A Fuzzy MLP Approach for Fault Diagnosis in Wireless Sensor Networks

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***Abstract*—This paper presents a fault diagnosis protocol for wireless sensor networks (WSNs) based on neural network approach. A particle swarm optimization based fuzzy multilayer perceptron used in the fault detection and classification phase of the protocol. The proposed protocol handled the composite fault model such as hard permanent, soft permanent, intermittent, and transient fault. The performance of proposed algorithm evaluated by using the generic parameter such that detection accuracy, false alarm rate, and false positive rate. The simulation is carried out by the standard network simulator NS-2.35 and the performance is compared with the existing fault diagnosis protocols. The result shows that the proposed protocol performs superior than the existing protocols.**

I. Introduction

Wireless sensor network (WSN) is a collection of sensor nodes, which gather physical data from the environment and process it. WSNs have great potential to support various applications such as environmental monitoring, industrial surveillance, and military surveillance operations etc [1] [2]. Due to the harsh and human inaccessible environment, the WSNs gives unexpected behavior, which leads to network failure. The imperfection behavior of sensor nodes called as a fault in the sensor network. The erroneous results of faulty sensor nodes infected the whole network, so the fault detection and fault diagnosis are truly needed to be handled with various types of faulty node.

The fault in the WSNs is broadly classified into two types, such as hard fault and soft fault [3] [4]. The hard fault is called as permanent hard fault, which the nodes do not respond to their environment. Whereas soft fault again classified as permanent, intermittent, and transient fault. In case of soft fault, respond with erroneous results each time called as permanent soft fault. The nodes behave arbitrarily means, unpredictable results for some continuous interval and predictable results for some continuous interval called as intermittent fault. The transient fault perish suddenly in the network and then vanish suddenly.

The fault detection and diagnosis are classified into various types such as test based, neighbor co-ordination based, soft computing based, and comparison based. The previous existing work on fault diagnosis of WSN focus on different types of faults such as hard, soft, intermittent and transient faults independently. Most of the previous research work on fault diagnosis in WSNs performance are not uniform for various environments.

The neural network approach is used extensively in various research applications. Neural network is an important technique, which could be applied for fault diagnosis in WSNs. The existing fault diagnosis algorithms are not considering the potential of neural network, which is the best alternative method for fault diagnosis. Considering the needs of fault diagnosis in WSNs, a fault diagnosis protocol was proposed by using fuzzy multilayer perceptron (MLP) neural network approach. The proposed fault diagnosis protocol focus on different types of faults such as hard permanent, soft permanent, intermittent, and transient fault at a time. The proposed fault diagnosis protocol classified into three phases, i.e. (i) clustering phase, (ii) fault detection & classification phase, and (iii) isolation phase. The performance of proposed protocol is compared with the existing algorithm Chen et al. [12] and Azzam et al. [18], based on the performance metrics detection accuracy, false alarm rate, and false positive rate.

The proposed protocol for WSN can be used into military applications, industrial applications, and environmental applications, etc. The military applications include enemy tracking and security detection. The industrial applications include mine tracking, structural monitoring, and inventory monitoring. The environmental applications include weather, temperature, humidity, and pressure monitoring.

The paper is organized as follows. Section I presents the introduction. Section II describes the literature survey. Section III represents the system model. The proposed fault diagnosis protocol for WSNs is presented in section IV. The simulation and results are shown in section V. In section VI, we give the conclusion and future scope.

II. Literature Survey

Many fault diagnosis protocols are proposed for WSNs to detect the faulty node effectively. The protocols are discussed as follows in the Table I. The existing fault diagnosis protocols are considering the different type of faults such as hard permanent, soft permanent, intermittent, and transient fault independently, whereas the proposed fault diagnosis protocol consider different type of faults at a time.

