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RESEARCH ARTICLE

Maximum Degree of Centrality for Cluster Head Selection and Data Security in WSN

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Abstract— Wireless Sensor Networks (WSNs) present a new generation of real-time embedded systems for a wide variety of applications. However WSNs have limited computation, energy, and memory resources. One of the approaches to minimize the energy consumption is to allow only some nodes in a cluster of sensor nodes, called cluster- heads, to communicate with the base station. Appropriate cluster-head election can drastically reduce the energy consumption and enhance the lifetime of the network. In this thesis, a fuzzy logic approach to cluster-head election is proposed based on three descriptors - energy, concentration and centrality. After modeling the energy consumption for the WSN, we applied the algorithm to check for the quality of the network by measuring the time it takes for the first node to die in the cluster. We compare our algorithm with Low Energy Adaptive Clustering Hierarchy (LEACH), a previously proposed technique, by adjusting the cluster-head selection probabilities.

Index Terms— Cluster head selection; intra cluster head selection; cluster Maximum degree centrality; energy efficiency; fuzzy logistics; fuzzy inference

1. Introduction

In wireless sensor networks (WSNs) energy efficiency and scalability are the prime factors in the design of the system. Further, due to small sized sensor nodes, they have limited computing, bandwidth and communicating capabilities. All these characteristics require efficient management of the network topology, self-configuration and robustness for the purpose of balancing the load and for the network lifetime prolongation [1] [2].

To address these issues, nodes in WSNs can be divided into a number of small groups called clusters. Certain nodes can be designated as 'cluster heads' (CH) and that take on additional functions, remaining nodes are termed as member nodes (MNs). This technique is known as clustering and it is one of the effective approaches in wireless sensor networks for organizing the sensor network into an efficiently connected hierarchy. However, due to more responsibilities executed by CHs and for uniform load distribution, the sensor nodes in the network are re clustered periodically [3]. In existing literature [3-10], several probabilistic as well as fuzzy logic based clustering methods exist. Residual energy is always taken as one of the parameter in selection of CHs. However, nodes in WSN are randomly deployed, thus leading to variable node density inside the sensing field. For maximum utilization of channel capacity and increased throughput, clustering of nodes requires optimum number of MNs in a cluster" as another CH selection parameter in addition to residual energy. In this paper, we have defined a new clustering parameter, "Cluster Optimal Degree Centrality" which considers both optimum member node degree for a cluster as well as distance of member nodes to their respective CH. We have also proposed a new clustering algorithm by adopting both cluster optimal degree centrality and expected residual energy as selection parameters for defining fitness of a node to become a CH. The simulation results have shown that the proposed clustering method has resulted in enhanced network lifetime and individual cluster characteristics. This paper is structured as follows. Section II presents related work. Section III presents the system assumptions of our work. In section IV, we have derived the clustering parameters and their respective calculations. In section V the detailed operation of the proposed work is presented. Finally we proposed an algorithm for CH selection process. In section VI simulation results are presented and effectiveness of our work is evaluated. Conclusions are given in section VII.

