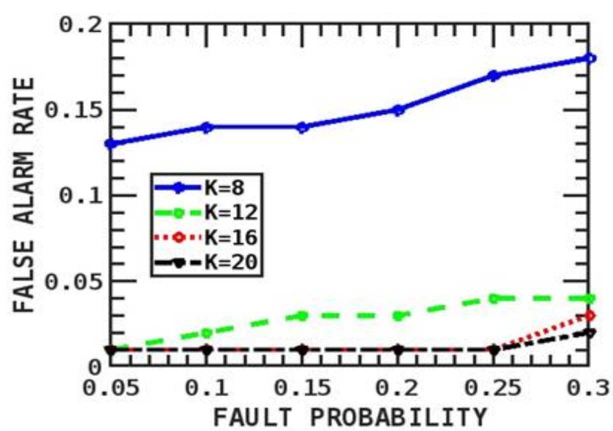
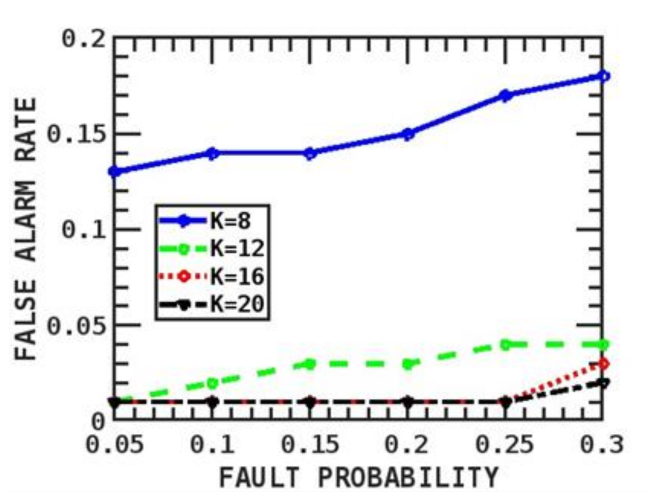
For a network of 2048 sensors and 30% damaged sensor nodes, figure 6 displays the false positive rate for different K values based on the clustering degree Na=10,15,20,25 where K = 8,12,16, and 20. It displays the performance false positive rate with regard to the defective nodes, as demonstrated by the values of 0.05, 0.1, 0.15, 0.2, 0.25, and 0.3 for each individual sensor in each cluster region under various cluster neighbour counts. Randomly selected nodes with degrees of 10, 15, 20, and 25 make up the cluster's neighbors nodes. Figures demonstrate how the DSFDD3SET method works better than the current approaches and offers a higher degree of low false positive rate. It has been demonstrated that when neighboring nodes grow, false positive rate grows but low as relative to every other approach now in use with regard to k values. False positive rate increases as the number of nodes with regard to k values increases but low as compare with low value, but message transmission also goes up at the same time. When the neighbors values are 30 or higher, the DSFDD3SET algorithm performs better than other algorithms in this situation with K = 8, 12, 16, and 20, as shown by the findings in figure 6 (a), (b), (c), and (d).



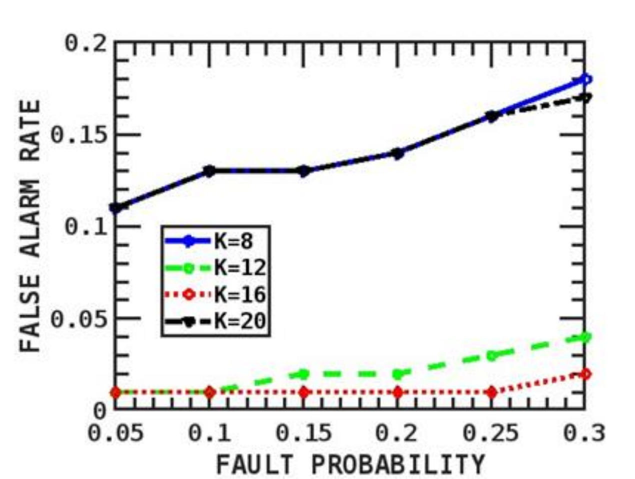
(a) Dense N_a =10



(b) Dense N_a =15



(c) Dense N_a =20



(d) Dense N_a =25

Figure 7 False Alarm Rate vs Likelihood of Fault for the DSFDD3SET Algorithm for Different Degree of Nodes (N_a= 10, 15, 20, 25)

