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Amalgamation of WSN & AI for Detection of Soft Faults

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Abstract

A wireless sensor network (WSN) consists of a large number of densely deployed sensor nodes which work in a collaborative manner to periodically sense the conditions of a monitored area, process the data, and transmit it to a sink. The advancements in technology have made the wireless sensor networks economically affordable, small and manageable. Nowadays, wireless sensor networks are being used for a wide variety of applications like ecological surveillance in the forest, underwater surveillance, automatic monitoring of social interactions, monitoring glacier dynamics, precision agriculture, monitoring the health of civil structures, monitoring of industrial cyber physical systems, battlefield surveillance etc., and are also evolving towards the internet of things. In the technology of wireless sensor network (WSN), wireless sensor fault diagnosis based on fusion data analysis has attracted attention in the wireless sensor network. It can detect and correct the faults of sensor nodes in time to improve the accuracy of sensor data fusion. In this research work, the data characteristics of WSN are analyzed, and a method is proposed for fault diagnosis of WSN based on sequence based approach model. First, the sensor fault diagnosis process is described based on the characteristics of a wireless sensor in WSN. Then, the characteristics of sensors are analyzed from the aspects of reliability, energy efficiency, and security. Finally, a fault diagnosis model is proposed based on artificial intelligence algorithm. To make the results more accurate, an evolution strategy algorithm would be used to optimize the initial parameters of the proposed model.

Keywords:: Soft Faults, Fault Diagnosis, AI, security, Energy, WSN.

1. Introduction

Wireless sensor networks (WSN) are an interesting area of networks consisting of low power wireless sensor nodes having a small central processing unit (CPU) and memory for high quality sensing of the environment (Welsh et al., 2004). In the early days, setting up of a WSN required very expensive and sophisticated equipment. Hence, these were used only for selective and crucial applications. However, the advancement of technologies like micro electro mechanical systems (MEMS), wireless communication and low cost manufacturing techniques have made WSNs economically affordable, small and manageable (Zheng and Jamalipour, 2009; Sohraby et al., 2007). As a result, nowadays, the WSNs are being used in a variety of applications like healthcare (Alemdar and Ersoy, 2010; Ko et al., 2010), precision agriculture (Kampianakis et al., 2014), environment and ecosystem monitoring (Matic et al., 2013; Zhao et al., 2013; Ojha et al., 2013; Martin et al., 2014; Dominguez-Morales et al., 2016), monitoring the health of civil structures, industrial machines, engines and processes (Gruden et al., 2014; Bhuiyan et al., 2015; Chen et al., 2015), development of urban train transportation environments (Aguirre et al., 2017; Mainetti et al., 2011), battlefield surveillance (Akyildiz et al., 2007; Yick et al., 2008) etc. Some specific characteristics of the wireless sensor networks like severe energy, computation and storage constraints, high unreliability of sensor nodes, deployment of sensor nodes in inaccessible terrains, denser node deployment etc. (Sohraby et al., 2007) make them unique. The following sub-section presents the characteristics of WSNs.

The distinctive features of wireless sensor networks differentiate them from the conventional wireless networks (Su et al., 2004; Zheng and Jamalipour, 2009; Wang et al., 2009). These characteristics and constraints are summarized in this section. In comparison with the conventional wireless networks, the number of sensor nodes deployed is much larger in wireless sensor networks. Most of the applications of wireless sensor networks require battery operated wireless sensor nodes to be deployed in hostile environments, making the replacement or recharge of their batteries difficult or sometimes impossible. Three crucial resources namely the energy available to, the computation capacity and the storage capacity of the wireless sensor network nodes are extremely limited (Zheng and Jamalipour, 2009; Wang et al., 2009). Wireless sensor networks are intended to be self-configuring. On deployment, the nodes in a wireless sensor network are expected to organize themselves into a communication network by themselves. Further, WSNs are being deployed for a broad spectrum of applications. This large variation in the application areas necessitates a large variation in the specifications of WSNs. Thus, it is very difficult to specify a general set of rules, topologies and parameters for WSNs. Once the network is deployed and starts working, the nodes may fail, get damaged or may deplete in energy. All these situations emphasize the need for a dynamic network topology. Since a huge number of WSNs are being set up and each is supposed to have a very large number of sensor nodes, developing a global addressing scheme for the WSNs is practically impossible (Zheng and Jamalipour, 2009). The traffic pattern of wireless sensor networks is also peculiar. Since most of the time, information is to be sent by the sensor nodes to the sink, it is a many-to-one traffic pattern. Further, in the wireless sensor networks with densely deployed wireless sensor nodes, the data generated by the nodes are highly correlated and redundant.

