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SINK LOAD MINIMIZATION USING ENERGY MAXIMIZATION AND DBSCAN IN WIRELESS SENSOR NETWORK

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ABSTRACT

Moving the sink node is an effective solution for improving the lifetime of wireless sensor networks (WSN). Different methods in the literature schedule sink movements and determine sink stay points. This paper provides another insight to the sink mobility problem in WSNs by incorporating node-load parameters into a matrix and using this matrix to determine which sink site to visit in each round. We first present a packet- (traffic) load–based sink movement algorithm that relies on the packet distribution of nodes in each sink site for a given topology construction algorithm. We extend this algorithm by considering the distances the packets are transmitted, and in this manner obtain an energy-load–based algorithm. We also provide Hybrid-EASR and DB-EMSRto compute optimal results. Our extensive simulations show that our energy- and packet-based algorithms significantly improve network lifetime compared to keeping the sink static or moving it randomly.

Keywords: Sink Mobility; Network Lifetime Improvement; Wireless Sensor Networks; Energy efficiency.

I.INTRODUCTION

A wireless sensor network (WSN) consists of small low energy sensing nodes capable of sensing a phenomenon and sending the data to the sink. The basic aim while structuring a WSN is to minimize the energy consumption and maximize the network lifetime. In a single sink WSN, the nodes need to send the data through multiple hops. In a large WSN, it becomes quite inefficient in terms of power consumption while gathering all information in a single sink [6]. Maximum energy consumption takes place in communicating the data from the nodes to the sink [7, 8]. To minimize the energy consumption while sending the data to the sink, multiple sinks are used. As there are multiple sinks, the distance from the node to the sink reduces; thus, there is no need of multiple hops. Multiple sinks reduce the distance the sensed data needs to travel and hence correspondingly reduce the energy consumption considerably [9]. Another disadvantage of a single sink WSN is that of energy imbalance between the nodes close to the sink and the ones which are far off [5]. The network is restructured by modifying the number of nodes connected to a sink. The current research work proposes an algorithm for network restructuring in a multiple sink WSN so as to reduce the energy consumption and increase the network lifetime. This energy balancing through network restructuring optimizes the network lifetime. The number of not connected nodes are also quite less. The implementation is done in MATLAB. The implementation results prove the aforesaid statements.

II.LITRATURE REVIEW

Guisheng Yin et al. [2008] [1] Since the nodes of wireless sensor networks are in the condition of a highly-limited and un replenish able energy resource such as battery power, computation, and storage space, the energy efficiency is the most important key point of the network routing designing.

Haosong Gou et al. [2010] [2] Wireless sensor networks (WSNs) have been considered as a promising method for reliably monitoring both civil and military environments under hazardous or dangerous conditions. Due to such environments, the power supplies for sensors in the network are not usually rechargeable or replaceable. Therefore, the energy efficiency is critical for the lifetime and cost of WSN. Numerous mechanisms have been proposed to reduce the impact of communication protocols on the overall energy dissipation of WSN. The low-energy adaptive clustering hierarchy (LEACH) and another improved centralized LEACH deploys randomized rotation of cluster-heads to evenly distribute the energy load among all sensors in a WSN.

HeikkiKarvonen et al. [2004] [3] has studied the effect of coding on the energy consumption inwireless embedded networks. An analytical model of the radio energy consumption is developed to study how different DC balanced codes affect the energy consumption for the one-hop case. A Rayleigh fading channel is assumed, the analysis is extended to include multihop scenarios in order to study the tradeoff between coding overhead and energy consumption.

HongjoongSinet al. [2008] [4] adopted biologically inspired approaches for wireless sensor networks. Agent operates automatically with their behavior policies as a gene. Agent aggregates other agents to reduce communication and gives high priority to nodes that have enough energy to communicate. Agent behavior policies are optimized by genetic operation at the base station. Simulation results show that our proposed framework increases the lifetime of each node. Each agent selects a next-hop node with neighbor information and behavior policies.

HuuNghia Le et al. [2012] [5] has proposed a distributed, energy efficient algorithm for collecting data from all sensor nodes with minimum latency called Delay-minimized Energy-efficient Data Aggregation algorithm (DEDA). The DEDA algorithm minimizes data aggregation latency by building a delay-efficient network structure. At the same time, it also considers the distances between network nodes for saving sensor transmission power and network energy. Energy consumption is also well balanced between sensors to achieve an acceptable network lifetime.

