ENERGY EFFICIENT CLUSTREING METHODS IN WIRELESS SENSOR NETWORKS USING BINARY CODED GENETIC ALGORITHM

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Abstract: *In this paper, a binary coded genetic algorithm is proposed to improve the lifetime of Wireless Sensor Networks (WSN). The proposed method selects the Cluster Heads (CHs) in each round that minimizes the energy consumption. The proposed method can be considered as a replacement for other conventional cluster based approaches like Low-Energy Adaptive Clustering Hierarchy (LEACH). The proposed clustering algorithm is simulated and tested using MATLAB for network architecture consist of 50 nodes that are distributed in the 100 square meters area. From the results it is observed that the proposed Energy Efficient Clustering Algorithm (GA-EECA) outperforms the conventional LEACH. The simulation results were very promising in terms of sensor node life time.*

Key words: *wireless sensor networks, LEACH, Binary coded Genetic Algorithm.*

1. Introduction

Wireless Sensor Network is used in many applications such as target tracking [2], habitat monitoring [3], and also in military applications such as surveillance and security [4]. A typical WSN will contain a number of sensor nodes that are smaller in size. These sensor nodes consist of transducers, data processing units and data transmission units. These sensor nodes are provided with built in battery for their energy requirement [1]. The replacement of these small batteries is very difficult and expensive and power saving is considered to a major issue [12]. One of the major factors that contribute for more energy consumption is data transmission from the sensor node to Base station [5]. Hence the design of WSN should limit the number of data transmissions of any sensor node in order to increase the life time of sensor node. To reduce the number of data transmissions, cluster-based protocols were proposed [6]. The cluster based approach divides the entire WSN network into a number of clusters. Each cluster group has a special sensor node called “cluster-head” (CH) that acts as a leader for that cluster members and aggregates the data from all member nodes within its cluster group. Then the CHs aggregate the collected data to transmit to the Base Station (BS). This approach greatly reduces the energy consumption of nodes and also increases lifetime of the network. The selection of cluster head is done based on some probability. The probability based approach may not yield good network clusters because the cluster having very low residual energy may also get high probability of being selected as Cluster Head [7]. In this paper, we address the problem of finding optimal CHs for WSN consist of 50 sensor nodes. The optimal solution that increases the life-time of the sensor node. Genetic Algorithm (GA) is one of the most commonly used population based optimization technique that can be applied to solve this problem.

2. Related work

Wireless Sensor Networks are classified into three categories based on the routing protocol such as One-hop model, Multi-hop model and Cluster-based Hierarchical Model [8]. Clustering approaches can be implemented using LEACH (Low-Energy Adaptive Clustering Hierarchy) protocol, which is a distributed Heuristic approach in which the clusters are used for the purpose of routing [9]. The entire wireless sensor network is divided into many clusters of sensor nodes. Any sensor node can act as cluster head and the selection of cluster head depends upon the probability [10]. The numbers of CHs are fixed to 5% of the number of sensor nodes. The LEACH has two stages during each round. First stage is the “Advertisement Phase” during which the random clusters are formed and CHs are elected. The node is selected as a CH if the energy of the node is above Zero and also the based on the value of probability. The second stage is “Steady state Phase”, in which the members of the cluster transmit the entire data to their respective CHs based on a Time Division Multiple Access (TDMA) schedule. Then the CHs aggregate all the data and sends the data to the BS [11]. In a WSN, a round is said to be completed if all CHs send its aggregated data to BS. After a completion of round, the cycle again starts with set-up (advertisement) phase and new clusters are created with new CHs. By this way, the workload of the cluster head is rotated dynamically. As the selection of cluster head does not rely on the power availability in the node, a node with low energy may be selected as a CH, this may cause that particular node to die quickly [12].

