© INTERNATIONAL JOURNAL FOR RESEARCH PUBLICATION & SEMINAR
ISSN: 2278-6848 | Volume: 08 Issue: 07 | July - September 2017
Paper is available at www.jrps.in | Email : info@jrps.in

`Enhancing the Wireless Sensor network life time using selection of nodes

Shakshi, Research Scholar, Department of ECE, IIET

Sharma.sakshi822@gmail.com

***Abstract* --- Clustering the Wireless Sensor Networks (WSNs) is the major issue which determines the lifetime of the network. The parameters chosen for clustering should be appropriate to form the clusters according to the need of applications. Some of well-known clustering techniques in WSN are designed only to reduce overall energy consumption in the network and increase the network lifetime. These algorithms achieve increased lifetime, but at the cost of overloading individual sensor nodes. Load balancing among the nodes in the network is also equally important in achieving increased lifetime. First Node Die (HND), and Last Node Die (LND) are the different metrics for analysing lifetime of network. In this paper, a new clustering algorithm, Genetic Algorithm based energy efficient Clustering Hierarchy (GAECH) algorithm is proposed to increase FND, HND, and LND with a novel fitness function. The fitness function in GAECH forms well-balanced clusters considering the core parameter of a cluster, which again increases both the stability period and lifetime of the network. The experimental results also clearly indicate better performance of GAECH over other algorithms in all the necessary aspects.**

ISSN : 2278-6848
© International Journal for Research Publication and Seminar

***Keywords*--- Clustering, LEACH, WSN, Genetic, Protocol, Energy conservation, CBCR**

1. Introduction

Wireless sensor networks have recently come into prominence because they hold the potential to revolutionize many segments of our economy and life, from environmental monitoring and conservation, to manufacturing and business asset management, to automation in the transportation and health care industries. The design, implementation, and operation of a sensor network requires the confluence of many disciplines, including signal processing, networking and protocols, embedded systems, information management and distributed algorithmsIn a typical sensor network, each sensor node operates untethered and has a microprocessor and a small amount of memory for signal processing and task scheduling. Each node is equipped with one or more sensing device such as acoustic microphone arrays, video or still cameras, infrared (IR), seismic, or magnetic sensors. Each sensor node communicates wirelessly with a few other local nodes within its radio communication range. Sensor networks extend the existing Internet deep into the physical environment. The resulting new network is orders of magnitude more expansive and dynamic than the current TCP/IP networks and is creating entirely new types of traffic that are quite different from what one finds on the Internet now. Information collected by and transmitted on a sensor network describes conditions of physical environments for example, temperature, humidity, or vibration and requires advanced query interfaces and search engines to effectively support user-level functions. Sensor networks may internetwork with an IP core network via a number of gateways. A gateway routes user queries or commands to the appropriate nodes in a sensor network. It also routes sensor data, at times aggregated and summarized, to users who have requested it or are expected to utilize the information. A data repository or storage service may be present at the gateway, in addition to data logging at each sensor. The repository may serve as an intermediary between users and sensors, providing a persistent data storage. It is well known that communicating 1 bit over the wireless medium at short ranges consumes far more energy than processing that bit.

2 Node Placement in Wireless Sensor Network

Genetic Algorithm :A genetic algorithm (GA) is a heuristic search technique that mimics the process of natural evolution. This heuristic is routinely used to generate useful solutions to optimization problems and search engines. Genetic algorithms belong to

© INTERNATIONAL JOURNAL FOR RESEARCH PUBLICATION & SEMINAR
ISSN: 2278-6848 | Volume: 08 Issue: 07 | July - September 2017
Paper is available at www.jrps.in | Email : info@jrps.in

the larger class of evolutionary algorithms (EA), the solutions to optimization problems using techniques inspired by natural evolution to generate as inheritance, mutation, selection and crossover. In a genetic algorithm to a population of strings developed (chromosomes), the candidate solutions (fitness value) to encode optimization problem to better solutions. Traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible. The development usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of each individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly randomly mutated) to form a new population. The new population is then used in the next iteration of the algorithm. Usually, the algorithm terminates when either a maximum number of generations has been produced, or has reached a sufficient condition for the population. If the algorithm is terminated by a maximum number of generations, a satisfactory solution may or may not be achived