A wireless sensor network comprises a large group of wireless sensor nodes deployed for the monitoring of a region. These units gather information regarding the parameters that are to be measured and report it to the data sink(s). The following subsections present the architecture of a wireless sensor node and a wireless sensor network. Figure 1 shows the structure of a wireless sensor node. A wireless sensor node is made up of a sensing unit, a processing unit, a communication unit and a power supply unit (Akyildiz et al., 2002; Raghunathan et al., 2002; Zheng, 2009).

1. ***Sensing Unit:*** The sensing unit is made up of the sensors for measuring the desired parameters and an analog to digital converter (ADC). The sensors generate analog signals in proportion to the measured parameters. These analog signals are converted to digital form by the ADC.
2. ***Processing Unit:*** It is basically the control unit of the wireless sensor node. It consists of a microprocessor/microcontroller and the associated memory. It processes the data received from the sensing unit to extract useful information.
3. ***Communication Unit:*** It consists of a short-range radio transceiver. It performs the function of data transmission and reception.
4. ***Power Supply Unit:*** All three of the aforementioned units need power for their operations. This power is supplied by the power supply unit consisting of a portable battery. The above-mentioned units are integral parts of any wireless sensing node. As per the requirements of the application, a wireless sensor node may also carry some additional circuitry like a global positioning system (GPS), a motor etc.

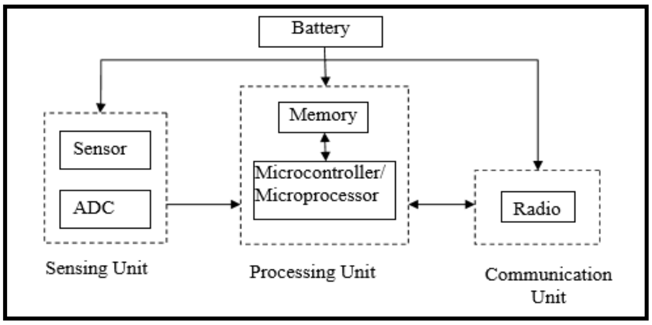

Figure 1 Wireless Sensor Node Structure

This research is organized as follows: Section 1 gives the introduction of wireless sensor networks background, architecture, energy efficiency, design issue and objective of theresearch. Section 2 gives literature survey collected through IEEE explore. Section 3 is forproblemidentification. Section 4 gives Fault Diagnosis WSNs introduction. Section 5 gives the proposed work of system model design for sequence based AI to detect soft faults in WSN. Finally section 6 defines results and discussion and future direction of research work.

1.1. Objective of Research

The aim of the research is to contribute towards improving the performance of wireless sensor networks by using sequential based on approach artificial intelligence algorithm. The work has been carried out to achieve the following objectives:

- To implement sensor deployment in WSNs by applying sequential based on approach artificial intelligence algorithm such as predator-prey optimization (PPO) and random search or pattern search.
- To design & code reliability approach, energy efficiency approach and security approach in WSN network with the help of simulation tools

2. Literature Review

Wei Fang et. Al. [1] introduced a two-layer sleep scheduling system in energy-harvesting WSNs with an aim to satisfy sustainable throughput by analysis and optimization of network performance. Evaluation results provide a typical demonstration of how to obtain the appropriate value of key parameters according to specific requirement.