2.1 Overview of genetic algorithm

Genetic algorithm is a population based optimization approach derived from Darwin's natural selection principle based on the survival of the fittest [13]. This algorithm found its applications in many engineering field to solve optimization problems [14]-[18]. The Variants of these algorithms are also applied in optimization of complex optimization problems. The operation of the GA is given in Fig 1. The algorithm starts with random initialized population or user supplied population and applies the reproduction operators such as crossover, mutation and elitism on selected individual from the initial generation population to produce next generation population. The reproduction operators are again applied on the new population to carry out generation cycle. The generation cycle is repeated till the set number of generations [19]. The genetic operators are discussed in the following section.

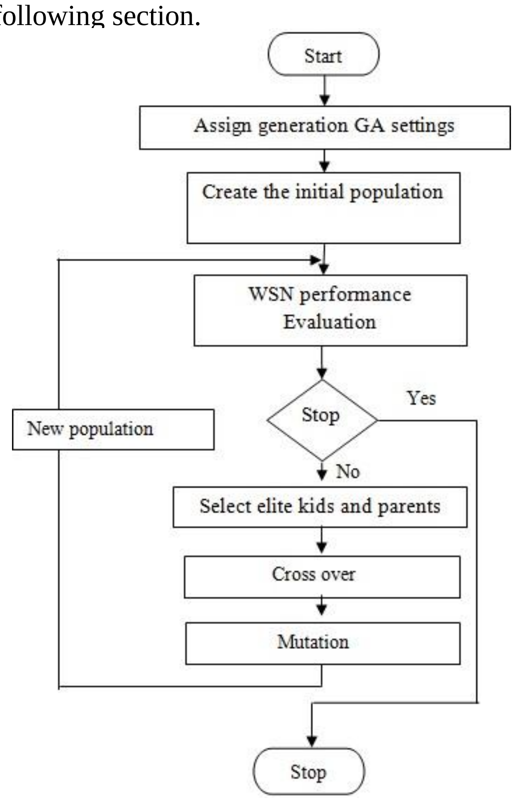

Fig.1. Genetic algorithm flow chart

2.1.1 Fitness Function

The mathematical representation of the minimization problem is called as fitness function. Every chromosome will be evaluated its fitness value by supplying that chromosome to the fitness function and this result is called as fitness value. The fitness value decides that weather the chromosome will survive for next generation or to be dropped out for the next generation.

2.1 .2 Selection

A population consists of chromosomes that represent complete clusters of sensor nodes and cluster heads (possible solution) to a defined problem. Each chromosome consists of a sequence of zeros and ones. A randomly initialized chromosome of genome length 50. If the chromosome is 1 then the sensor node is assigned as cluster head and if 0 then the sensor node is not assigned as cluster head.

2.1.3 Crossover

In crossover, two parent chromosomes recombine at the crossover site to generate the "crossover offspring". In this paper, we have used two-point cross over method. The selected bits of binary chromosomes are exchanged at random crossover sites to produce better offspring [20].

2.1.4 Mutation

During the generation cycle, there is a chance for errors while coping the chromosomes form current generation to the next generation. This random error introduces new sequence of genes and that causes genetic variability. The per-bit based mutation method is used to generate new mutation off spring. Unlike crossover rate, the mutation rate is set for very low value to avoid more random search [21].

2.1.5 Elitism

The chromosome that has more fitness is passed to the next generation and it is called as elitism. The chromosome which is transferred to the next generation is known as elite kits. The elite count is kept very minimum value such as 2. Increasing elite count value will make the GA to converge in local minimum [25].

3. System Model

3.1 Energy model

The network and node model used in this paper are discussed in this section. Based on the distance between the transmitter and receiver, the free space and multi path models are selected. A threshold value d_0 is asserted to some value and if the distance is less than threshold d_0, then the designed model selects free space (fsp) model, otherwise the multipath (mulp) model is selected. Let E_{elect} be the energy required for the circuit in the sensor node, ε_{fsp} be the energy requirement of the amplifier in the free space and ε_{mulp} be the energy required by the amplifier circuits in multi path. Then the energy (E_{Trans}) required by the node to transmit an *l*-bit message over a distance (d) is given as follows:

$$E_{Trans}(l, d) = lE_{elect} + l\varepsilon_{fsp}d^2 \quad \text{for } d < d_0$$
$$E_{Trans}(l, d) = lE_{elect} + l\varepsilon_{mulp}d^4 \quad \text{for } d \geq d_0$$