III.PROBLEM STATEMENT

In this segment, the optimal multi-sink positioning problem in a sensor network has already been addressed in the literature. However, major propositions as [12], [14], which formulated this problem as a maximum flow issue, have restricted the solutions space since the sinks are chosen among the nodes. This constraint, which chooses p sinks among n nodes, is very strong and will be released in our paper. Besides, all these works focused on the initial positioning of sinks and considered that the network remains static since the optimal position is discovered. None of these works mentioned to optimize the network efficiency throughout its lifetime. None has put forward the idea of combining the optimal placement and the ability of moving sinks in order to manage, in real time, the network all over its lifetime. All these proposals mainly based their solutions on nodes position and not nodes energy consumption. Even if in [13], it appears that the authors tried to find the sink placement within a cluster using an energy-aware algorithm but the clusters pattern is definitely based on nodes position and not their energy supply. B.

IV. SYSTEM MODEL AND ASSUMPTIONS

(1) Sinks are randomly deployed and then they are fixed. Since random distribution is used, the complexity in determining the position of the sink is removed.

(2) The nodes after random deployment are fixed.

(3) The density of nodes deployed is high such that the data from a node reaches a sink in single hop.

(4) The network is heterogeneous. The sinks have more power than the sensing nodes. The sinks have additional computational capacity as well.

Pseudo code

(1) The sensor nodes and the sinks are randomly deployed and after the deployment the nodes and sinks are stationary. Combination of sink and sensor nodes will make the network heterogeneous.

(2) N is the set of p nodes deployed in the area to be sensed in the given network:

$$N = \{n1, n2, n3,...,\} \quad (1)$$

(3) S is the set of q sinks deployed in the area to be sensed in the given network:

$$S = \{S1, S2, S3,...,\} \quad (2)$$

(4) Calculate the Euclidean distance from each sink to every node. DSi is the set of distances of all the nodes from the ith sink

$$D_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \quad (3)$$

i = sink ID = 1, 2, . . . ,q, j = node ID = 1, 2, . . . , p;
$DSi = \{Di1, Di2, Di3,...,Dip\}$.

So it will form a [q, p] order distance matrix (D) which will contain the distances of all the sinks from all the nodes. The distance between the nodes is calculated using a method based on RSSI [11].

(5) The threshold energy of the sink is E_0.

(6) The transmission range of a node is T_x.

(7) The neighboring nodes of every sink are calculated based on the transmitting range. Nb_i is the set of all the neighboring nodes of ith sink (S_i):

$$\mathrm{Nb}_i \subseteq N, \quad \text{where } \{\mathrm{Nb}_i \mid D_{ij} < T_x \in j,\ j \in N\}. \tag{5}$$

(8) A new connection matrix (C) is formed based on D. A flag is set for every element where the distance from node to sink is less than the transmission range Tx. Thus C is in the binary form.

(9) The energy consumed by ith sink Ei is calculated by

$$E_i = k \sum_{j=1}^{|\mathrm{Nb}_i|} D_{ij}^{\ 2}, \tag{6}$$

where $|\mathrm{Nb}_i|$ is the total number of neighbor nodes of i^{th} sink (S_i) and D_{ij} is the distance of ith sink from the jth node where $nj \in \mathrm{Nb}i$, and k is the constant for first order radio energy model [10].

(10) Calculate the $E_{\max}$ = maximum (E_i), where i=1 to q, and find the maximum energy consumed by any sink S_i.

(11) If ($E_0 > E_{\max}$),
{
No need to optimize the network

Iteration = 0;

Set the E_0 below the $E_{\max}$

Repeat step (10)
}
(12) else

(a) Calculate the unique nodes connected to a sink. A unique node to a sink is the one which is not connected to any other sink.

Ui is the set of unique nodes for Si
$Ui \in \mathrm{Nb}i$
$Ui = \{n1, n2, n3, ...,\} \in \mathrm{Nb}i \,\&\notin \mathrm{Nb}j$ Where
$j = 1, 2, 3, \ldots, q$ and $i \neq j$

Based on the above step and (7) we can easily calculate the nodes, having connectivity with more than one sink. MCi is the multiple connecting nodes set having the connection with multiple sinks.

(b) MC_i nodes of the ith sink are arranged into the descending order of the distance from the ith sink.