TABLE I: Literature Survey

Authors	Protocol	Method	Types of Fault Detection
Panda et al.,2015 [9]	Distributed fault detection technique in WSNs based on hypothesis testing	Neighboring co-ordination method using Neyman-Pearson method to detect the faulty sensor nodes.	Byzantine fault
Panda et al.,2015 [10]	Distributed self fault diagnosis for WSNs using modified three sigma edit test	Neighboring co-ordination method using modified three sigma edit test. Mean replaced by median and standard deviation replaced by normalize absolute deviation.	Hard permanent and soft permanent fault
Sahoo et al.,2014 [11]	Distributed fault diagnosis in WSNs (FDA)	Comparison based neighboring sensor node values and their residual energy values.	Soft permanent and intermittent fault
Chen et al.,2006 [12]	Distributed fault detection of WSNs (DFD)	Majority voting based by neighboring nodes.	Soft permanent fault
Xianghua xu et al.,2008 [13]	Distributed localized fault diagnosis algorithm	It based on local comparisons of sensed neighboring nodes data and dissemination of the test results to the remaining sensors.	Soft permanent and intermittent fault
Saha et al.,2011 [14]	A system level distributed fault diagnosis algorithm in WSNs	Comparisons of observed remaining energy and sensor values of all the neighboring nodes.	Soft permanent and intermittent fault
Elhadef et al.,2012 [15]	Comparison based system level fault diagnosis in adhoc networks	Back propagation neural network based diagnosis algorithm using generalized comparison model and simple comparison model.	Hard and soft permanent fault
Zhang et al.,2006 [16]	Fault diagnosis of sensor network using information fusion defined on different reference sets	Fault diagnosis scheme for WSNs based on a three layer redial basis function neural network (RBFNN) with two inputs and one output.	Hard and soft permanent fault
Jabbari et al.,2007 [17]	Sensor fault detection and isolation using computational intelligence	Fault detection and isolation based on two separate artificial neural network (ANN) phase. In the first phase a generalized regression NN is used and second phase probabilistic NN is used to detect the faulty sensors.	Hard and soft fault
Azzam et al.,2008 [18]	Fault detection of WSNs using modified recurrent neural networks	A modified recurrent neural network (RNN) used to detect faulty sensor. This modeling of WSNs divided in to two phases, learning phase and production phase for considering the faulty nodes.	Soft permanent faults
Zhu et al.,2010 [19]	A multi fault diagnosis method for sensor systems based on principle component analysis	Principle component analysis (PCA) and neural network used for diagnosis model. A fault situation is detected when squared prediction error (SPE) suddenly increases.	Soft permanent fault

III. System Model

System model consists of assumptions, network model, fault model, and energy consumption model. In the network model, we described the network topology and their communications. The fault model, we presented the behavior of different types of faulty nodes in the networks. In the energy model, described the energy consumption.

A. Assumptions

i All the sensor nodes are static in nature, having same initial energy and transmission range.
ii The links in the network are assumed to be fault free.
iii The cluster head in the network assumed to be fault free and GPS enabled.
iv The sensor networks are homogeneous in nature.

B. Network Model

The N number of sensor nodes randomly deployed an area of side A, which is larger than the transmission range T_r. Each sensor node is assigned a unique identifier. The node N_a communicate with node N_b, if the two nodes are within the transmission range of each other. The link between the nodes is calculated using Eq. (1).

$$l_{ab} = \begin{cases} 1, dis_{ab} \leq T_r \\ 0, dis_{ab} > T_r \end{cases} \quad (1)$$

where l_{ab} defines the link between node N_a and node N_b, dis_{ab} defines the distance between node N_a and node N_b, and the T_r defines the transmission range. The distance between two sensor nodes is defined in the Eq. (2).

$$dis_{ab} = \sqrt{(x_a - x_b)^2 + (y_a - y_b)^2}, \quad (2)$$

where (x_a, x_b) and (y_a, y_b) are the position of sensor nodes N_a and N_b respectively. The nodes are communicated through IEEE 802.15.4 MAC protocol with their neighboring nodes.

C. Fault Model

The proposed protocol consider four types of faults in the network. According to the behavior of faulty sensor nodes, the faults are classified as hard permanent, soft permanent, intermittent, and transient fault. The hard permanent faulty nodes are unable to communicate with other sensor nodes. In case of soft permanent faulty nodes are communicate with other sensor nodes with continuously faulty behavior. The intermittent faulty nodes are given unpredictable behavior for some random amount of time and then persist good behavior. The transient faulty nodes are given unpredictable behavior for instant time and persist good in the remaining time. The links are under taken care of the MAC layer protocol.