The energy required by the radio (sensor node) to receive an *l*-bit message is given by following equation and this model is same as discussed in [22].

$$E_R(l) = lE_{elect}$$

The energy required by the circuit E_{elect} depends on many factors such as digital coding, modulation, filtering the signals, and spreading of the signal, whereas the amplifier energy, $\varepsilon_{fsp}d^2/\varepsilon_{mulp}d^4$, depends on the distance between the transmitter and the receiver and also on the bit error rate tolerance. This is a simplified model and does not include complete radio wave propagation model. The modelling of the radio wave propagation is very difficult and it is finding a great attention among researchers [26].

3.2 Network model

We assume randomly deployed sensor nodes. After deployment, they become stationary as shown in Fig 2. These sensor nodes are assigned with a few gateways (5% of number of nodes). The hardware configuration of these gateways are same as other sensor nodes. If a sensor node is within the range for any gate way, then the sensor node is assigned to that gateway. In LEACH, the data acquisition is divided into several rounds. In each round, all sensor nodes collect local data and sends to respective CH. The CHs perform data aggregation to discard the redundant and uncorrelated data and send the aggregated data to the base station. Between two adjacent rounds, all nodes turn off their radios to save energy. A wireless link is established between two nodes only if they are within the communication range of each other. All communications are carried out over wireless link. The Current implementation deals with the Cluster-based Hierarchical Model as shown in Fig 3.

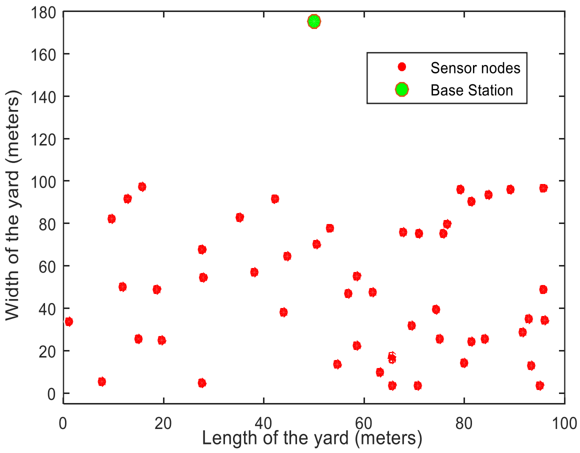

Fig.2. Node locations in 100 square meter area

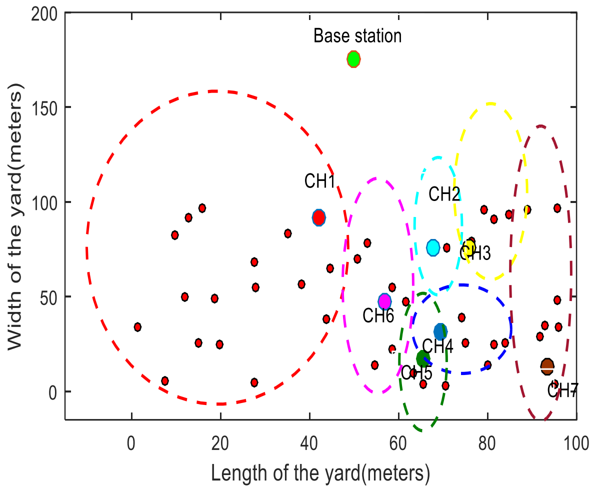

Fig.3. Cluster-based Hierarchical Model

In Fig.3, the cluster heads (CH1 to CH7) aggregates the data from its respective sensor nodes and sends the data to the Base station as on hop model.

4. Proposed Work

The WSN model discussed in previous section is implemented with Genetic Algorithm based Clustering Approach. The development of Pseudo code for the implementation of GA based Energy Efficient Clustering(GA-EEC) is given in this section. The binary chromosome of 0's and 1's represents the sensor nodes in WSN. A node is assigned with 1 if the node is selected as a cluster head. The sensor nodes that are not assigned as a cluster head is assigned with 0. The proposed algorithm has two phases of implementation. The first phase sets up the configurations for GA-EEC, where the details of configuration are listed in the Table 1. and the second phase is cluster head optimization.