(c) Select the nodes having the minimum distance from the ith sink and disconnect the connection of remaining nodes those are far from the ith sink, and update the overall connection matrix C based on the distance matrix D.

(13) Repeat the steps (9)–(12) by recalculating the sink energy with modified C. The iteration count is also increased. The steps are repeated until Emax becomes constant.

(14) Now the network is optimized and the routing is started by the nodes. The lifetime of the network is calculated by counting the number of rounds done by the network before the first node dies out.

V. PROPOSED METHOD

In WSN, when any node sends the data to the sink through the link, it has to find a shortest travel route to minimize the latency. To reduce the latency, EAPRclustering method was introduced using different algorithms and the second method is a clustering method namely DB-EMSR method. Using these two methods, travel route can be shorter. To make a travel route shorter, we have to find optimize routing path which can cover all the sensor nodes and the sink collects the data from all sensor nodes and sends this directly to the base station. For that, routing path has been decided before sink starts moving. The problem is that if we can find a nearest anchor point from the sink, then the travel route becomes much shorter. Because travel route becomes shorter thensink can easily collect data from the sensor node in less time.

To reduce the latency, the new DB-EMSRalgorithm has been proposed in this paper. The two methods have been combined which are estimate and clustering method. Necessary assumptions have been taken for the proposed work. One mobile sink is considered which is moving. When it starts moving, it collects the data from all sensor nodes. We have set the sensor nodes' positions using graphical representation. And Sink knows the entire sensor node's position geographically.

A. CLUSTERING

The EM procedure is labelled as follows anywhere the boundary vector θ^i is the present best approximation for the full delivery bounds and $\theta$is the applicant for a better estimate. The mutable i is the iteration pawn besides $T$is the meeting criterion. Given the obtainable data$X$, the misplaced data$Z$, and the unidentified parametersθ, sideways with the probability function$L(\theta;X,Z)=p(X,Z|\theta)$, the supreme likelihood estimation of the unidentified parameters is strong-minded by the marginal likelihood of the obtainable data$L(\theta;X)=p(X|\theta)=\sum_Z p(X,Z|\theta)$. The EM procedure finds the supreme likelihood approximation of the bordering likelihood through iteratively execution the next steps:

$Begin\ initialize\ \theta^0, T, i=0$

$$Do: i=i+1$$

$$E\ Step: compute\ Q(\theta;\theta^i)$$

$$M\ Step: \theta^{i+1}=\arg\max Q(\theta;\theta^i)$$

$$Until\ Q(\theta^{i+1};\theta^i)-Q(\theta^i;\theta^{i-1})\leq T$$

$Return\ \hat{\theta}=\theta^{i+1}$

End

B. DBSCAN clustering

The DBSCAN clustering algorithm is recalled. The algorithm takes three inputparameters, namely: D the set of data points, ∈– the radius of the neighborhood, MinPts -the minimal number of points within ∈-neighborhood (methods for determining the values ofand Min_{Pts}parameters are described e.g. in (Ankerst, Breunig, Kriegel, & Sander, 1999)and (Ester, Kriegel, Sander, &Xu, 1996)). Each point in + has an attribute called Cluster Idwhich stores the cluster's identifier and initially is equal to UNCLASSIFIED.Firstly, the algorithm generates a label for the first cluster to be found. Next, the points in Dare read. The value of the Cluster Id attribute of the first point read is equal toUNCLASSIFIED.

Algorithm 1.DBSCAN (set of points D, ∈, MinPts)

Cluster Id = label of a first cluster;
for each point p inset D do
if(p. ClusterId= UNCLASSIFIED) then
ifExpand Cluster(D, p, Cluster Id, ∈, MinPts) then
ClusterId = Next Id (Cluster Id)
End if
End if
end
for

Function 2 Expand Cluster(D, point p, ClId,∈ , MinPts)

seeds= Neighborhood(D, p, ∈);
if|seeds| <MinPts then
p.ClusterId= NOISE;
returnFALSE
else
for each point q in seeds do // including point p
q.ClusterId= ClId;
endfor
deletep from seeds;
while|seeds| > 0 do
curPoint= first point in seeds;
curSeeds= Neighborhood(D, curPoint, ∈);
if|curSeeds| >= MinPtsthen
for each point q in curSeedsdo
ifq.ClusterId= UNCLASSIFIED then
/ Nε(q) has not been evaluated yet, so q is added to seeds */*
q.ClusterId= ClId;
appendq to seeds;
elseifq.Cluster Id = NOISE then
/ Nε(q) has been evaluated already, so q is not added to seeds */*
q.ClusterId= ClId;
end if
end for
end if
deletecur Point from seeds;
end