D. Energy Consumption Model

A transceiver used in WSNs for data communication between nodes. For transmitting the data WSNs required transmitter electronics and power amplifier whereas for receiving it required receiver electronics. Both these free spaces d^2 power loss model and multi-path fading d^4 power loss model are used for data transmission and reception [20]. Let θ_1, θ_2, and θ_3 are the amount of energy required for transmitter electronics, power amplifier, and receiver electronics respectively. The free space coefficient is chosen, depending upon the distance between the transmitter and receiver. The total amount of energy spent by the transmitting of p-bit packet over distance d is given by:

$$E_T(p,d) = p \times (\theta_1 + \theta_2 \times d^{\alpha}) = \begin{cases} p\theta_1 + p\theta_2 d^2, d < d_0 \\ p\theta_1 + p\theta_2 d^4, d \geq d_0 \end{cases} \quad (3)$$

The energy spent by receiving of p-bit packet over distance d is given by:

$$E_T(p,d) = p \times \theta_3 \quad (4)$$

The total amount of energy required E is the sum of the transmitting energy E_T and receiving energy E_R.

$$E = E_T + E_R \quad (5)$$

IV. Proposed Fault Diagnosis Protocol

The proposed fault diagnosis protocol follows in three phases. The phases are (i) clustering phase, (ii) fault detection and classification phase, and (iii) isolation phase.

A. Clustering Phase

The sensor nodes are non-uniformly deployed in the terrain area. The fault-free nodes having higher transmission range and higher initial energy than other sensor nodes, added uniformly in the network acting as cluster head. Initially, the cluster head broadcast message in the transmission range and the sensor nodes after receiving the signal calculate the strength of the receiving signal. The sensor nodes form a cluster using the strength of the receiving signal with their cluster head. We set a threshold value of the receiving signal for the cluster formation. Each cluster head, maintain a table containing all the information of its cluster nodes. The sensor nodes are sent the data to the particular cluster head and the cluster head also communicates to the base station. All these inter and intra cluster communication takes place using multi-hop fashion. The Fig. 1 shows the clustering overview of the sensor network. The number of cluster head depends on the network size. The received power p_r is calculated by the Friss propagation loss model [21]. So the p_r is computed as:

$$p_r = p_t \times g_t \times g_r \times \frac{\lambda^2}{(4\pi d)^2}, \quad (6)$$

where p_t is the transmitted power of the antenna, g_t is the transmitting gain of the antenna, g_r is the receiving gain of the antenna, d is the distance between the transmitter and receiver, and λ is the signal wavelength.

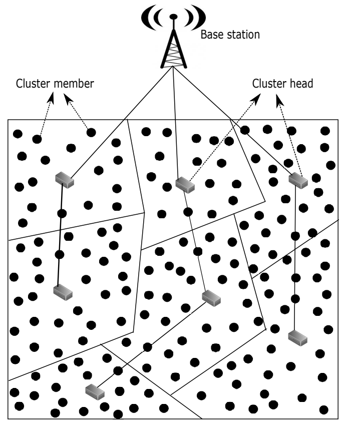

Fig. 1: An overview of clusters

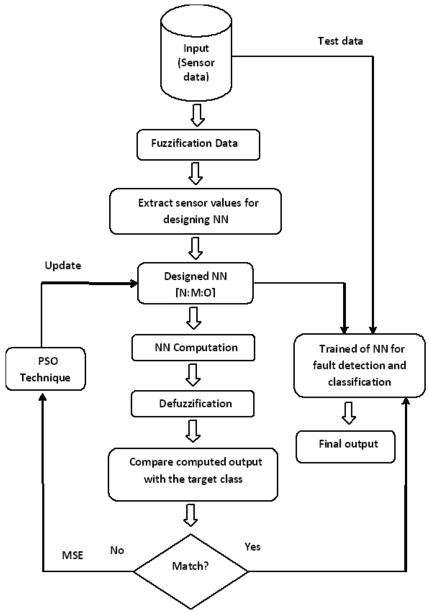

Fig. 2: Fault detection model

B. Fault Detection and Classification Phase

In the section, we describe the fault detection and classification phase. In this phase the neural network fuzzy feed forward multilayer perceptron (MLP) is used [22] [23]. The fault detection model is described in the Fig. 2 [24]. Initially the historical data with fault classification collected for the training of the neural network. The sensor temperature data are collected from the network. Then set a particular range within which the node is declared as fault free otherwise faulty node. The sensor node values are initially input for the neural network training. These sensor input values are fuzzify using spline membership function. The function is defined in the Eq. (7). After fuzzification, the data are designed for a multilayer feed forward neural network of $N : M : O$. The N is defined as the number of input layer nodes, M is defined as the number of hidden layer nodes, and the O is defined as the number of output layer nodes. After designing the neural network model, we update the knowledge base by a population-based technique called particle swarm optimization (PSO). The final stage testing data are given to the neural network for detection and classification. The closest match with the fault type gives the decision results. The fault-free nodes and faulty nodes are classified according to the fault classes.