Table 1(Parameters for network configuration)

Parameter	Value
Number of nodes	50
Width of the yard(meters)	100
Length of the yard(meters)	100
Type of yard	Rectangle
Base station location(x,y) in meters	(50,175)
Initial energy of node in watts	0.5
Energy required for transferring 1 bit to Base station	5.00e-8
Energy required for receiving 1 bit from sensor node in watts	5.00e-8
Energy for free Space	1.00e-11
Energy for multi Path	1.30e-15
Energy required for data aggregation (cluster heads)	5.00e-09
Packet Length	6400

4.1 pseudo code

Step 1:
/*Phase 1: Network configuration*/
Initialize the network parameters to the values given in the table 1
/* GA Initialization*/
Initialize the GA parameters as in Table 2.
Step 2:
For all rounds repeat the steps from 3 to 6
For all generations do the steps from 3 to 5
Step 3:
Represent network as array of bits
/*Assign the sensor nodes with 1 for CH*/
/*Assign the sensor node with 0 for Non-CH*/
Chromosome ⟵ array;
Step 4:
Evaluate the chromosome to calculate fitness
/*fitness =energy dissipation if the node is selected as CH*/
Step 5:
Select the parents based on the fitness
/*Apply reproduction operators*/
Crossover the selected parents
Mutate the parents
Copy elite kits
New population=[crossover kit+elite kits+mutataion kits]
Goto step 3 with new population for all generation and return the optimized cluster Heads
Step 6: Set up new cluster model for next round and goto step 2

Table 2 (GA parameters)

Parameter	Value
Population size	20
Chromosome length	50
Crossover rate	0.8
Elite count	2
Number of generation	20
Crossover type	Two point
Selection method	Rank selection

The crossover rate 0.8 refers that 80% of new population is made up of crossover kids and 2% of new population is made up of elite kids and remaining 18% of new population will be produced based on Mutation.

5. Results and discussions

The proposed node and network architecture was simulated for 100 rounds to test the energy optimization efficiency of the proposed GA-EEC. The total energy of the WSN with respect to round is presented in the Table No.3. The results show that proposed GA-EEC optimizes the selection of node as cluster head and prevents the total energy to drain out quickly. The sensor nodes were provided with the 0.5 watts of power and the energy is utilized by the sensor node in each round. The total energy of the network is 25 Watts and the GA-EEC effectively monitors the total energy and creates energy efficient clusters.

Table 3 (LEACH and GA-EEC Total energy of WSN)

Round	Leach	GA-EEC
1	24.960	24.985
10	24.322	24.902
20	23.773	24.814
30	23.149	24.679
40	22.508	24.561
50	21.862	24.463
80	19.906	24.113
100	18.667	23.899

The Fig 4 depicts the cluster heads selected by GA. The number of Cluster Head is three during the first round of the network. The Fig 5 shows that the total energy spent on each round and clearly indicates the proposed GA-EEC utilizes the minimum energy to complete each round.