For a network of 2048 sensors and 30% damaged sensor nodes, figure 7 displays the false alarm rate for different K values based on the clustering degree Na=10,15,20,25 where K = 8,12,16, and 20. It displays the performance false alarm rate with regard to the defective nodes, as demonstrated by the values of 0.05, 0.1, 0.15, 0.2, 0.25, and 0.3 for each individual sensor in each cluster region under various cluster neighbor counts. Randomly selected nodes with degrees of 10, 15, 20, and 25 make up the cluster's neighbor nodes. Figures demonstrate how the DSFDD3SET method works better than the current approaches and offers a higher degree of low false alarm rate. It has been demonstrated that when neighboring nodes grow, false alarm rate grows but low as relative to

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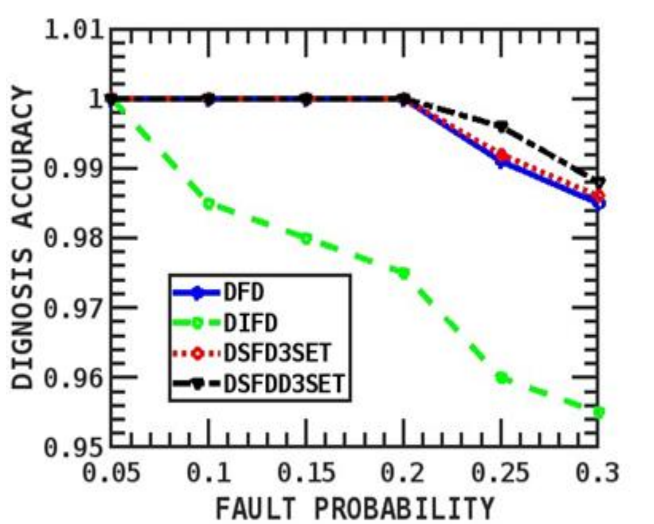
every other approach now in use with regard to k values. False alarm rate increases as the number of nodes with regard to k values increases but low as compare with low value, but message transmission also goes up at the same time. When the neighbor's values are 30 or higher, the DSFDD3SET algorithm performs better than other algorithms in this situation with K = 8, 12, 16, and 20, as shown by the findings in figure 7 (a), (b), (c), and (d).

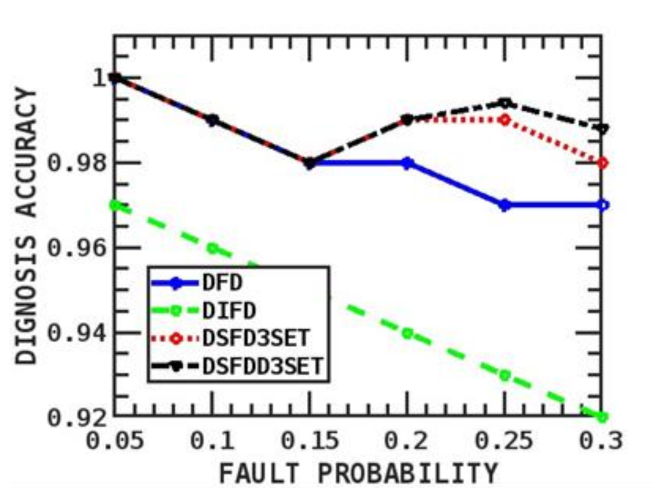
Each sensor node in the simulation exhibits erroneous behavior over a period of time T = 350 s. Each sensor node is tested for fault status 8, 12, 16 and 20 times throughout this period by selecting the time intervals T as 39s, 27s, and 20s, respectively. The Bernoulli distribution is used to create the data for a cluster sensor node that experiences intermittent failure. Figures 5, 6, and 7, respectively, display the DA, FAR, and FPR performances for various cluster degrees. The outcome demonstrates that, for a fault likelihood of PR = 32% with a cluster degree of 25, and an intermittent fault likelihood of = 92%,

The diagnosis accuracy provided by the DSFDD3SET algorithm is 100%, has a 0% FPR, and has a 0% FAR. To find the intermittently malfunctioning sensor node, at least 20 testing iterations must be performed. The DFD and DIFD method, in contrast, requires 31 iterations to reach the same level of performance [5].