A typical genetic algorithm steps:

1. A genetic representation of the solution domain,
2. A fitness function to evaluate the solution domain.

Generally the solution is represented as an array of bits. Arrays of other types and structures can be used in essentially the same way. The main property that makes these genetic representations convenient is that their parts are easily aligned due to their fixed size, which facilitates simple crossover operations. Variable length representations can be used, but in this case of complicated crossover. Tree-like representations are explored in genetic programming and graphic representations in the form of evolutionary programming. The fitness function is defined over the genetic representation and measures the quality of the represented solution. The fitness function is always problem dependent. Once the genetic representation and the fitness function defined, GA is an order (usually random) initialize a population of solutions and then improved it by repeated application of mutation, crossover, inversion and selection of contractors.

3 CLUSTERING IN WIRELESS SENSOR NETWORK

Fitness Parameters in Wireless Sensor Network --The fitness of a chromosome determines the extent to which the consumption of energy is minimized and coverage is maximized. In what follows, some important fitness parameters in

(1) Direct distance to base station (DDBS): it refers to the sum of direct distance between all sensornodes and the BS represented by as

$$\mathrm{DDBS} = \sum_{i=1}^{m} d_i, \qquad \textbf{(2)}$$

Where stands for the number of nodes. Clearly, consumption of energy, reasonably, is subject to the number of nodes and for large WSN the energy is extreme. Moreover, DDBS is acceptable for smaller networks where number of close nodes is not considerable.

(2) Cluster based distance (CD): The total CHs and BS distances and the sumof the distance between the determined member nodes and their cluster heads (3).

$$\mathrm{CD} = \left(\sum_{i=1}^{n} \left(\sum_{j=1}^{m} d_{ij} \right) + D_{is} \right) \quad \textbf{(3)}$$

Where “” and “” stand for the number of clusters and related members, respectively; “” represents the distance between a node and its CH; and “” stand for distance between the CH and the BS. The solution suits networks with a large number of widely-spaced nodes. Higher cluster distance leads to higher energy consumption. For minimization of energy consumption, the CD must not be too large [11]. The density of the clusters is controlled by adopting this measurement, while density is the count of nodes in each cluster.

(3) Cluster-based distance-standard CDSD: instead of an average cluster distance, standard derivation measures the changes of distances of the cluster. CDSD is a function of the placement of sensor nodes (random or deterministic). There are clusters with different sizes in random placement so that a SD within a specified variation in the cluster distance is acceptable. If so, the differences in cluster distance is not zero, while the variation must be adopted based on the deployment of information [12]. At any rate, under deterministic placement with uniform distribution of node positions, cluster distance change must be minimized. Generally, changes of uniform cluster-based distances show that the network is poor, which is not the case when the nodes are placed randomly:“” in equations (4)

$$\mu = \frac{\sum_{i=1}^{n} d_c}{n},$$

$$\mathrm{SD} = \sqrt{\sum_{i=1}^{n} (\mu - d_c)^2}, \quad \textbf{(4)}$$

Stands for the average of the cluster distances, which is the standard SD formula for obtaining cluster distance variation.

(4) Transfer energy (): it stands for the amount of consumed energy required for transferring all the collected data to the BS. Let “” be the number of associated nodes in a cluster; then, is obtained by

$$E = \sum_{i=1}^{n} \left(\sum_{j=1}^{m} e_{jm} + m^{*} E_R + e_i \right) \quad \textbf{(5)}$$

Where “” stands for the required energy to transfer data from a node to the corresponding CH. Thus, the first term in the summation of “” stands for the total consumption of energy for transfer of aggregated data to CHs. Moreover, the second term in the summation “” pictures the total required energy to collect data from members, and finally, “” stands for the required energy for transmission from the cluster head to the BS.

(5) Number of transmissions (): in general, the BS dictates the number of transmissions that occurs at every monitoring period. This measure is obtained based on the conditions and the energy level of the network; therefore, “” stands for a long time stage for which

the superior optimum solution for maximizing and an inferior solution for minimization are acceptable. The quality of the best solution or chromosome determines the performance of previous GA-based solutions.