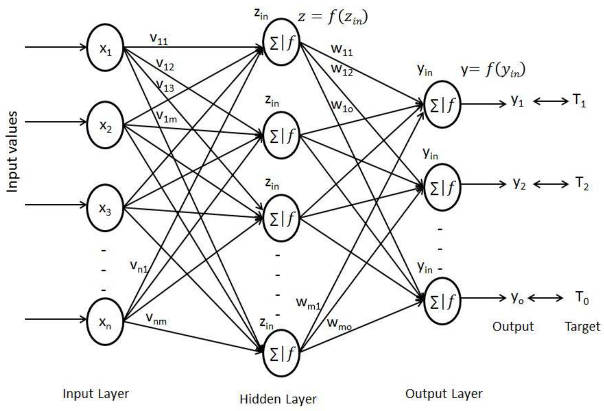

Fig. 3: Architecture of neural network approach

The Fig. 3 represents the neural network architecture [25]. The architecture shows the $N : M : O$ layer. Here N is the number of input nodes depends on the number of sensor nodes in the network, M is the number of hidden nodes depends on the input nodes, and O is the number of output nodes depends on the fault type. In this protocol, we consider four types of fault, so the output node contains four neurons. The parameter V denotes the weight vector between input to hidden layer and the parameter W denotes the weight vector between hidden to output layer. The bias b_1 is denoted for input to hidden layer and bias b_2 is denoted for hidden to output layer. The Z_{in} defines in the Eq. (8) is denoted as output of input layer and Y_{in} defines in Eq. (9) is denoted as output of hidden layer. The binary sigmoid function defines in the Eq. (10), used for activation function. The Z is denoted as output of hidden layer, which is calculated by using activation function to Z_{in}. Similarly, the Y is denoted as output of output layer, which is calculated by using the activation function to Y_{in}. The mean square error (MSE) define in the Eq. (11) is calculated by using the target output and neural network output. The error is reduced by the knowledge updation technique. In the last step, the sensor values generating by the sensor node given to the input for the testing phase, which detects the behavior of the nodes. Finally, it classified the faulty nodes with their fault types.

The proposed fuzzy MLP in this work uses a S-shaped membership function (MF) to fuzzify the input dataset. The Eq. (7) describe the spline MF which is used to fuzzify the sensor value x. In this Eq. (7) the value a and b locate the extremes of sloped portion.

$$f(x,a,b) = \begin{cases} 0, & x < a \\ 2(\frac{x-a}{b-a})^2, & a \le x \le \frac{a+b}{2} \\ 1 - 2(\frac{x-a}{b-a})^2, & \frac{a+b}{2} \le x \le b \\ 1, & x > b \end{cases} \tag{7}$$

$$Z_{in} = b_1 + \sum_{i=1}^{n} X_i V_{ini} \tag{8}$$

$$Y_{in} = b_2 + \sum_{i=1}^{m} Z_i W_{ini} \tag{9}$$

$$Sig(x) = \frac{1}{1 + e^{-X}} \tag{10}$$

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (X_i - T_i)^2, \tag{11}$$

where X_i and T_i are computed value and target value respectively for i^{th} instance of the sensor nodes.

Algorithm 1 PSO Based Training Algorithm

Require: Initialize: particle dimension, no. of particles, inertia weight (w), maximum and minimum inertia weight (w_{max}, w_{min}), coefficients (c_1, c_2), delta (δ), velocity (v), position (x) of each particle, local and global best score ($pBestScore$, $gBestScore$), $gBest$ to 0;

while (termination condition is not achieved) **do**
  for (each particle) **do**
    Calculate activation of Fuzzy MLP;
    Calculate average fitness;
    If the fitness is better than the previous, set the current $pBestScore = fitness$;
    Set the best position of the particle;
    Calculate the best fitness for neighbor particles ($gBestScore$);
    Update inertial weight w;
    Update velocity and position of particle using Eq. (12) and (13) respectively;
  end for
end while
Test the trained Fuzzy MLP neural network for finding the fault detection accuracy;
Stop.