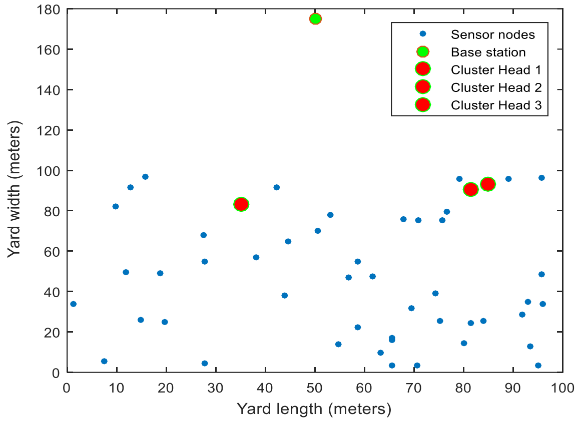

Fig.4. GA based Energy Efficient Clustering

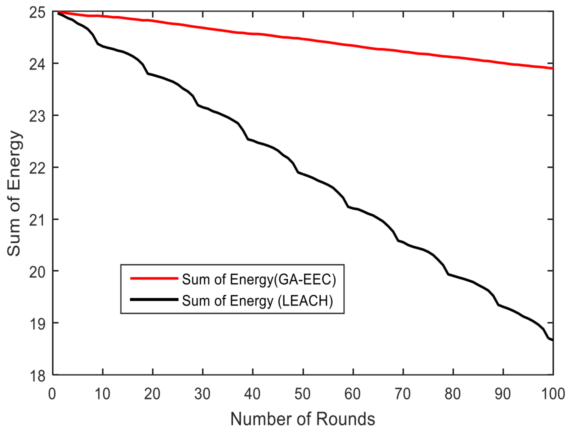

Fig.5. Sum of energy in WSN.

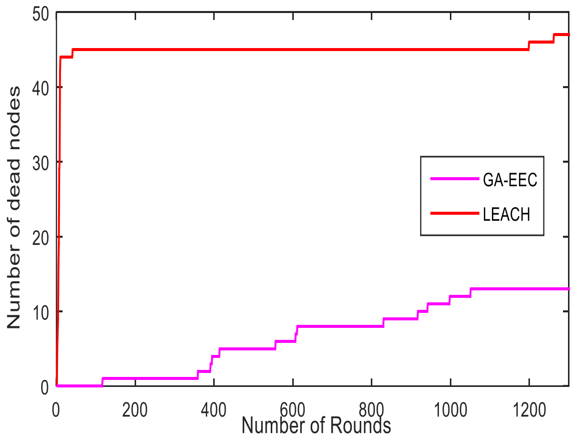

Fig.6. Number of dead node per round.

Table 4 (Statistical analysis of Number of dead node Versus Number of rounds).

Parameters	Leach	GA-EEC
Minimum value	0	0
Maximum value	48	15
mean	45.029	8.608
median	45	9
Standard deviation	2.5633	5.195

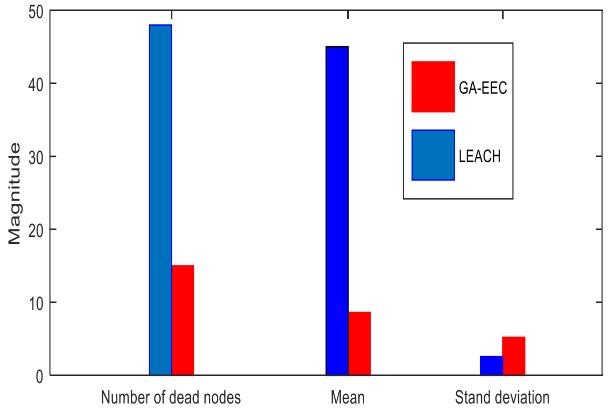

Fig.7. Statistical analysis.

In GA-EEC the number of dead nodes per round was considerably reduced and the standard deviation for number of dead node versus round is 5.195 as shown in the Fig 7. This is more than the value of standard deviation of LEACH. This is because the number of dead nodes were not scattered to other values from the round number 41 to 1198 as indicated in Fig 6. The number of dead nodes after completing 1378 round was 48 in leach based clustering, whereas in proposed GA-EEC the number of dead nodes was only 15. Hence by using GA-EEC we can extend the life is sensor node greatly.

6. Conclusion and future work

The proposed Genetic algorithm based cluster head selection approach was simulated in MATLAB. The results were very encouraging and the number of dead nodes against the round was well reduced. The proposed algorithm is aware of the residual energy in the sensor node and manage the workload of sensor node effectively to prevent the node from dead. In future the cluster head optimization can be implemented with other optimization approaches.

References

[1]. I. Mandourarakis and E. Koutroulis, *"Unified System-and Circuit-Level Optimization of RES-Based Power-Supply Systems for the Nodes of Wireless Sensor Networks,"* IEEE Transactions on Industrial Informatics, vol. 14, no. 2, pp. 598-607, Feb. 2018.