In what follows, using genetic algorithm, a fitness function formula to improve each main operational aspects of WSNs (e.g., node placement, network coverage, clustering, and data aggregation) is introduced and discussed. In other words, fitness functions are mainly used to improve energy consumption and lifetime parameters. Simulation results confirmed improvement of the protocols.

Coverage Problem Formulation to ECEP -- To find the proper fitness functions as a part of genetic algorithm, the formula introduce by Quintão et al. [17] was used; the formula is an improved version of Nakamura's formula [18], where "" is given monitoring area, "" is set of sensor nodes, "" is a set of demanded points, "Ad" is a set of areas needed to be monitored by sensors, "NC" is penalty cost of lack of coverage for the needed point, "AE" is turning energy on, and "PC" is penalty costs of the path stretching from every node to BS (obtained via Dijekstra's algorithm for a processing phase which is dedicated to each node to differentiate expensive nodes). The variables of the model are

= 1 when node "" covers demand point and 0 otherwise,

= 1 when nodes "" is active and 0 otherwise,

= 1 when demand point "" is not covered

$$\min \quad \sum_{i \in S} (\mathrm{AE}_i + \mathrm{PC}_i) \times y_i + \sum_{j \in D} \mathrm{NC}_j \times h_j, \tag{9}$$

.subject to

$$\sum_{ij} \left(x_{ij} + h_j \right) \geq 1, \quad \forall j \in D \;\&\; \forall ij \in A^d,$$
$$x_{ij} \leq y_i, \quad \forall i \in S \;\&\; \forall ij \in A^d,$$
$$0 \leq x_{ij} \leq 1, \quad \forall ij \in A^d, \qquad h_j \geq 0, \quad \forall j \in D,$$
$$y \in \{0,1\}, \; \{x,h\} \in \Re. \tag{10}$$

The formula (9) enables us to have minimum required active nodes (more energy to the network) and minimum cases of lack of coverage as well. Every demanded point for monitoring by a sensor or keeping uncovered is represented by constraints (10); they dictate that only active nodes are able of sensing, respectively.

By taking into account penalty cost of overlapping cluster-in-charge errors and consumption of energy marked by OPCE and EC, respectively, an improvement was made in the fitness function (FF). We have

$$\mathrm{FF} = \min\left(\mathrm{Usage\_Cost} + \mathrm{Penalty\_Cost}\right),$$

$$\mathrm{Usage}_{\mathrm{Cost}} = \sum_{i \in s} \left(\mathrm{AE}_i + \mathrm{PC}_i + \mathrm{EC}\right) \times y_i,$$

$$\mathrm{Penalty}_{\mathrm{Cost}} = \sum_{j \in M} \sum_{k \in D} \left(\mathrm{NC}_{jk} + \mathrm{OPCE}_{jk}\right) \times h_k, \qquad \textbf{(11)}$$

subject to

$$M \in \{A, B, C\} \qquad \textbf{(12)}$$

As a dependent to sensor's mode in the network, EC is measured numerically. Clearly, high communication range is obtained by sensor working in mode "" featured with highest rate energy consumption. By assuming 4 and 2 times power usage comparing with "" for mode "" and "", respectively, we have for EC,

$$\mathrm{EC} = \frac{4n_A + 2n_B + n_C}{\sum_{i \in S} n_i} \qquad \textbf{(13)}$$

Taking into account OPCE in FF, wasted energy for overlapping error in cluster-in-charge is obtained.

1 The Proposed Fitness Function --For defining energy consumption and improve lifetime of the network, the parameters of the genetic algorithm were set according to software services. There is a negative relation between energy consumption and distance parameters. One way to lessen the distance between member nodes and pertinent CH is to use more clusters; each cluster may have one or more cluster head(s), which is not economic regarding the energy consumption. However, by using more clusters we avoid longer distances. Because of this, to achieve average amount of energy consumption by each node, a ratio of total energy usage to the total distances of nodes was defined. We propose a formula to achieve optimal WSN energy consumption and coverage (14).