C. Proposed Approach algorithm

1) Initialize cluster centroids to random location , Eps and MinPts
2) Calculate clusters' parameters mixing coefficient and covariance matrix.
3) Calculate responsibility(R) and loglikelihood (LL).
4) While the distinction between the fresh calculated LLnew and antecedently calculated LL becomes lesser than small number calculation are repeatedly executed.
5) By using the updated responsibility(R) cluster
6) centroids, and covariance matrix, are recalculated, and also the number of nodes which belongs to k^{th} cluster is calculated
7) Return cluster centroids, covariance matrix and the number of nodes that belongs to each cluster.
8) Check the nodes which do not have any cluster id.
9) For each node in wsn, if node is visited continue next node mark node as visited.
10) If number of neighbor node < number of MinPts mark node as noise otherwise form cluster and expand the cluster.

12) And then communication by cluster head takes place.

13) Repeat Step 4 until node energy consumption gets maximized.

14) end.

D. PSEUDO DB-EMSR DBSCANMINPTS$_{min}$, MINPTS$_{MAX}$)

Step 1: Start

Step 2: Require Dataset density threshold for Min$_{Pts}$ and Max$_{pts}$

Step 3: Require Initial cluster (c)

Step 4: Assign distance = 0,

Step 5" farthest = 0.

Step 6: For each data point x perform the following

Step 7: Initialize sum =0

Step 8: for Input: D = {t1, t2, t3 … tn}

// Set of elements

Step 9: MinPts //Number of points in cluster

Ɛ // Maximum distance for density measure

//Apply the DB-EMSRto specify the boundary state data values in DBSCAN
Step 10: K = {K1, K2, K3 …, Kk } // Set of clusters

Step 11: Method: k=0; // initially there are no clusters

Step 12: For each of the cluster centers c assigned so far perform the

Step 13: Find the distance between c and x

Step 14 : sum += d

Steps 15: If sum >dist then assign dist = sum and farthest = x

Steps 16: for i = 1 to n do

Steps 17: if ti is not in a cluster, then

Steps 18: X = {tj | tj is density-reachable from ti};

Steps 19: if X is a valid cluster, then

Steps 20: k = k+1;

Steps 21: Kk = X;

Steps 22: variable farthest represents the farthest data point from all the centers assigned so far.

VI.RESULT

In this section, we present the results of the experiments that evaluate the performance of the algorithms presented in the previous part. We use MATLAB as the simulation environment. Simulations are done to observe the performance of the sink-site determination algorithms, movement criteria, and the topology reconstruction algorithm. Different metrics (network lifetime, packet latency) are examined for each category. We compare our movement scheme not only with the static sink case but also with random movement, where the sink randomly moves between predetermined sites after the sojourn time expires.

Scenarios and Parameters of the Simulation: Sensor networks generated in the simulation have *N* static sensor nodesand a single mobile base station (mobile sink). Those nodes are deployed to a region of interest in random and uniform manner. Square areas are used in the simulations, which are generally either 300×300 m^2 or 400×400 m^2. After the mobile sink moves to its initial location, it broadcasts messages in order to construct a tree-based multihop routing topology (sensors can reach to sink via their neighbors) from top to bottom (if a balanced tree-based topology construction is not used) The energy model and the radio characteristics used in the simulations come from. Transmission energy cost is related to the number of bits and the square of distance, whereas receive energy cost is related to the number of bits. In our simulations, this energy model is applied with below table:

Table 1: Simulation parameter

Parameters	Value
No of nodes, n	100
N/w size X × Y	100 × 100
Receiver Energy, ERX	50nJ
Transmitter Energy, ETX	50nJ
Free space Energy Consumption, E_{fs}	.01nJ
Multipath Energy Consumption, E_{mp}	.0013pJ
Initial Energy, E_0	0.5J
Data Aggregation Energy, EDA	5nJ
Percentage of advanced nodes, m	0.1, 0.2& 0.3
Multiple of normal node energy, a	1, 2, 3