Zhiliang Zhu et. Al. [2] the distributed intelligent fault diagnosis system is presentation based on ZigBee technology and particle filter. Multi variable data's acquisition and centralized treatment is realized through the wireless sensor network, and the accurate estimation of the state of monitored objects and intelligent prediction of faults is based on the particle filtering algorithm. The system can achieve the real-time remote monitoring and fault prediction, meanwhile, effectively enhance applicable scope and diagnostic level of the fault diagnosis system.

Rakesh Ranjan Swain et. Al. [3] a real time soft fault diagnosis model is proposed for wireless sensor networks (WSNs) using particle swarm optimization (PSO) based classification approach. The proposed model follows in three phases such as initialization, fault identification, and fault classification phase to diagnose the composite faults (combination of soft permanent, intermittent, and transient fault) in the sensor network. The faulty nodes are identified in the network based on Analysis of variance (ANOVA) method. The feed forward neural network (FFNN) technique with PSO learning method is used for classification of the faulty nodes. We evaluate our model by carrying out the testbed experiment in an indoor laboratory environment.

Santoshinee Mohapatra et. Al. [4] an Artificial Immune System (AIS) based fault diagnosis for WSN (WAIS) algorithm has been proposed where the performance measures average diagnosis latency, detection accuracy, false alarm rate improved by 32.79%, 1.76%, 0.8% with respect to the existing algorithms such as dynamic distributed self diagnosis protocol (D DSDP), adaptive distributed self diagnosis protocol (A DSDP), mobile distributed self diagnosis protocol (M DSDP).

Salah Zidi et.al [5] Support Vector Machines (SVM) classification method is used for this purpose. Based on statistical learning theory, SVM is used in their context to define a decision function. As a light process in term of required resources, this decision function can be easily executed at cluster heads to detect anomalous sensor. The effectiveness of SVM for fault detection in WSNs is shown through an experimental study, comparing it to latest techniques for the same application.

SHUANGYIN LIU et.al. [6] proposed a hybrid water quality monitoring devices fault diagnosis model based on multiclass support vector machines (MSVM) in combination with rule-based decision trees (RBDT).In the modeling process, the rule-based decision trees (RBDT) is used to diagnose the gateway fault and wireless transmitter fault at the same time as a feature selection tool to reduce the number of features. Multiclass support vector machine classifier is employed to diagnose the faults of water quality sensors due to its robustness and generalization. We adopted an RBDT-MSVM algorithm to construct a fault diagnosis model. The diagnostic results indicate that RBDT-MSVM model has great potential for fault diagnosis of online water quality devices. RBDT-MSVM was tested and compared with other algorithms by applying it to diagnose faults of water quality monitoring devices in river crab culture ponds. The diagnostic results indicate that the model has great potential for fault diagnosis of online water quality devices. The experimental results show that the proposed model RBDT-MSVM can achieve classification accuracy as high as 92.86%, which is superior to the other three fault diagnosis methods. The results clearly confirm the superiority of the developed model in terms of classification accuracy, and that it is a suitable and effective method for fault diagnosis of water quality monitoring devices in intensive aquaculture.

Haibin Zhang et. Al [7] a Bayesian network model based sensor fault detection scheme is proposed in this paper, which relies on historical training data for establishing the conditional probability distribution of body sensor readings, rather than the redundant information collected from a large number of sensors. Furthermore, the Bayesian network-based scheme enables us to minimize the inaccuracy rate by optimally tuning the threshold for fault detection. Extensive online dataset has been adopted to evaluate the performance of our fault detection scheme, which shows that our scheme possesses good fault detection accuracy and a low false alarm rate.