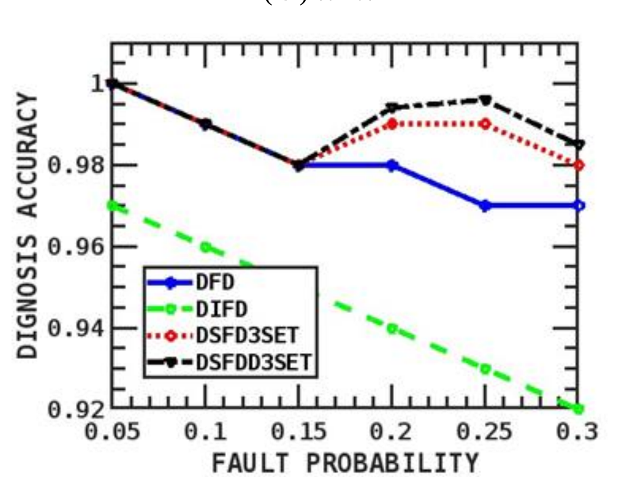
As a result, the suggested technique conserves 33% of the sensor node's energy, which may be used for the sensor network's typical workloads. The DSFDD3SET algorithm performs diagnosis with less iterations. To make a diagnosis, the suggested approach models the cluster fault behaviour using the Bernoulli distribution with KNN and a modified dense 3sigma edit test technique.



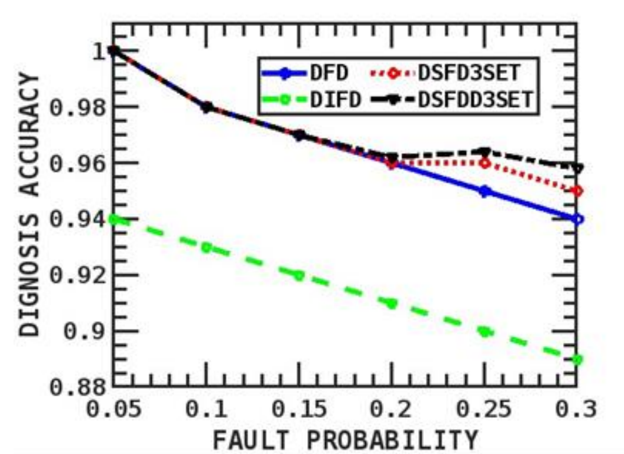
(a) α=0.6



(b) α=0.7



(c) α=0.8



(d) α=0.9

Figure 8 The DSFDD3SET, DFD and DIFD Algorithms' Diagnosis Accuracy vs Fault Probability Charts for Various Na and α

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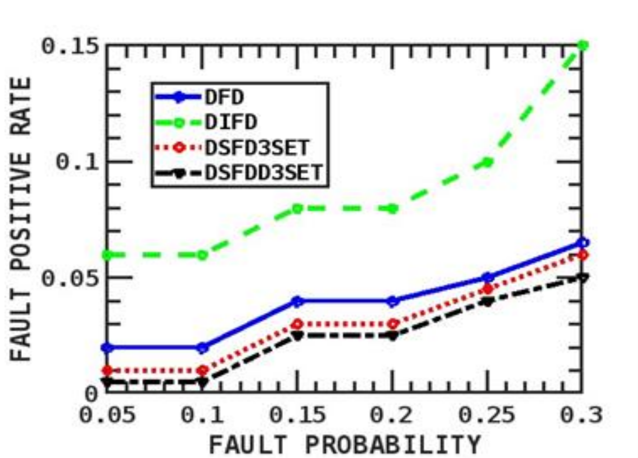
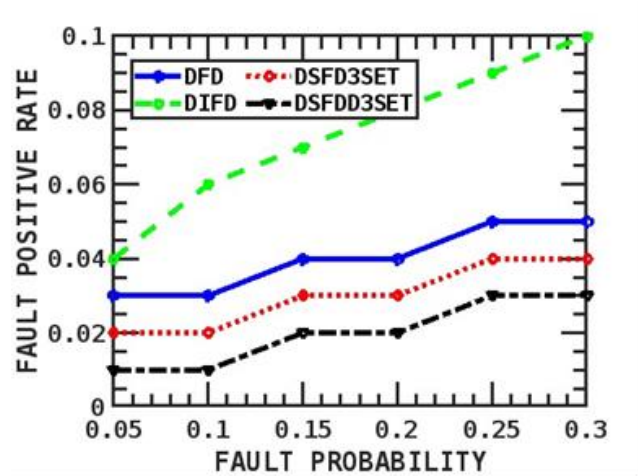
For each sensor in each cluster, respectively, under various numbers of neighbors, figure 8 illustrate the performance of the diagnosis accuracy with respect to the defective node at values of 0.05, 0.1, 0.15, 0.2, 0.25, and 0.3. The neighbors' sensors n are randomly selected to be at values of 0.6, 0.7, 0.8, and 0.9. The figures demonstrate that the DSFDD3SET method outperforms the current approach by demonstrating greater diagnosis accuracy, as stated. In comparison to the current approach, the accuracy of the diagnosis increases as the number of neighbors increases. Even in the worst situation, the detection accuracy of the DSFDD3SET is 94%, which is significantly better than the other conventional approaches' 94% and the current approach's 94% for problematic nodes. All algorithms perform better as the number of nodes increases, but message transmission also increases at the same time. In situations where the neighbor value is 30 or higher, the DSFDD3SET approach outperforms other algorithms. Figures 8(a), (b), (c), and (d) show that the DSFDD3SET approach outperforms the other three currently employed algorithms, DFD, DIFD, DSFD3SET, and DSFDD3SET.