Where, is the total energy consumption and is the total distance between nodes and each cluster is multiplied by total distance between cluster heads.Represents the maximum achievable value for the ratio. Taking into account the negative relation between number of cluster heads and number of nodes/CHs and the same relation between and on one hand and amount of and on the other hand, the maximum value of ratio action is a trade-off of energy consumption and number of blusters [17]:

$$F(i) = \left(\frac{e_i \times T}{D_a \times \#\mathrm{Nodes}}\right) \times \left(\frac{e_j \times T}{D_b \times \#\mathrm{CHs}}\right)$$

$$\therefore D_a = \frac{\mathrm{Width} \times g_i}{\sqrt{\#\mathrm{Clusters}}} \qquad [14]$$

© INTERNATIONAL JOURNAL FOR RESEARCH PUBLICATION & SEMINAR
ISSN: 2278-6848 | Volume: 08 Issue: 07 | July - September 2017
Paper is available at www.jrps.in | Email : info@jrps.in

$$\forall g_i \in \{\text{DDBS}, \text{CD}, \text{CDSD}\}$$
$$[g_i = \text{DDBS}] = 1 \because [\#\text{clusters} = 1] = 1$$
$$\therefore (D_a = D_b = \#\text{CHs} = 1).$$
[15]

in the intelligent suitability function is capable of grading any chromosome both through cluster based method or direct method. To achieve the optimum solution, the optimum chromosome choice is made based on passing generation

4. Simulation & Results

A comparison is made between the GA-based approach proposed here and other cluster-based protocols (e.g., LEACH).
The parameters used in the simulation are listed in Table 5 and the clusters are featured with only one CH, while the generic algorithm process is used to obtain the number of CHs

Simulation parameters represents the parameters of GA in the simulation. It is possible to adopt the chromosomes through random selection. The number of iterations is constant at 100.

Network size	100 m
Node no.	200
Initial energy	2 J
E_e	50 nJ/bit
ε_l	0.0013 pJ/bit/m^2
ε_s	10 pJ/bit/m^2
Network area	100 * 100 m^2
BS distance	200 m
Packet size	200 bits
$d_{co} = d_{crossover}$	85 m

Number of candidate individuals	100
Length of chromosome	20
Crossover rate	.5
Mutation rate	.2
Iteration	100

GA parameter values

© INTERNATIONAL JOURNAL FOR RESEARCH PUBLICATION & SEMINAR
ISSN: 2278-6848 | Volume: 08 Issue: 07 | July - September 2017
Paper is available at www.jrps.in | Email : info@jrps.in