1) PSO Based Training Algorithm for NN: PSO is a population based stochastic optimization technique developed by Eberhart and Kennedym [26] [27]. In PSO the system is initialized with a set of random population and searches for optimum by updating generations. PSO starts with the random initialization of a population (swarm) of individuals (particles) in the n-dimensional search space. In PSO, each particle keeps two values in its memory: (i) its own best experience, that is one with the best fitness value (best fitness value corresponds to least objective value since fitness function is conversely proportional to objective function), whose position and objective value are called p_i and p_{best}, respectively, and (ii) the best experience of the whole swarm, whose position and objective value are called p_g and g_{best}, respectively [28]. Let denote the position and velocity of particle i with the following vectors: x_i = (x_{i1}, x_{i2}, x_{i3}, $\cdots$ x_{in}) and v_i = (v_{i1}, v_{i2}, v_{i3}, $\cdots$ v_{in}). The updated velocities and positions of the particles can be calculated according to the following Eq. (12) and (13) :

$$v_{i+1} = w.v_i + c_1\theta_1 \times (p_i - x_i) + c_2\theta_2 \times (p_g - x_i) \tag{12}$$

$$x_{i+1} = x_i + \delta \times v_{i+1}, \tag{13}$$

where δ is a random number, w is the inertia weight, c_1 and c_2 are two positive numbers, and θ_1 and θ_2 are two random numbers with uniform distribution in the interval of [0,1].

C. Isolation Phase

After the fault detection and fault classification, we follow the fault isolation phase. In the isolation phase the faulty nodes are isolated from the network and the fault-free nodes remain as it is. The cluster head maintains a table contains the fault percentage of sensor nodes of its cluster region. Then the fault isolation is performed in the following steps.

i Initially, cluster head broadcast the fault percentage of sensor nodes in its region.
ii Each node maintains a neighbor table and periodically update as it monitors in the environment.
iii In the routing phase source broadcast a route request message (RREQ) and the message spreads throughout the network.
iv Then the destination node is unicast route reply (RREP) message and the routing path is generated.
v If the node is fault free the RREP is sent back to the neighboring node otherwise, if node N_1 learns that N_2 is a faulty node. It sends the RREP message to another neighboring node N_3.

In this way, the faulty nodes are eliminated from the path.

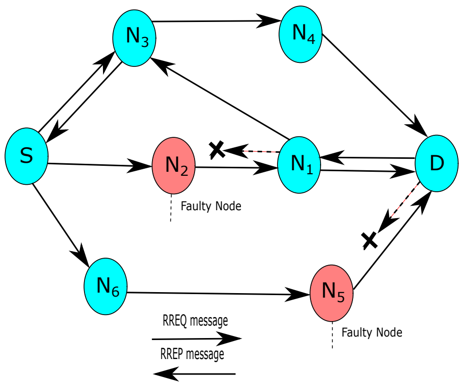

Fig. 4: An overview of isolation phase

V. Simulation and Results

In this section presented the performance evaluation of the proposed protocol with the other existing protocol through simulations. The simulation is carried out by the Matlab 2010a and network simulator NS-2.35. The proposed protocol is compared with two existing protocol Chen et al. [12] and Azzam et al. [18], which are implemented by NS-2.35 simulator. The performance metrics such as fault detection accuracy (FDA), false alarm rate (FAR), false positive rate (FPR), and false classification rate (FCR) are considered for the performance evaluation. The simulation is carried out by an average of 50 times run.

A. Simulation Parameters

The parameters used in the simulation are shown in Table II. The sensor nodes are randomly deployed in the area of $(1000 \times 1000)m^2$. The number of faulty sensor nodes and simulation time varies according to the simulation environment. In this simulation, we collected the temperature data of WSNs and set a threshold range of θ_1 to θ_2 for fault free sensor nodes. The sensor node violated the threshold range consider as a faulty node in the network. According to our fault model, four types of fault class are considered for this simulation.

Initially, all the sensor nodes are fault free in nature. In the simulation, we added composite fault such as hard fault, soft fault, intermittent fault, and transient fault gradually. We consider a random composition of different faults for composite faulty nodes. The composite faulty nodes are added 5% to 40% of normal nodes.