5.2. The Performance Measures for False Positive Rate, Diagnosis, and False Alarm Rate

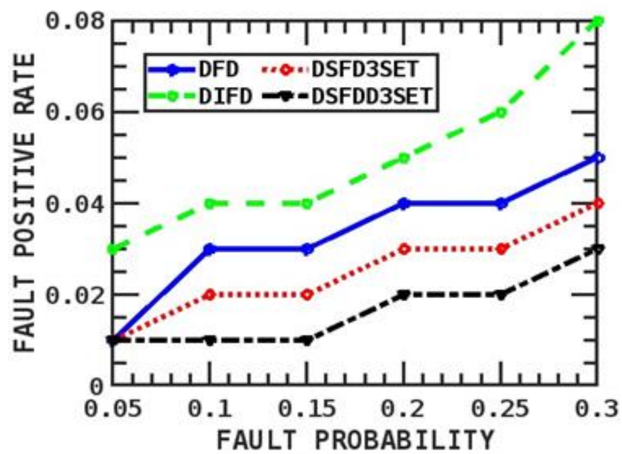
The effectiveness of the DSFDD3SET algorithm is tested for various intermittent cluster fault likelihood (α) after computing the bare less quantity of testing interaction, necessary to identify cluster sensor nodes and nearest cluster nodes associated with the cluster head and identify the fault free or faulty. Identification of intermittently defective sensor nodes is highly reliable when they produce inaccurate data for prolonged periods of time. The issue arises when a sensor node's sensed data becomes suspicious for a short duration. The algorithm's resilience is tested across different parameter values, and it is observed that if the likelihood of intermittent defects in a cluster node is less than 0.6, the algorithm's performance deteriorates.



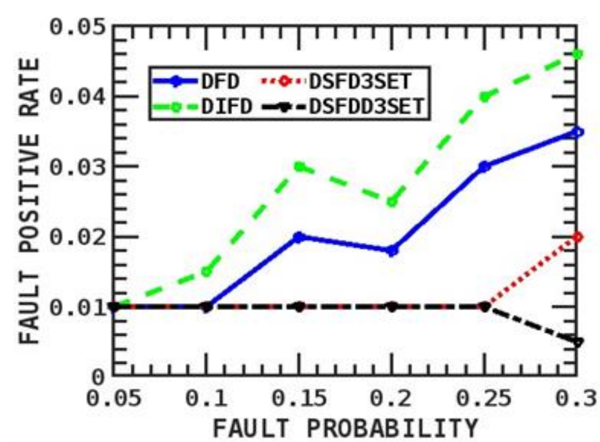
(a) α=0.6



(b) α=0.7



(c) α=0.8



(d) α=0.9

Figure 9 The DSFDD3SET, DFD and DIFD Algorithms' False Positive Rate vs Fault Probability Charts for Various Na and α

