ACHIEVING ENERGY EFFICIENCY AND STABILITY IN WSN USING A NOVEL MOBILE SINK APPROACH BASED ON BIOGEOGRAPHY BASED OPTIMIZATION

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Abstract–Wireless sensor networks are constrained with limited battery lifetime. Cluster head near the base station act as relays to the cluster heads far from the base station resulting in fast depletion of the cluster head close to the base station. To overcome this problem mobile sink have been used in the past. The proposed algorithm finds the optimum path and sojourn location of the mobile sink using biogeography based optimization (BBO). BBO not only converge faster as compared to GA but it also gives more optimized results. The proposed algorithm is compared with previous protocols such as LEACH, GA based clustering, PSO based clustering. The algorithm is implemented using MATLAB simulation tool. The proposed algorithm performs better both in terms of lifetime of the cluster heads as well as lifetime of the entire network.

Keywords – wireless sensor networks, mobile sink, biogeography based optimization, cluster head.

I. INTRODUCTION

Wireless sensor networks (WSNs) are an emerging technology[1] that has potential applications in surveillance, environmentand habitat monitoring, structural monitoring, healthcare, anddisaster management [2]. AWSN monitors an environment by sensingits physical properties. It is a network of tiny, inexpensive autonomousnodes that can acquire, process, and transmit sensory data over wirelessmedium. One or more powerful base stations serve as the destinationof the data. The properties ofWSNs that pose technical challengesinclude dense ad-hoc deployment, dynamic topology, spatial distribution,and constrains in bandwidth, memory, computational resources,and energy.WSN issues such as node deployment, localization, energy-awareclustering, and data aggregation are often formulated as optimizationproblems. Traditional analytical optimization techniques require enormouscomputational efforts, which grow exponentially as the problemsize increases. An optimization method that requires moderate memoryand computational resources and yet produces good results is desirable,especially for implementation on an individual sensor node. Moreover, the sensor nodes near the static sink act as relays for sensors that are far from it and thus will deplete their energy very quickly, resulting energy holes in the sensor field. The energy hole problem leads to a premature disconnection of the network and thus sink gets isolated from the rest of the network due to the death of its neighbours, while most of the sensor nodes are still alive and fully operational. WSN structure is shown in figure 1.
Exploiting the mobility of the sink has been widely accepted as an efficient way to alleviate the energy hole problem in WSNs and further prolong the network lifetime by avoiding excessive transmission overhead at nodes that are close to the sink [3] [4].
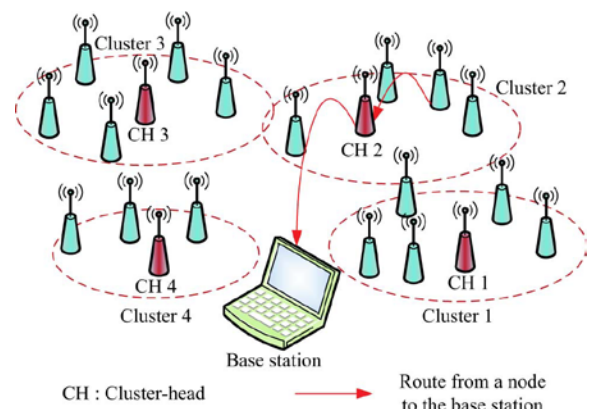

Figure 1 – Structure of a WSN

Clustering algorithms can effectively organize the sensor nodes in the network and using a controlled mobile sink can solve the energy hole problem. However, finding the optimum number of CHs and the optimal moving trajectory for the mobile sink are Non-Deterministic Polynomial -time hard (NP-hard) problems. In this paper, a Mobile Sink based clustering Protocol has been proposed to improve the lifetime of WSNs and to mitigate the energy hole problem. Proposed work uses the Biogeography Based Optimization (BBO) to find the sojourn locations of the mobile sink and the optimum number of CHs and their locations based on minimizing the total dissipated energy in communication process and overhead control packets of all sensor nodes within the network.