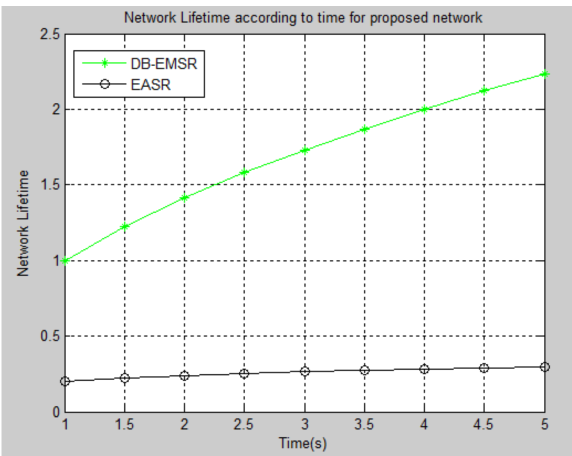

Figure 1: Network lifetime of EASR and DB-EMSR

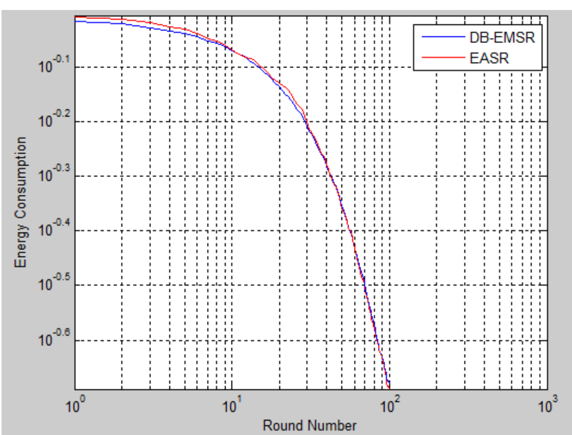

Figure 2: Energy consumption of EASR and DB-EMSR at round

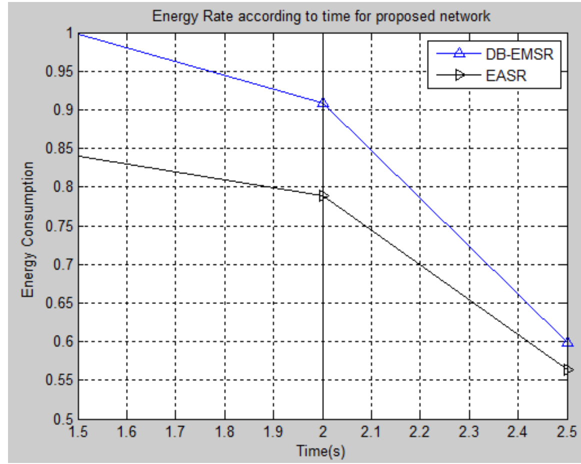

Figure 3: Energy consumption of EASR and DB-EMSR at time

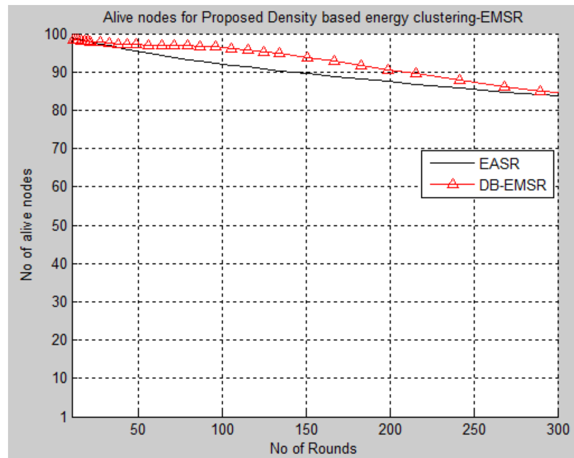

Figure 4: No of alive nodes of EASR and DB-EMSR at no. of round

VII.CONCLUSION

In this paper we have extensively compared the energy efficiency of static and mobile sink-based routing protocols in a WSN in SEASR protocol [15]. In our result we have also taken into account channel contention and the resulting congestion effects. Our result revealed that it is important to consider both E_{max} and E_{min} in the energy analysis of a routing protocol, as improvement in one can result in degradation of the other and vice versa. It has also been observed that adopting a mobile sink and reducing the duty cycle of the nodes does not necessarily reduce the energy dissipation of the WSN. Instead, a careful selection of duty cycle value of the nodes and of mobility radius of the sink is required in order to achieve higher energy efficiency than with a duty cycle value of 100% and a static sink.

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