Akmal Yaqini et. Al [8] proposed a fault detection and diagnosis approach for enhancing performance of WMNs based on Artificial Neural Networks (ANN). The artificial neural network is trained to detect and classify individual or composite faults. We consider node failure, link failure and traffic congestion as the target faults. The approach is implemented in NS3 network simulator and its performance is evaluated considering detection rate, false positive and false negative.

WEI HE et. Al [9] the data characteristics of WSN are analyzed and a method is proposed for fault diagnosis of WSN based on a belief rule base (BRB) model. First, the sensor fault diagnosis process is described based on the characteristics of a wireless sensor in WSN. Then, the characteristics of sensors are analyzed from the aspects of time, space, and attributes. Finally, a fault diagnosis model is proposed based on the hierarchical BRB model. To make the results more accurate, a covariance matrix adaptation evolution strategy algorithm is used to optimize the initial parameters of the proposed model. A case study using the Intel lab data set of sensors is designed to verify the effectiveness of the proposed model. The results show that the proposed method is effective in fault diagnosis of WSN.

KholoudALshammari et.al [10] presented a fault detection algorithm for wireless sensor networks based on Clustering. The faulty sensor detection process is run by the cluster heads depending on the neighbors voting. Detected faulty nodes information will be sent to the base station. Simulation results show that the proposed algorithm has good performance indicators in terms of smaller energy consumption and better detection accuracy.

3. Problem Formulation

Since WSNs have limited resources and are usually deployed in inaccessible, uncontrolled, and autonomous environments, each node in the network must be monitored to avoid adverse effects of faulty nodes on normal network operations. Low-cost sensor nodes often become error prone and unreliable due to hardware, software, and/or other imperfections manifesting as ‘‘glitches.’’ Consequently, fault diagnosis is required to identify, detect, isolate, reuse, or let the fault-free sensor work to address faulty events. This allows the network to be operational even in the presence of faults. Fault diagnosis can be observed at either side of the network, such as at the BS (centralized), node sides (distributed), or a combination of both (hybrid). Hybrid networks have a larger picture of the whole network compared to that in the node-based approach, and therefore decisions can be made from a relatively broader perspective.

The node side avoids traffic overhead and delay, which increases the overall lifetime of the network. As a result, the hybrid approach achieves the advantages of the other approaches while avoiding their disadvantages. Thus, by using this approach, a better fault diagnosis protocol or algorithm can be proposed. Significant work could be done on sorting out the issues of reliability, robustness, and lifetime in WSNs.

4. Fault Diagnosis in WSN

Fault diagnosis approaches have different classification methods and are of three types depending on where the decision of sensor node status is made [11]–[12]:

1) Centralized Approach: A geographically or logically centralized node, e.g., central controller or manager, the sink node, takes responsibilityfor fault managementofthe overall network.

2) ***Distributed Approach:*** Every sensor node is able to make decisions at certain levels; the decision center is transferred from the sink node to a common node.

3) ***Hybrid Appraoch:*** Between the centralized and distributed approaches, in which both the sink and common nodes have the right to decide the status of nodes.

4.1. FAULT TYPES

This section contains the common definitions of faults, classification methods, and concrete manifestations to help readers gain a basic understanding of fault types.

(i) Fault Definition

A fault is an unexpected change or malfunction in a system, although it may not lead to physical failure or breakdown [13].Unless ground truth is known or given by something with high confidence, the term fault can only refer to a deviation from the expected model of the phenomenon. A data fault is data reported by a sensor that is inconsistent with the phenomenon of interest's true behavior [14].

(ii) Fault Classifications

There are different ways of classifying fault types found in literature. Generally, faults can be mainly divided into two categories, as shown in Fig. 2:

- Hard faults: a sensor node is not capable of communicating with the rest of the network.
- Soft faults: a sensor node continues to operate and communicate with altered behavior, e.g., produces faulty data, cannot act as a stable routing node. Hard faults are also called permanent faults. They result from the failures of some hardware modules [15]:
- Communication module faults or transceiver module faults
- Battery depletion
- Out of communication range of entire mobile network Soft faults are always temporary or intermittent, which means nodes with soft faults act arbitrarily and are difficult to predict and detect [16], [17]:
- Byzantine, a node behaves arbitrarily or maliciously.
- Omission, a failure by omission is determined by a service sporadically notresponding to requests.
- Timing, timing failure occurs when a node responds to a request out of the time interval,which is alwaysinthe situation that demand higher real time performance.