2. RELATED WORK

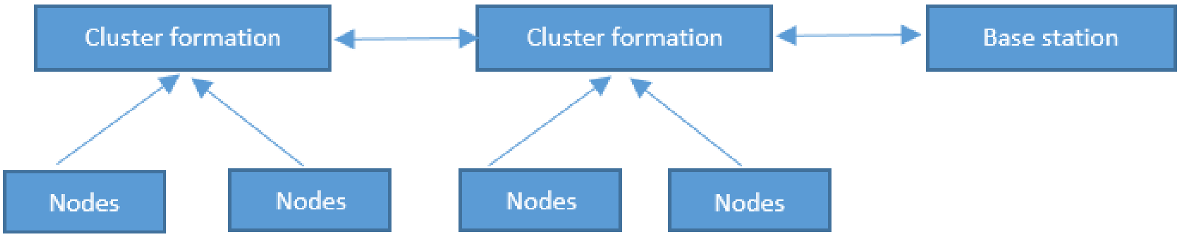
Clustering of sensor nodes has already been widely used in wireless sensor networks. Although the clustering can improve QoS in wireless sensor networks, it has some inherent problems. The main problem is that the energy consumption is uneven between CHs and other member nodes. In order to overcome this problem, most of the research focuses mainly on rotation of CHs. The first major approach towards rotation of CHs is LEACH protocol [3]. LEACH uses probabilistic model to select CHs and to rotate CHs periodically. LEACH being a pure probabilistic model, some CHs may lie in each other's communication range or may be the edge nodes of WSNs that leads to inefficient clustering. Also, energy of nodes is not considered in LEACH for the election of CH, which may result in selecting nodes with insufficient residual energy as cluster heads. Failure of these nodes can lead to partitions and inappropriate/incomplete results for the respective cycle. Fuzzy logic, due to its comparatively less computational burden and less processing demands, has also been widely used in WSNs for clustering purpose [4-8]. In most of the fuzzy clustering algorithms fuzzy rule based system is opted to make selections using different clustering parameters to elect CHs. Gupta et. al. in [4] has presented a centralized fuzzy logic based CH selection mechanism. In this method [4] Base station has to collect three fuzzy variables (concentration, energy and centrality) from all sensor nodes. Based upon the collected information election of a CH is done. This approach is a centralized one and thus the method does not present a realistic image and is unsuitable for large scale WSNs. Overheads and control communication resulted from centralized method would be very high and unsuitable for energy constrained WSNs. Further, the simulation resulted in selection of one CH per round and the work is silent about centrality calculations. In [5], author has proposed a fuzzy logic based approach (CHEF: Cluster Head Election mechanism using Fuzzy logic). This method proposed is a localized election mechanism using two fuzzy variables (residual energy and local distance). In this paper, node degree is not taken as a selection parameter; hence for nodes having equal residual energy, a node with less number of neighbor nodes has more chances to become CH and hence may result in inefficient clustering. CHEATS proposed in [6] considers the distance of a node from base station and remaining energy of a node as CH selection parameter. In [7], Anno et al. has proposed different fuzzy variables that include the residual energy, distance from cluster centroid, node degree, and network traffic. LEACH-ERE [8] is also a fuzzy logic based CH selection criteria. In LEACH-ERE, the expected residual energy (ERE) is proposed to act as a fuzzy variable during CH selection process. ERE is predicted by using the expected energy consumption (EEC). Where EEC is calculated via using an off-line trained neural network model. The proposed approach has adopted the LEACH protocol architecture but with a modification to the energy predication based on the ERE. EECS [9] is an Energy Efficient Clustering Scheme in wireless sensor networks. During CH election phase, a constant number of candidate nodes are elected and compete for cluster heads according to the nodes' residual energy. The candidate nodes send out a broadcast message containing its residual energy within a predefined radio range. If candidate finds a candidate with more residual energy, it will give up in the competition. Otherwise it will become CH. In the cluster formation phase, based upon distance cost from the node to the CH and distance cost from the CH to the base station, member nodes decide which CH to join. Method proposed in [10], takes distance from the sink (base station) to each node as well as the residual energy of each node as the selection criterion of cluster-head election. Energy-Efficient Cluster Head Selection (NECHS) [20] is a mechanism based on fuzzy rule based method where number of neighbor nodes and remaining energy are the input variables of fuzzy system. Most of the fuzzy based clustering algorithms stated above are based on LEACH and taken residual energy and some local parameters while electing CHs. In the method proposed by us apart from energy metric and local parameters, we have taken optimal node degree centrality for calculating fitness of a node to become CH. In this way, our proposed algorithm has led to enhanced coverage of sensor nodes by CHs. Also the proposed algorithm has led to decrease excessive load handling problems of CHs during local intra cluster communications.

3. SYSTEM ASSUMPTIONS

We consider a WSN with a large number of sensor nodes randomly deployed over a 2-D planer area. All the sensor nodes are identical in computational capabilities and have the same amount of initial battery energy. The sensor nodes can communicate with each other through short-range radios. The received signal strength is measurable and hence node can adjust their transmission range. Nodes transmit and receive packets with Omni-directional antennas. Further the following assumptions have been made: 1. Wireless sensor nodes and the sink/base station are stationary after initial deployment. 2. All sensor nodes are energy constrained i.e. Battery recharges or replacement is not possible. 3. All member sensor nodes can communicate directly with their respective cluster head(s). 4. Links are symmetric. Thus, two nodes can communicate using the same transmission power.