II. LITERATURE REVIEW

Traditional-optimization methods include linear, nonlinear, and quadratic programming, Newton-based techniques, and interior-point methods. Their computational complexities

grow exponentially with the problem size. Resource requirements and cost of mathematical programming engines (such as IBM ILOG CPLEX) used for linear, nonlinear, and quadratic programming make them unattractive for resource constrained nodes. This is the motivation for heuristic algorithms such as PSO, genetic algorithm (GA), differential evolution (DE), and bacterial foraging algorithm (BFA). GA facilitates evolution of the population generation by generation using operators such as crossover, mutation, and selection [5]. DE is similar to GA, but it uses a differential operator [6], In LEACH, CH collects and aggregates data from the sensors in its own cluster and passes the data to the sink directly. The problem of LEACH protocol is the randomly selection of CHs. LEACH requires the user to specify the desired probability of CHs that uses in determining whether a node becomes a CH or not. However, Genetic Algorithm based LEACH (LEACH-GA) proposed in [5] uses GA to find the optimal probability of CHs. LEACH-GA improves the CHs threshold function, but still CHs are randomly selected and the residual energy of each node is not considered in CH selection process. A new protocol called Amend LEACH (A-LEACH) was developed in [6] [7], for electing CHs in a distributed fashion and improving the stability period of two-level hierarchical heterogeneous WSNs. WSNs with mobile sinks have attracted a lot of attention recently. In [8] authors developed an Intelligent Agent-based Routing (IAR) protocol to guarantee efficient datadelivery to sink and reduces signal overhead. The idea of IARis choosing some sensors as agents. Then, the sink moves nearan agent and receives data if it is in the range of the agent,and if not, the sink chooses a sensor as a temporary relaynode which receives data from agent and forwards it to sink.Authors in [9] formulated the distance constrained mobile sinkproblem as a mixed integer linear programming and deviseda novel heuristic to find an optimal sojourn tour for the sinkbased on maximizing the sum of sojourn times during the tour.Mobile Sink based Routing Protocol (MSRP) for prolongingthe network lifetime in clustered WSN has been addressedin [10]. In MSRP, the sink moves to CHs having higher energyin the clustered network to collect sensed data from them.A new optimizing LEACH clustering algorithm with mobilesink and rendezvous nodes was introduced in [11]. This algorithmcombines the use of the LEACH algorithm, mobile sinkand rendezvous points to preserve the benefits of the LEACHalgorithm and improve the CH selection process. Moreover,it decreases energy consumption in WSNs further than intraditional LEACH, particularly when the network is large.Mobile sink Improved Energy-Efficient PEGASIS-Basedrouting protocol (MIEEPB) has been presented in [12].MIEEPB introduces the sink mobility in the multi-chainmodel and divides the sensor field into four regions, there fo reachieving smaller chains and decreasing load on the leadernodes. The sink moves along its trajectory and stays for a time at fixed location in each region to guarantee data collection.

III.   PROBLEM FORMULATION

The main constraint of a WSN scenario is that sensor nodes are battery operated. When a sensor node aggregates the data, it sends this data to thebase station. If the base station is too far away the sensor node dissipates too much energy and dies. To overcome this problem clustering technique was introduced. In clustering, all the sensor nodes aggregate their data and sends it to a cluster head or gateway. Then this gateway sends the aggregated data to the base station. But this clustering technique suffers with the same bottleneck as the cluster heads are battery operated and they die as soon as their battery gets dissipated [13] [14].

In the proposed algorithm, we device a new mechanism of making the base station or the sink mobile. Rather than sensor nodes or cluster head sending the data to the sink, the sink moves in the vicinity of the cluster heads.