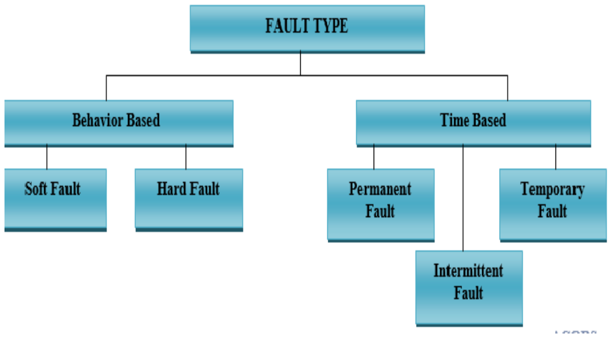

Figure 2: Fault Types

A. Centralized Approach : In centralized approaches, one centralized sensor node, always a SN or BS, is responsible for performing fault management. The statuses of the other nodes are decided by this centralized node, which possesses high computational power, abundant memory size, and persistent energy supply. Most times, the centralized node receives information from the rest of nodes forwardly or passively. By analyzing the information, the centralized node can confirm the statuses of the other nodes. In terms of papers published in recent years, the centralized approaches can be classified into the following methodologies.

(i) Probabilistic Approach: In the probabilistic method, fault diagnosis is considered a pattern-classification problem. Many classification algorithms are applied to this problem, e.g., the naïve Bayes classification algorithm and the maximum posterior probability hypothesis.

Lauetal.[18] proposed the centralized naïve Bayes detector to classify sensor nodes by analyzing the end-to-end transmission time collected at the sink. As with the CNDB algorithm, Tang and Chow [19] modeled the network as a graph using an extended algorithm known as a neighborhood hidden conditional random field (NHCRF). The NHCRF judges a faulty sensor node in the network by collecting its signal strength, frequency, and signal delay. It subsequently relaxes the independent assumptions that help determine non local dependencies among states and observations. Thus, the status between sensor nodes and transmission paths can be determined. Furthermore, because of inclusion between state dependencies, performance evaluations show that NHCRF is very effective and efficient atfault diagnosis under different sizes and traffic loads. Furthermore, Dhal et al. [20] proposed an approach that regards a classification problem as a maximumposterior probability hypothesis testing problem.

(ii) Support Vector Machine (SVM): The SVM is one type of supervised learning model with associated learning algorithms that analyze data used for classification and regression analysis in machine learning. Yu et al. [21] proposed a new direction of fault node diagnosis. Their algorithm tried to reduce fault information in order to decrease diagnosis time. As we know, fault diagnosis has significant communications overhead, calculation complexity, and large energy consumption. This paper claims to use rough set (RS) theory to filter out less important data and build a new simple dataset that is used to train the SVM. Therefore, RS-SVM fault diagnosis is done using the aforementioned methods. Furthermore, RS-SVM can effectively and diagnose and detect faulty network nodes more accurately than other methods.

(iii) Fuzzy Classification: This approach is also one of the common machine learning approaches. Compared to the probabilistic method, observed values do not have a necessary relation to a certain status. One certain status is always decided by several observed values, and each value has its own weight. Chanakand Banerjee [22] demonstrated a fuzzy rules-based faulty node classification and management scheme (FNCM) for the detection of physical and environmental conditions, e.g., road monitoring, smart home automation, and lives to ck management. It distinguishes itself from existing approaches in four ways. First, it uses an efficient data routing algorithm for the recovery and reusability of faulty nodes. Second, it overcomes the problem of uncertainty. Third, it assigns work to anodeperits hardware capabilities and status. Finally, its management of nodes not only helps to achieve an efficient routing scheme, but also increases overall network performance.