4. PROPOSED CLUSTERING APPROACH

Architecture



Flow diagram

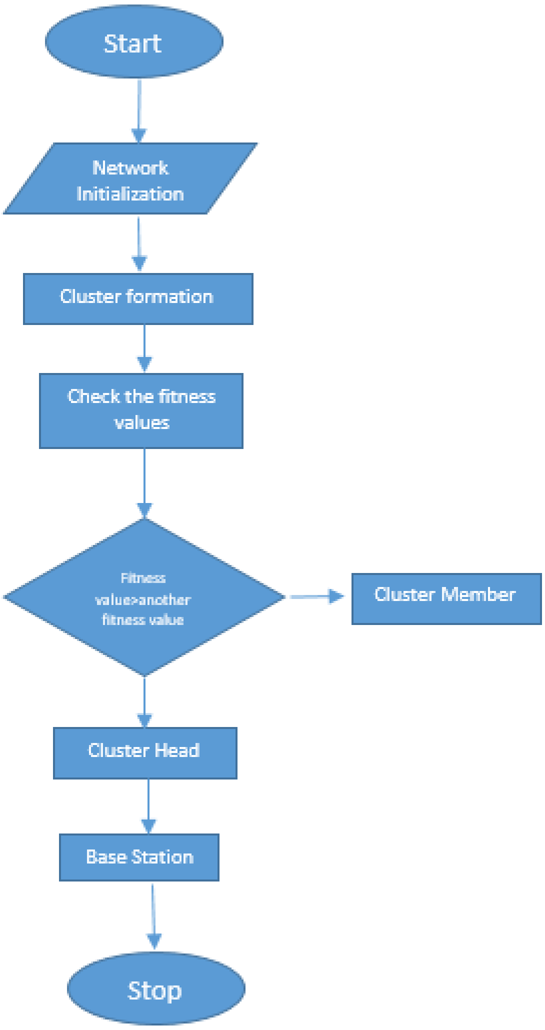


Fig a: flow diagram

A. Clustering Algorithm In the proposed clustering algorithm, during set up phase each node generates a random number. If this random number is less than a pre-defined threshold, those particular nodes become candidates for current CH selection round. All other nodes switch to sleep mode for a duration equivalent to that of electing final CHs. The candidate nodes calculate the fitness to become CH by using fuzzy logic. The inputs for fuzzy inference are ERE and cluster optimal degree closeness centrality (CODC). After calculating Fitness, the candidate nodes broadcast candidate message containing Fitness value. Candidate nodes which fall in communication range of each other, receive these messages and the candidate node having high value of fitness becomes final CH. By this time, member nodes become active and Final CHs broadcast their id to all nodes present in their neighborhood. Member nodes join CHs from which they have minimum distance. After the steady phase, the process repeats itself until network become nonfunctional. The proposed clustering algorithm is as follows:

Input:

Nt, �: a communication network N at time t with L links

s : a sensor node

V: {v I v is s neighbor node which is CH candidate}

No: {c I neighbor nodes ofs ,for a (s,c» Uopt

T: a fitness value to become a CH candidate

R: the number of rounds after which a node again becomes eligible for CH competition

r: number oftimes a node does not serve as CH

Output:

CH(s): the cluster head ofthe node s

Fit (s): a fitness ofthe node s to be a CH

ClusterHead(s): true ifCH(s)=s

Network Initialization:

1. ClusterHeads(s) = false;

2. r(s) +-R Main: 1* for every setup round *1

3. if (r(s) < R)

4. ClusterHead(s) +- false;

5. T+-0;

6. r(s) = r(s)+ I;

7. else T+-Popt ;

8. end if

10. if (rand(s)(O, I) < T)

11. CH(s) +- s;

12. Fitness (s) +- fuzzy logic [ERE , CODq

13. Broadcast (fit(s), id); II cluster head Candidate-Message 14. On receiving Candidate-Messages from CH candidates;

15. for each v in V

16. if (fit(s) < fit(v))

17. CH(s) +-v;

18. ClusterHead(s) +- false;

19. else ClusterHead(s) +- true;

20. end if

21. end if

22. if (ClusterHead(s) = true)

23. broadcast (fin-CH-Message, V)

24. r(s) +-0

25. end if

B. Fuzzy System Model The proposed method has taken advantage of fuzzy inference system to calculate Fitness value for a candidate CH node. Fuzzy inference system consists of a fuzzifier, fuzzy rules, fuzzy inference engine and a defuzzifier. In the proposed Fitness computation is accomplished by using predefined fuzzy "if-then" mapping rules. These fuzzy if-then mapping rules are shown in Table I.