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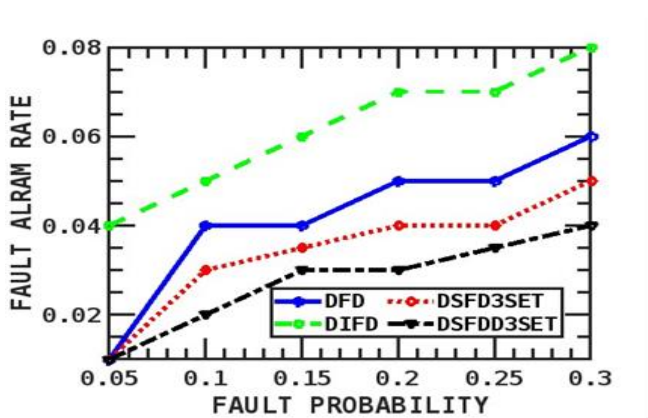
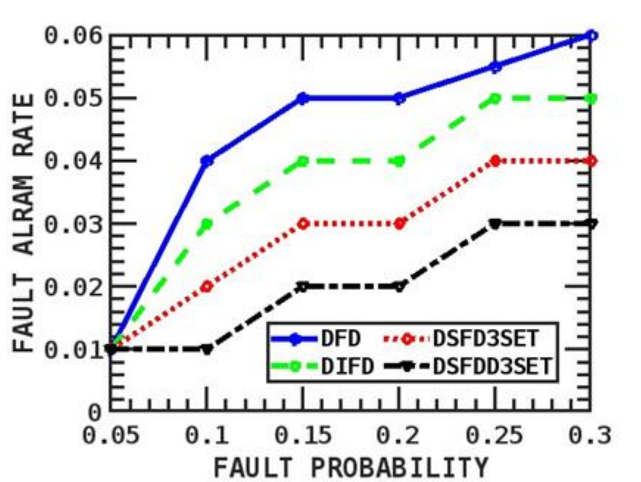
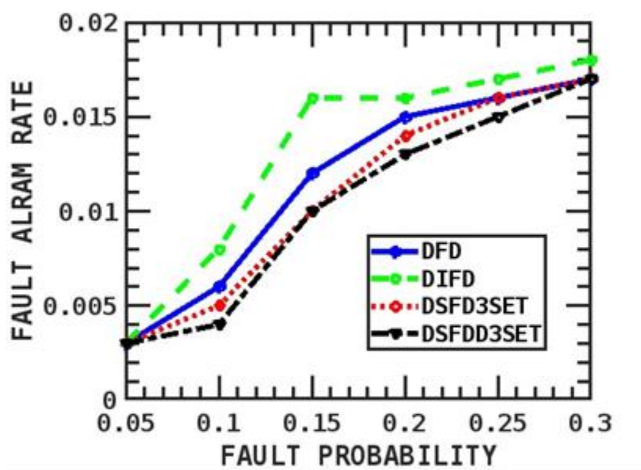
Figure 9 illustrates the performance of the false positive rate for each sensor in different clusters, considering various numbers of neighbors. The defective node probability values considered are 0.05, 0.1, 0.15, 0.2, 0.25, and 0.3. The neighbor sensors 'n' are randomly selected with probabilities of 0.6, 0.7, 0.8, and 0.9. The results show that the DSFDD3SET method performs better than the current approach, exhibiting a higher false positive rate but lower compared to other existing algorithms. When compared to the current approach, the false positive rate increases with an increase in the number of neighbors, but it remains lower than the other algorithms. Even in the worst-case scenario, the false positive rate of DSFDD3SET is 84%, which is significantly better than the other conventional approaches, which have a false positive rate of 94%, and the current approach, which has a false positive rate of 84% for problematic nodes. All algorithms perform better as the number of nodes increases, but message transmission also increases at the same time. In situations where the neighbor value is 30 or higher, the DSFDD3SET approach outperforms other algorithms. Figure 9 (a), (b), (c), and (d) show that the DSFDD3SET approach outperforms the other three currently employed algorithms, DFD, DIFD, DSFD3SET, and DSFDD3SET. Figures 8, 9, and 10 present the results of the DSFDD3SET algorithm for various fault probabilities, average degree Na, and cluster sizes. The evaluation is done in comparison to the current DFD and DIFD methods [5]. The proposed approach achieves an intermittent fault probability of 0.6% with a diagnosis accuracy of approximately 90%, a false positive rate (FPR) of 10%, and a false acceptance rate (FAR) of 7%. Specifically, when the intermittent cluster fault probability (α) is set to 0.7, the cluster degree node (Na) is 25, and the cluster size comprises 2048 nodes, the DSFDD3SET algorithm improves the analysis accuracy by 6%, reduces the FPR by 7%, and lowers the FAR by 5% compared to DIFD and DFD methods.