IV.   PROPOSED ALGORITHM

The proposed algorithm uses the concept of mobile sink. The algorithm is executed in the following steps:

1. Initially random deployment of sensor nodes is made throughout the deployment area.
2. The entire deployment area is divided into fixed sized hexagonal shaped partitions.
3. Sensor nodes are assigned to corresponding cluster heads and sensor nodes are assigned a unique id.
4. Base station is initially located at the corner of the deployment area.
5. Now for each cell we compute the sojourn location of the mobile sink in such a way in can sense and aggregate data from the cluster head by moving to each cell one by one. Also for each cell we minimize the energy consumption be minimizing the distance between a sensor node and the cluster head, distance between cluster head and the sink and total dissipated energy by the cluster head using BBO
6. Here inside each cell, location of the mobile sink is very important. The location should be chosen in such a way that minimum energy is dissipated in the process of mobile sink sensing and aggregating data from the corresponding cluster heads.
7. For finding the sojourn location of the mobile sink and minimize the energy consumption, we use biogeography based optimization. An illustration of the BBO is given below.

Most energy of the sensor node dissipates in the communication process and overhead control packets. So, the main factor we need to minimize is the dissipation energy. In addition, the numberof CHs can factor into the objective function. Fewer CHs result in greater energy efficiency and higher CHs consumemore energy as CHs drain more power than non-cluster-heads.Therefore, BBO is used to determine the mobile sink locationand the optimal number of clusters and their locations.

A.   *Overview of BBO*

BBO is an evolutionary algorithm based on biogeography based optimization. Biogeography is the way nature distributes species and is analogous to general problem solutions [5]. In past many algorithms like genetic algorithm, particle swarm optimization and ant colony optimization were implemented for obtaining an optimum and fittest solution. BBO is an evolutionary algorithm that is

implemented with the migration of species from one habitat to another habitat to maintain diversity in the population. [6].In BBO an individual is represented by a habitat. A population may contain many habitats like chromosomes in genetic algorithms. For each habitat in the population, habitat suitability index (HSI) value is calculated. HSI is a measure of the goodness of the habitat or solution. A habitat having high HSI value is considered to have higher fitness or more, suitable for population to grow and vice versa for habitat having low HSI value [7]. Based on this HSI value rank of each individual is calculated. Migration operation is performed to maintain diversity in the population in BBO. Migration involves migration of species from habitat having higher HSI value to habitat having lower HSI value [5]. Migration operation is based on immigration rate and emigration rate. A habitat having high HSI value will emigrate its suitability index variable (SIV) to habitat having low HSI value and habitat having low HSI value will immigrate SIV from habitat having high HSI value [8]. This emigration and immigration are done on the basis of emigration rate (mue) and immigration rate (lambda) which are calculated as follows:

Immigration rate (lambda) = I (1 – k_i/n)　　　　(1)
Emigration rate (mue) = E(k_i/n)　　　　(2)

Where
I = maximum immigration rate.
E = maximum emigration rate.
k_i= rank of the habitat.
n = total number of habitats.

B. Calculation of HSI

BBO is analogous to the genetic algorithm. In GA we use to calculate the fitness of every chromosome in the population. In BBO we calculate habitat suitability index value of each habitat of the population. The HSI value of a habitat is calculated using the following equation:

HSI = k * Energy (C.H) + (1/(Distance (Sink, C.H) + Distance(Node, C.H)))　　　(3)

where k = constant
Energy (C.H) = residual energy of cluster head.
Distance (Sink, C.H = distance between sink and cluster head.
Distance (Node, C.H) = distance between a node and cluster head.

C. Biogeography based optimization

Now wireless clustering and performed using BBO and energy efficient clusters are made using the following technique.

D. Habitat initialization

36 sensor nodes are placed at a fixed location. S_N = {s1, s2, s3, s4……………. s36}. 6 gateways are chosen as G = {g1, g2, g3…. g6}. Initialize habitats in the ecosystem with each habitat containing 2 vectors, one containing sensor nodes from s1 to s36 and another containing corresponding gateways randomly assigned to sensor nodes. The length of both the vectors is same. Entire population contains many habitats like this. Calculate HSI value of every individual gateway in gateway vector of each habitat with following formula:

HSI = k * Energy (C.H) + (1/(Distance (Sink, C.H) + Distance(Node, C.H)))　　　(4)

For every gateway vector of each habitat, take the sum of HSI of all individual gateways. This will give a total HSI value of entire habitat. Now we have all possible habitats and their HSI values. Sort HSI values in increasing order and assign a rank to each habitat such that worse habitat gets the first rank and best habitat gets the last rank.