B. Distributed Approach: Unlike the centralized approach, each sensor node in the model-less or distributed approach makes decisions about their health status by gathering and analyzing diagnostic response results from neighboring nodes. Then, they update the BS accordingly. Therefore, the model-less approach transfers a little information to the BS, which helps prolong network lifetime. It further reduces much traffic overhead, and minimizes the end-to-end delay over the network. There are many recent techniques described in the literature that follow distributed approaches for fault detection and diagnosis.

(i) Spatial Temporal Coordination: In this kind of approach, diagnosis methods depend on spatial and temporal coordination. In terms of spatial coordination, one sensor node, e.g., node si, is used to monitor the local temperature, and another sensor node, sj, is the neighboring node, which means it is in the transmission radius of sj. Both nodes have similar data. In terms of temporal coordination, one node, if it is fault free, has relatively stable data over a period of time. Miao et al. [23] demonstrated agnostic diagnosis to discover silent failures in WSNs. This is a sink-based technique that collects data from all sensor nodes in the network. This technique is different from other techniques in the following ways: (i) it does not consider pre defined rules; it relies on a priori knowledge as little as possible, and it can be applied to a large number of applications in WSNs; (ii) it generates a correlation graph that can efficiently characterize correlations between metrics and can describe the latent status inside a node; and (iii) it demonstrates an agnostic diagnosis (AD) algorithm, an online lightweight failure detection approach, and checks its effectiveness through a 330-GreenOrb-node deployment. The effectiveness of this algorithm was demonstrated through studies of different cases and statistical analysis. Furthermore, since it is a sink-based technique, there is a delay between fault time and fault detection time. In fault detection, there is a trade-off between detection accuracy and detection latency. More tests or operations on the status of one node are certain to improve detection accuracy, but can also lead to superior detection latency or detection delay. During this period, the status of a node may change. Mahapatro and Panda [24] proposed a method based on multi-objective swarm optimization to solve this problem. This fault detection method still depends on neighboring nodes, so it can be classified ass patial-temporal coordination.

(ii). Self Diagnosing:In this type of approach, sensor nodes are required to compare their sensor data with that of their neighbors. Sensor node statuses are determined by the neighbors. These algorithms can work properly at the early stage of deployment, as most sensor nodes are normal and their judgments are correct. As time goes by, the performance of algorithms degrade, especially the common mode failures (CMFs), which are impossible for comparative methods to detect. In this approach, to reduce the effect of neighboring nodes' data, a sensor node is capable of detecting its own status. Babaie et al. [25] suggested a new self-diagnosing approach. This approach reduces the effect of neighboring nodes and uses Petri nets and a correlation graph to analyze the behavior of sensor nodes. By using Petri nets, which are actually flow charts, sensor nodes are capable of detecting different kinds of faults, i.e., permanent faults and transient faults. The correlation graph is used to diagnose the failure of inner links between sensor components.

(iii). Probabilistic Approach

Titouna et al. [26] also presented a fault detection scheme (FDS) for WSNs. Their method used probabilistic classifiers employing the formalism of Bayesian networks. This method represents the network in the form of a directed a cyclic graph that shows a probability distribution. Each node is represented by a random variable Xi,and the edge between two nodes shows a probabilistic dependency of a child. The network structure illustrates that each Xi from its parent is conditionally independent from its non-descendants. According to these assumptions, a conditional probability table is associated, illustrating that each Xi distribution assigns any possible values to its parents. A Bayesian network is simply a Bayesian classifier used for task classification.