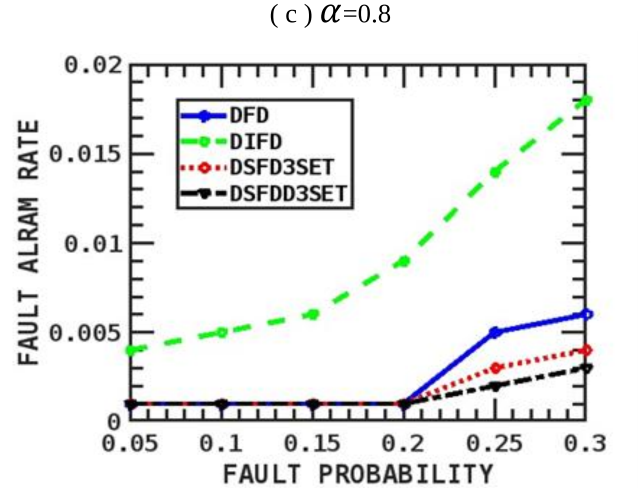
(a) α=0.6



(b) α=0.7



(c) α=0.8



(d) α=0.9

Figure 10 The DSFDD3SET, DFD and DIFD Algorithms' False Alarm Rate vs Fault Probability Charts for Various Na and α

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For each sensor in each cluster, respectively, under various numbers of neighbors, figure 10 illustrate the performance of the false alram rate with respect to the defective node at values of 0.05, 0.1, 0.15, 0.2, 0.25, and 0.3.

The neighbors' sensors n are randomly selected to be at values of 0.6, 0.7, 0.8, and 0.9. The figures demonstrate that the DSFDD3SET method outperforms the current approach by demonstrating greater false alram rate but low as comparative to other existing algorithm, as stated. Compared to the current approach, as the number of neighbor's increases, the false alarm rate also increases but remains lower than that of other methods. Even in the worst situation, the false alram rate of the DSFDD3SET is 85%, which is significantly better than the other conventional approaches' 95% and the current approach's 85% for problematic nodes.

All algorithms perform better as the number of nodes increases, but message transmission also increases at the same time. In situations where the neighbor value is 30 or higher, the DSFDD3SET approach outperforms other algorithms. Figures 10 (a), (b), (c), and (d) show that the DSFDD3SET approach outperforms the other three currently employed algorithms, DFD, DIFD, DSFD3SET, and DSFDD3SET.

6. CONCLUSIONS

This paper describes a dense diagnosis method for intermittently malfunctioning DSNs based on the distance measuring function. The Manhattan and Euclidean distances are determined exactly using measurement data and sensor node data. In general, the Manhattan-based strategy performs better than the Euclidean distance-based KNN approach. Utilizing statistics from upcoming data, the threshold value is calculated. The proposed method is a onetime test used to determine the intermittent defect condition of a sensing node in DSNs. It involves calculating the median and variance for both incoming data and the kept statistics set. Formerly, it evaluates the statistical against a threshold value, while considering a certain tolerance. Using the DSFDD3SET-based fault diagnosis method, the troublesome node can be identified with an impressive 98.9% exposure accuracy, a false alarm rate of only 0.8%, and a false positive rate of 0.4%, particularly when the probability of defective data exceeds 25%. But when a distributed network forms many clusters, the cluster fault probability is 34%, the intermittent cluster fault probability is 74%, the cluster degree is Na = 15, and the cluster size is 2048, suggesting that DSFDD3SET outperforms the DFD and DIFD algorithms by 11%, 7%, 8%, and 12% in DA, FPR, and FAR, respectively. Future research will expand the study's focus to include additional wireless sensor network issues and improve the false-positive rate's performance.

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