E. Immigration and emigration rates

Emigration and immigration rates are calculated as follows:
Immigration rate (lambda) = I (1 – k_i/n)　　　　(5)
Emigration rate (mue) = E(k_i/n)　　　　(6)

Where I = maximum immigration rate.
E = maximum emigration rate.
k_i= rank of the habitat.
n = total number of habitats.
Habitats having high HSI value will have a low immigration rate and high emigration rate. SIV will migrate from high HSI value or high emigration rate habitat to the low HSI value of high immigration rate habitat.

F. Migration operator

A random number r is generated. For habitat = i, If r < immigration rate (i), choose i as immigrating habitat. Choose habitat with highest HSI value as emigrating habitat. Make a crossover between the two habitats using MPX. This will result in a modified gateway habitat/vector let corresponding to sensor node vector to which gateways have been assigned now using this modified vector. In this the way, we will obtain many modified vector/habitat assigned to sensor nodes. Calculate HSI values of all these resulting habitats again. Retain the habitat with best HSI value. If the HSI value after modification is better than the HSI value before modification, a batter network performance is achieved. The whole scenario is then simulated and optimum output is achieved.

V.　RESULTS AND SIMULATION

In this section, several tests are performed using MATLAB 8.1to evaluate the proposed protocol and compare it with otherprotocols [4-6], [11], [12]. In these tests, we assume thatsensors are homogeneous, and each one generates one datapacket per round to be transmitted to the sink. To eliminate theexperimental error caused by randomness, each test was runfor 5 times and the average was taken as the final result. TheAIA parameters are set as p_s=30, p_r=0.9, p_c=0.1, p_h=0.4,w=0.9 and *Maxgen*= 100.
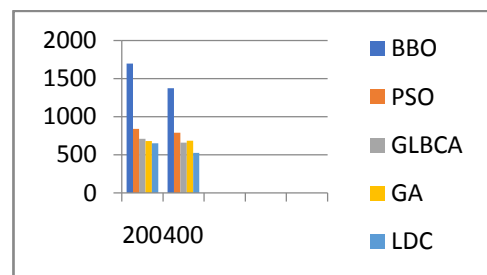

Figure 2 – Proposed work compared with the existing work in terms of network lifetime
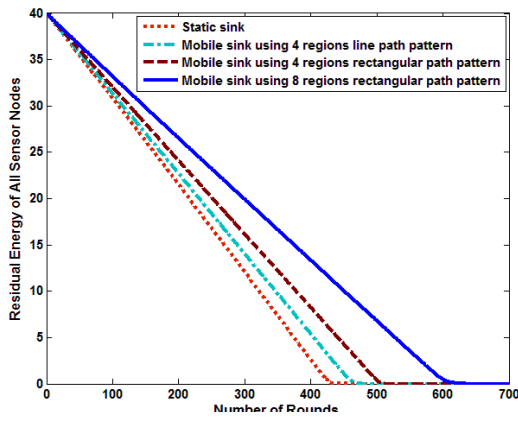
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Figure 3 – Proposed work compared with the existing work in terms of relative energy of the sensor nodes.
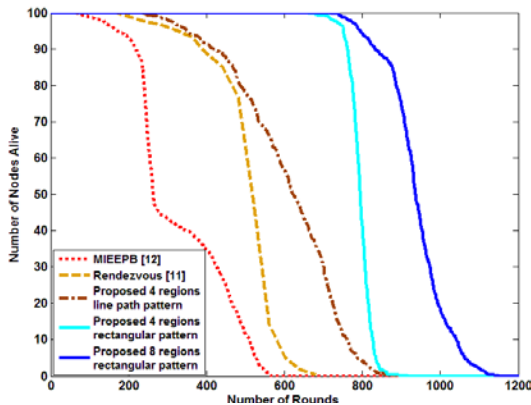

Figure 4 – Proposed work compared with existing work in terms of number of nodes alive.

VI.   REFERENCES

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