TABLE II: Simulation parameters

Parameter	Value
Number of nodes	1000
MAC protocol	IEEE 802.15.4
Simulation time	1000 s
Network size	(0,0) to (1000,1000)m
Initial energy	10 J
Carrier sense range	350 m
Transmission range	150 m
Packet size	32 bytes
Receive power	83.1 mW
Idle power	105 μW
Transmit power	52.2 mW
Sleep power	48 μW
Channel rate	250 kbps

B. Impact of Fault Probability

In this simulation, 1000 nodes are deployed in the area. The faulty nodes are added in the network with probabilities 0.05, 0.1, 0.2, 0.3, and 0.4 respectively. The two existing protocols and the proposed protocol compared using the performance metrics. Fig. 5 shows the graph between fault probability percentage and fault detection accuracy (FDA). Fig. 6 shows the graph between fault probability percentage and false alarm rate (FAR). Fig. 7 shows the graph between fault probability percentage and false positive rate (FPR). So in this simulation, we observed the proposed fuzzy MLP fault diagnosis protocol performs better than other two existing protocols.

In the Chen et al. protocol the fault detection dependent upon the neighboring sensor nodes. So the increasing the fault probability percentage the performance degrades for Chen et al. protocol. In the case of Azzam et al. for more sensor nodes, increasing the fault probability the RNN complexity increases, so it's performance also degrades. Both of this existing protocols can not identify all types of fault classes. The proposed fuzzy MLP fault diagnosis protocol is identified all types of fault classes and also gives better performance than two existing protocols.

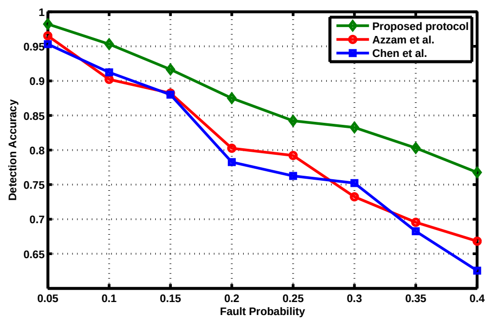

Fig. 5: DA vs Fault probability

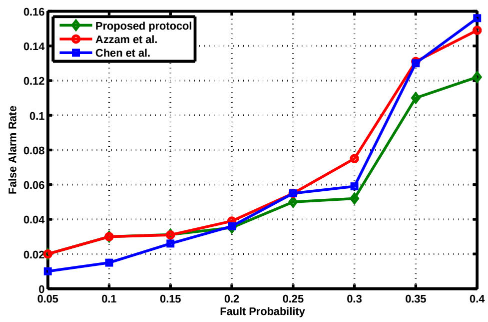

Fig. 6: FAR vs Fault probability

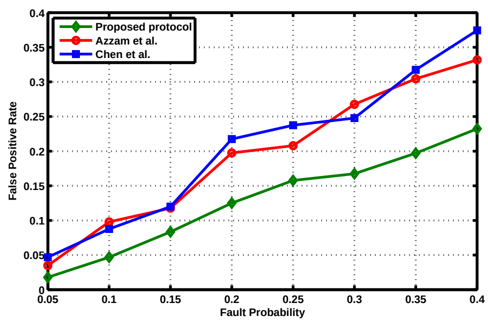

Fig. 7: FPR vs Fault probability

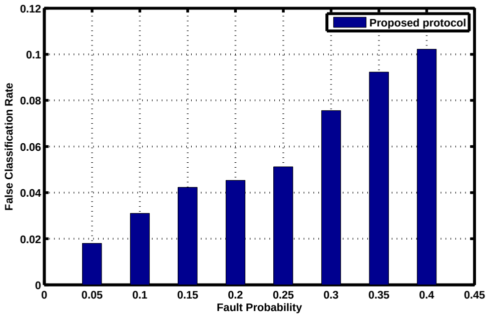

Fig. 8: FCR vs Fault probability

In this observation, we found the diagnosis accuracy of proposed algorithm improved 6.82% over Azzam et al. algorithm and 8.13% over Chen et al. algorithm.

VI. Conclusion and Future Scope

A fuzzy MLP based fault diagnosis protocol has been proposed for WSNs to handle faulty sensor nodes such as hard permanent, soft permanent, intermittent, and transient fault in the network. The proposed fault diagnosis based on three phases: (i) clustering phase, (ii) fault detection and classification phase, and (iii) fault isolation phase. The proposed algorithm not only detect the faulty nodes but also classify the fault types and isolate the faulty nodes in the network. The simulation results show that the proposed protocol performs better in terms of fault detection accuracy, false alarm rate, and false positive rate than the existing Chen et al. and Azzam et al. protocols. The proposed protocol extended to the real application scenario. In future work the proposed protocol will be use to handle the faults in dynamic and mobile networks.

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