We have used Mamdani Method (Zimmermann, 2001), as fuzzy inference technique, because it is the most frequently used fuzzy inference technique (Gupta et aI., 2005). The fitness value of each candidate CH will change according to the current value of ERE and cluster optimal degree closeness centrality. The fuzzy set that describes the input variable of ERE is shown in Fig 1. The linguistic variables for this fuzzy set are Low, Medium and High and Very high. We have selected a trapezoidal membership function for Low and Very high due to nature of our present study. On the other hand, the membership function of Medium and High is triangular membership function. The second fuzzy input variable is cluster optimal degree centrality of the candidate CH node. The fuzzy set which describes this input variable is illustrated in Fig. 2. Low, Optimal and Very high are the linguistic variables of this fuzzy set. Low and Very high linguistic variables have a trapezoidal membership function while Optimal variable has a triangular membership function.

The fuzzy output variable for our method is the Fitness of the candidate CH. Fuzzy set for Fitness variable is shown in Fig. 3. For fitness of a candidate CH we have defined 4 linguistic variables which are Low, Mediwn, High, and Very high. Very high variable have a trapezoidal membership function. The remaining linguistic variables Low, Medium and High are represented by using triangular membership functions. To obtain a crisp Fitness value, we perform de-fuzzification using COA (Center of Area) method. Unlike [8], in order to minimize the computation at a sensor node the numbers of rules are optimally selected. VI. PERFORMANCE EVALUATION AND SIMULATION In this section, the performance analysis of our proposed method using clustering parameters ERE and fuzzy optimal degree closeness centrality is presented. The analysis includes the comparison of the proposed algorithm against LEACH, CHEF, and LEACH-ERE. Simulation results have shown that our proposed approach presents enhanced performance.

A. Simulation Environment The performance of proposed algorithm is evaluated through NS2 [18] simulation (NS-2, 2000). A random network deployed in an area of 200m x200m is considered. The sink is assumed to be situated at (100,100) m of the above specified area. For the present simulation 10% aggregation ratio is assumed. The simulated traffic is CBR with UDP source and sink. In the proposed simulation, P opt is imported from [6] and is equal to 0.3. � is taken as 20, m = l.. B. Performance Metrics and simulation result The performance of proposed method is compared with the LEACH, CHEF and LEACH-ERE. For comparison we run all the methods on an identical wireless network and use same random seed to generate the identical wireless sensor network topology. The performance is evaluated, according to the following metrics. J) First of the nodes dies (FND) and Half of the nodes die (HNA) FND is metric which defines estimated value for the round for which the first node dies. HND defmes estimated value for the round in which half of the sensor nodes dies respectively [19]. Figure 4 shows the rounds in which first node and half of the nodes die for each algorithm and show that our proposed algorithm performs better than LEACH, CHEF and LEACHERE. Simulation for FND shows that our proposed method is more efficient than LEACH by 45.71%, CHEF by 13.97% and LEACH-ERE by 10.27%. For RNA, results show that our proposed method is more efficient than LEACH by 43.24%, CHEF by 2.91% and LEACH-ERE by l.53%. Performance of LEACH is lowest, because it uses a pure probabilistic model and does not consider the residual energy and other useful local parameters. CHEF performs better than LEACH, as it has used residual energy and local distance of neighbor nodes into consideration. LEACH-ERE has considered residual energy as well as expected residual energy as selection metrics and hence has a better performance. Our method has considered expected residual energy and optimal degree centrality parameter to calculate fitness of a node to become CH. Hence it maintains the even load distribution among both the cluster heads and the nodes, which results in more number of functional rounds before first node dies and half of the nodes die. 2) No. of Alive nodes This metric examines the energy efficiency by calculating the network lifetime. It is defined as the distribution of Alive sensor nodes with respect to each round. Figure 5 shows the number of nodes alive sensor nodes over the simulation time for LEACH, CHEF, LEACH-ERE and our proposed method. Our proposed method results in deferment of death of half of the nodes indicating thereby highest operational network life. Moreover, our method has more balanced energy consumption among CHs as indicated in Fig. 6.