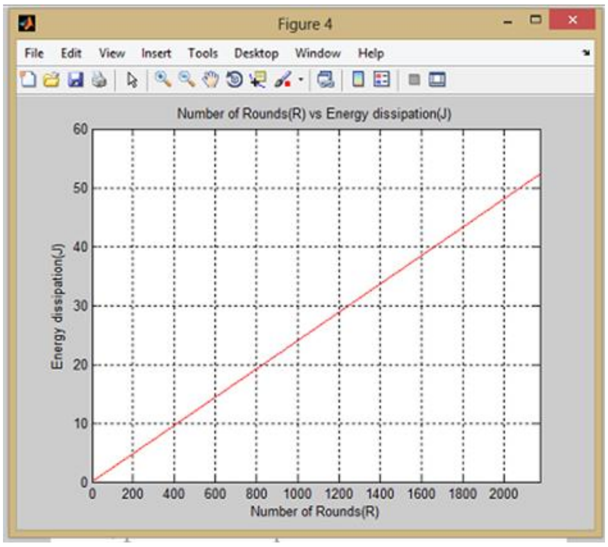


Fig 1: Energy Dissipation vs. Number of Round

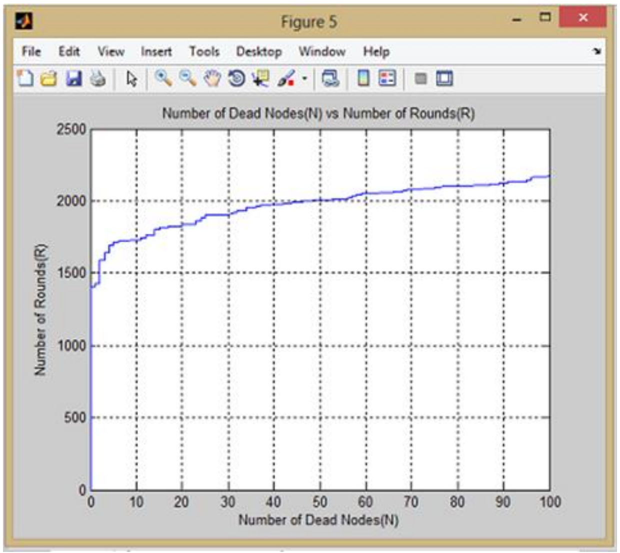
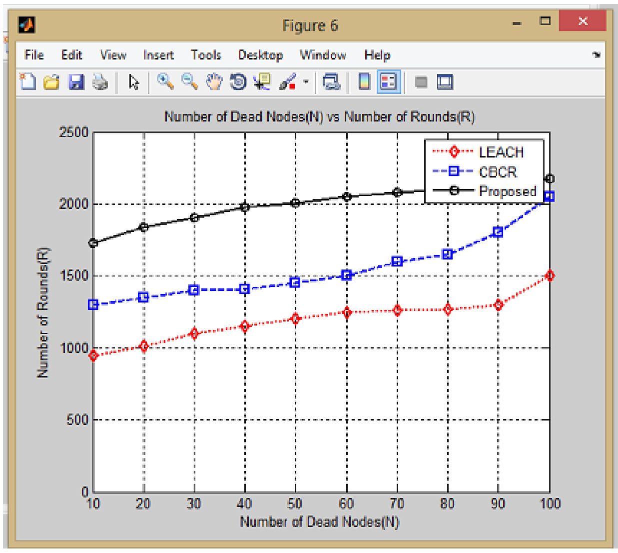


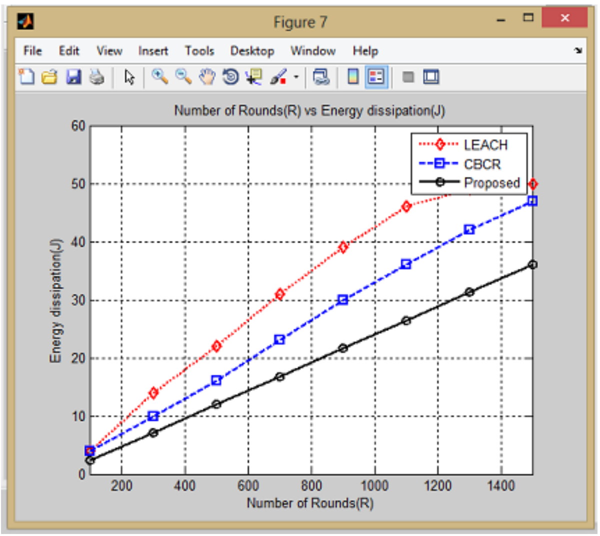
Fig. 2 Number Of Rounds Vs Dead Nodes (Number of round consider to be about 2500)



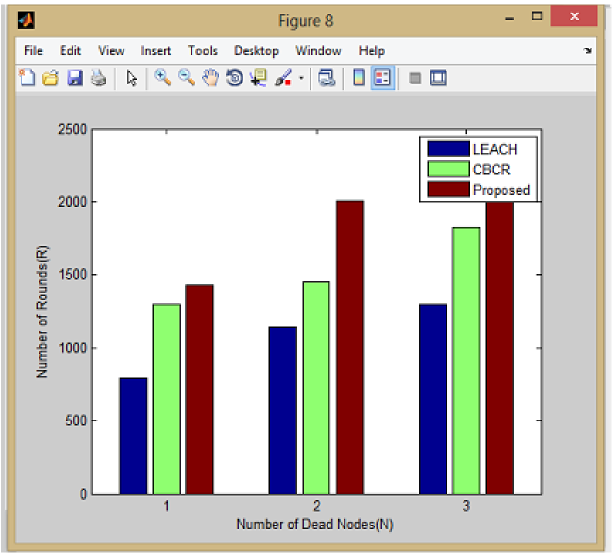
© INTERNATIONAL JOURNAL FOR RESEARCH PUBLICATION & SEMINAR
ISSN: 2278-6848 | Volume: 08 Issue: 07 | July - September 2017
Paper is available at www.jrps.in | Email : info@jrps.in