(iv). Topology Control: Sensor nodes with limited energy will be dead when their battery power is exhausted. If these nodes are routing nodes, they could affect network connectivity. Compared to the energy scarcity in the latter stage, most energy is wasted in the first stage, when most nodes are deployed closely and can communicate with all the nodes in their transmission range, and it is unnecessary and wasteful. In order to prolong the lifetime of a network, Deniz et al. [27] proposed an adaptive energy-aware and distrusted fault-tolerant topological control algorithm (an adaptive disjoint path vector, or ADPV, algorithm), as schematically depicted in 6. The protocol works in two phases: initialization and restoration. In the initialization phase, the ADPV finds all alternative paths based on a set-picking method pre-existing in the network. The restoration phase initiates whenever k-vertex connectivity with the stationary super node is broken. To restore connectivity, the ADPV uses the calculated alternative paths and readjusts the nodes' transmission ranges accordingly. The ADPV is distributed in nature, and simulation results have illustrated that it prolongs the lifespan of heterogeneous nodes connected to the super node. It also guarantees network connectivity durability, ranging from 5% to 95%, against node failures. Moreover, in cases of 75% and 90% node failure, the network remains connected to the super node through three or two vertexes, respectively.

(v).Cluster based: A cluster head is a kind of supernode with rich energy and abundant computation capability, the characteristics of which are adaptive for performing fault diagnosis in WSNs. Afsar [28] proposed a fault-tolerant service (FTS) based on a hierarchical network. This service can be divided into three steps:

• Fault detection: this step can be divided into two types, cluster head (CH) fault detection and cluster member (CM) fault detection. A CH fault is detected by a spare cluster head, the neighboring CHs, and the CMs. Fault detection of a CM is accomplished by the CHs. Both CHs and CMs have to send heartbeat, summary, and update messages periodically to their corresponding nodes. If these corresponding nodes receive none of these messages, the CHs or CMs are considered to be faulty and the process advances to the next step.

• Fault diagnosis: the FTS uses time redundancy to detect transient faults around both CMs and CHs. If a fault cannot be affirmed to be transient fault, it is a permanent fault.

• Fault recovery: CH fault recovery is a replacement of the spare cluster head.CM recovery is removal of the faulty CMs from the routing table.

C. Hybrid Approach: Based on decision center, a hybrid approach has two decision components, one in the sink node and one in the common nodes. This approach originated from the acknowledgement of two main drawbacks in centralized and distributed approaches. A centralized approach cannot be applied in large-scale networks, and has relatively higher diagnosis latency. The main problem in a distributed method is keeping the detection accuracy high. In order to solve these problems, a hybrid approach was proposed. Up to now, the basic thought of a hybrid approach has been to add extra equipment, e.g., a mobilizer, to achieve diagnosis reliability, robustness, energy efficiency, and minimization of traffic overhead.

(i). Mobile Sink:In order to overcome the limitations in both distributed and centralized approaches, and due to the improvisational nature of WSNs, the lack of insight into internal running status,and, in particular, since network structure can frequently change due to link failure, Chanaketal. [23] presented a mobile sink based distributed fault detection scheme, which identifies the health status of each software and hardware component separately. In this algorithm, the mobile detector starts its fault diagnosis from the BS. As it explores each deployed node it obtains its health status. It then uploads the information from all nodes in the network. It completes its operation by returning to the BS. This information helps the administrator recover and reuse faulty sensor nodes. It also helps maintain reliability, and improves the lifespan of the network. Experiments concluded that this scheme outperforms existing fault detection techniques because single-hop communication for detection is followed.

5. Proposed System Design Model

The basic structure of WSN is shown in Fig.3. A typical WSN consists of four parts: sensor node, wireless transmission channel, sink node and information processing center. The wireless sensor node is used for collecting different types of environmental data. The wireless transmission channel is used for data communication between different nodes. The sink node is used to detect the connection between the area and the external network. The processing center summarizes data sent by different sensors and processes data. The data from all the sensor nodes is collected in the data processing center of WSN. By analyzing the sensor data, abnormal values can be detected, and the faults can be diagnosed in WSN.