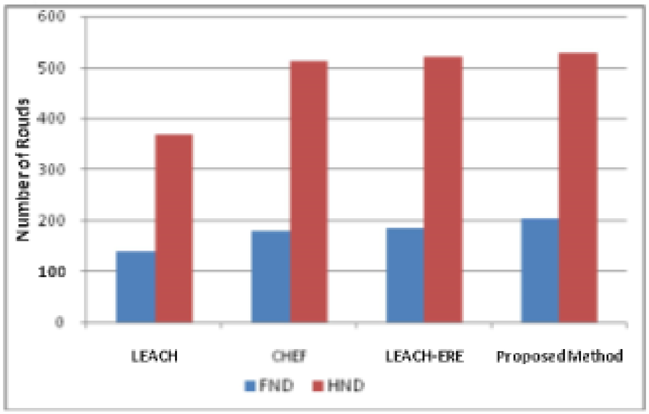


Fig 1: FND and HNA metrics of performance

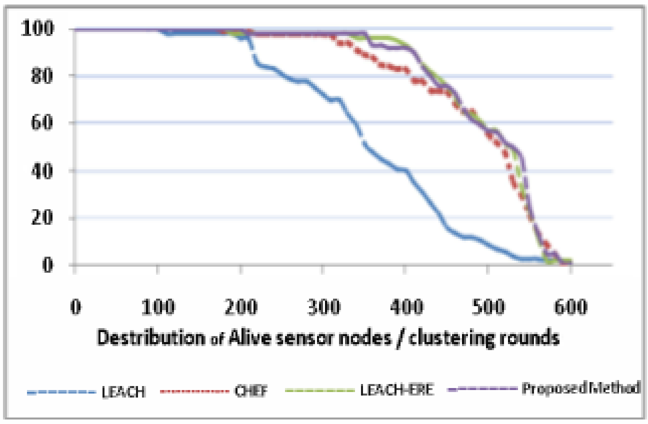


Fig 2: Number of Alive nodes

3) Energy consumption of cluster heads It is the average energy consumed for the data transmission and reception by CHs for randomly selected round. 100 rounds of simulations are sampled and amount of total energy spent by CHs during each round is depicted in figure 6. It is clearly indicated from the figure that energy consumed by CHs in our proposed method, CHEF and LEACH-ERE is less than that in LEACH. This is because of the reason that LEACH has not considered local selection parameters.

4) Throughput This is the average number of packets received per second at the base station for randomly selected rounds. Figure 7 shows that the proposed method has better results.

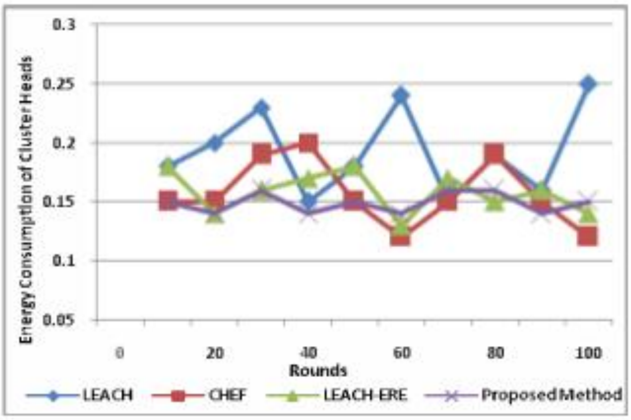


Fig 3: Per round energy consumption by cluster heads

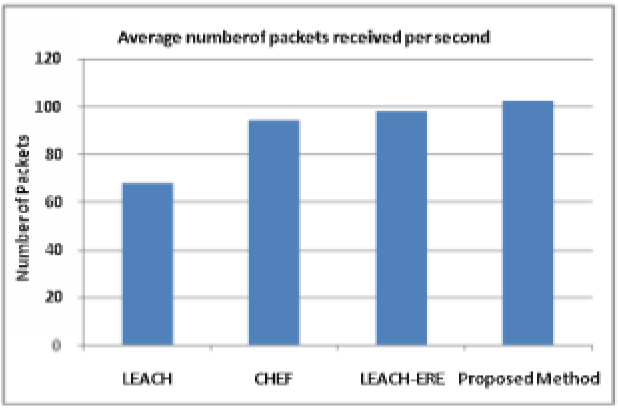


Fig 4:Throughput

5. CONCLUSION AND FUTURE WORK

In this paper, we have proposed a new method of clustering based upon cluster optimal degree centrality and expected residual energy. The proposed method has been compared with LEACH, CHEF and LEACH-ERE and shows better results in terms of network lifetime, individual cluster qualities and intra-cluster communication. A further direction of this work will be to apply the proposed technique for multi-hop routing and can also be extended for optimal placement of sink as well as relay nodes.

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