Fig. 3 Number of Rounds Vs Number of Dead Node

This above is comparative result in which LEACH, CBCR and Proposed work (Based on GA)



Energy dissipation vs. number of rounds



Number of rounds vs. number of dean nodes

This research shows after applying the genetic algorithm, less energy dissipation in network appears after increasing number of rounds. Proposed work uses genetic algorithm to improve the network lifetime (dead node) and energy dissipation value of the wireless sensor networks by finding the optimum number of cluster heads and their locations based on minimizing the energy consumption of the sensor nodes. MATLAB simulation results showed that the proposed work is less energy dissipation, less number of dead nodes. After comparing the existing work as LEACH and CBCR, this simulative result found very good result.

5. Conclusion

By finding the drawbacks and optimizing them, ideal parameters of the network were achieved. Finally, using genetic algorithm, a fitness function with optimum formula was obtained and the present protocols were optimized. The results of simulations in JPAC, MATLAB, and NS were compared with are of the present protocols and optimization of the two parameters confirmed. It is also noticeable that the diagrams obtained from the simulations showed an improvement in energy consumption parameters and lifetime of the network; this means more ideal WSNs. An application based protocol without specific limitation regarding its application—suitable for military, medical, and commercial applications—will be subject of our future studies.

6. References

[1] Alain Bertrand Bomgni, Jean Frédéric Myoupo "An Energy-Efficient Clique-Based Geocast Algorithm for Dense Sensor Networks" Communications and Network, 2010, 2, 125-133 Amandeep Kaur Rupinder Kaur. "International Journal of Advanced Research in Computer Science and Software Engineering" Volume 4, Issue 6, June 2014 ISSN: 2277 128X*

[2] Kamanashis Biswas1, Vallipuram Muthukkumarasamy1, Elankayer Sithirasenan1, Kalvinder Singh2 "An Energy Aware Heuristic-based Routing Protocol in Wireless Sensor Networks" 17th Int'l Conf. on Computer and Information Technology, 22-23 December 2014, Daffodil International University, Dhaka, Bangladesh

[3] Kamanashis Biswas, Vallipuram Muthukkumarasamy, Elankayer Sithirasenan, Muhammad Usman. "An Energy Efficient Clique Based Clustering and Routing Mechanism in Wireless Sensor Networks" School of Information and Communication Technology, Griffith University Gold Coast, Australia

[4] Sajid Hussain, Abdul Wasey Matin, Obidul Islam "Genetic Algorithm for Hierarchical Wireless

[5] Sensor Networks" JOURNAL OF NETWORKS, VOL. 2, NO. 5, SEPTEMBER 2007

*[6] Kapil Uraiya , ** Dilip Kumar Gandhi "Genetic Algorithm for Wireless Sensor Network With*

[7] Localization Based Techniques" International Journal of Scientific and Research Publications, Volume 4, Issue 9, September 2014 ISSN 2250-3153

[8] Ali Norouzi1, Faezeh Sadat Babamir2, Abdul Halim Zaim "A New Clustering Protocol for Wireless Sensor Networks Using Genetic Algorithm Approach" Wireless Sensor Network, 2011, 3, 362-370 doi:10.4236/wsn.2011.311042 Published Online November 2011

[9] Hossein Jadidoleslamy Information Technology Engineering Group, Department Of Information Technology, Communications And Security University Of Malek Ashtar, Tehran, Iran "An Introduction To Various Basic Concepts Of Clustering Techniques On Wireless Sensor Networks" International Journal Of Mobile Network Communications & Telematics (Ijmnct) Vol. 3, No.1, February 2013

*[10] Mukesh Prajapat#1, Dr. N.C. Barwar*2 "Performance Analysis of Energy Dissipation in WSNs Using Multi-Chain PEGASIS" Mukesh Prajapat et al, / (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 5 (6) , 2014, 8033-8036*