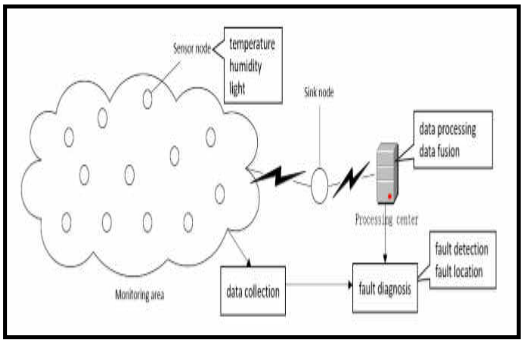

Figure 3: WSN basic structure diagram

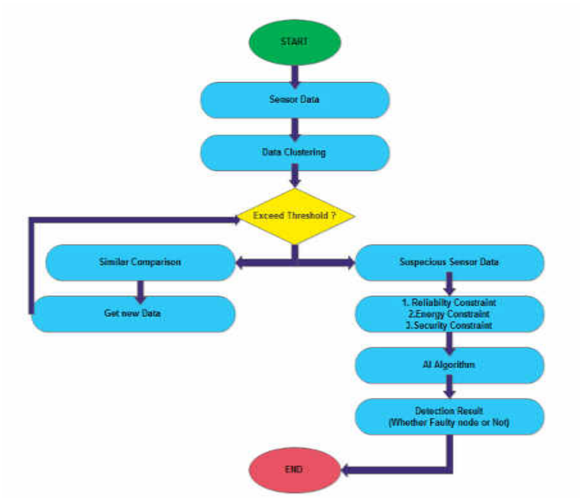

Fig 4: System Design Model Overview

The proposed system design model would work in following steps:

Step 1: When a WSN network is deployed, each sensor node sense data and communicate with each other for sharing information like location, hop count, sequence number, energy level etc.

Step 2: The sensed data would be sent to nearby cluster head node; and this cluster head node would further communicate with other cluster head node and send it for further communication over the network so as to reach the sensed data to SINK node.

Step 3: A constant value is defined for threshold value of energy level of each sensor node and each node checks this threshold energy level before sending data to nearby nodes.

Step 4: If all the nodes are at normal working manner then the suitable comparison would be made and we get new data every time which would be updated regularly. This data keeps doing comparison with the threshold value.

Step 5: If there is node found which is lesser thanthreshold energy level then suitable faultdiagnosismechanism would be checked.

Step 6: A new proposed algorithm would be developed for this phase which checks suitability of nodes via three TIER levels. The first TIER level checks whether the node have reliability issue in terms of packet drop, throughput or QoS constraints. If this issue is considered then node would be termed as Reliability faulty node else checks for next TIER level. The second TEIR level checks whether the node has energy level issue i.e. energy of the node is continuously decreasing then node would be termed as Energy faulty node else checks for next TIER level. The third TEIR level checks whether the node has security issue or some attacker activity then the node has security issue then the node would be termed as Security faulty node. In this manner the proposed algorithm performs three TEIR fault diagnosis in terms of Reliability, Energy and Security.

Step 7: In this an AI algorithm would be adopted which classifies these nodes that which node falls into above three categories and declare them faulty nodes in a network.

6. Result and Conclusion

For research work simulations, considering the node as 'sensor node' and knowing only the parent to whom it is assigned to communicate with is a major factor in determining an effective algorithm which adhered to this reality of WSNs. Because of this, the complexity of coding greatly increased and many more considerations emerged.

This research work will implement proposed method in NS-2 and compare it with existing method. Since we are very new in the fields of wireless sensor networks and the network simulation, we spent a lot of time to learn how to write OTcl script in NS-2 and solve some NS-2 problems such as installation problems. Although NS-2 is the most widely used for the network simulator, it does not support directly the wireless sensor network, and to use this simulator with the sensor networks, some implemented modules are needed. Furthermore, some applications in the wireless sensornetworks require some new modules for generating real data packets or new artificial intelligence techniques.

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