[2]. R. Ghazalian, A. Aghagolzadeh and S. M. Hosseini Andargoli, *"Wireless Visual Sensor Networks Energy Optimization With Maintaining Image Quality,"* IEEE Sensors Journal, vol. 17, no. 13, pp. 4056-4066, July1, 1 2017.

[3]. Roland Kays, Sameer Tilak, *Margaret Crofoot "Tracking Animal Location and Activity with an Automated Radio Telemetry System in a Tropical Rainforest,"* IEEE-

The Computer Journal, vol. 54, no. 12, pp. 1931-1948, Nov. 2011.

[4]. Lei Chen, Zijian Wang, Boleslaw Szymanski *"Dynamic Service Execution in Sensor Networks,"* IEEE- The Computer Journal, vol. 53, no. 5, pp. 513-527, June 2010.

[5]. S. Croce, F. Marcelloni and M. Vecchio, *"Reducing Power Consumption in Wireless Sensor Networks Using a Novel Approach to Data Aggregation"* IEEE- The Computer Journal, vol. 51, no. 2, pp. 227-239, March 2008

[6]. Anindita Ray, Debashis De, *"Energy efficient clustering protocol based on K-means (EECPK-means)-midpoint algorithm for enhanced network lifetime in wireless sensor network,"* in IET Wireless Sensor Systems, vol. 6, no. 6, pp. 181-191, 12 2016.

[7]. W. Wu, N. Xiong and C. Wu, *"Improved clustering algorithm based on energy consumption in wireless sensor networks,"* in IET Networks, vol. 6, no. 3, pp. 47-53, 5 2017.

[8]. M. Soleimani, M. M. Bhuiyan, M. H. MacGregor, R. Kerslake and P. Mousavi, *"RF channel modelling and multi-hop routing for wireless sensor networks located on oil rigs,"* in IET Wireless Sensor Systems, vol. 6, no. 5, pp. 173-179, 10 2016.

[9]. Asaduzzaman. and H. Y. Kong, *"Energy efficient cooperative LEACH protocol for wireless sensor networks,"* in Journal of Communications and Networks, vol. 12, no. 4, pp. 358-365, Aug. 2010.

[10]. S. K. Singh, P. Kumar and J. P. Singh, *"A Survey on Successors of LEACH Protocol,"* in IEEE Access, vol. 5, pp. 4298-4328, 2017.

[11]. I. Sohn, J. H. Lee and S. H. Lee, *"Low-Energy Adaptive Clustering Hierarchy Using Affinity Propagation for Wireless Sensor Networks,"* in IEEE Communications Letters, vol. 20, no. 3, pp. 558-561, March 2016.

[12]. P. Nayak and A. Devulapalli, *"A Fuzzy Logic-Based Clustering Algorithm for WSN to Extend the Network Lifetime,"* in IEEE Sensors Journal, vol. 16, no. 1, pp. 137-144, Jan.1, 2016.

[13]. C. Perales-GravÁn and R. Lahoz-Beltra, *"An AM Radio Receiver Designed With a Genetic Algorithm Based on a Bacterial Conjugation Genetic Operator,"* IEEE Transactions on Evolutionary Computation, vol. 12, no. 2, pp. 129-142, April 2008.

[14]. Hongbin Dong, Tao Li, Rui Ding, Jing Sun, *"A novel hybrid genetic algorithm with granular information for feature selection and optimization"* Applied Soft Computing, Vol. 65, pp. 33-46, 2018.

[15]. Anwar Said, Rabeeh Ayaz Abbasi, Onaiza Maqbool, Ali Daud, Naif Radi Aljohani, "*CC-GA: A clustering coefficient based genetic algorithm for detecting communities in social networks,"* Applied Soft Computing, Vol. 63, pp. 59-70,2018.

[16]. Bernardo Jubert de Almeida, Rui Ferreira Neves, Nuno Horta, "*Combining Support Vector Machine with Genetic Algorithms to optimize investments in Forex markets with high leverage"* Applied Soft Computing, Vol.64, pp. 596-613,2018.

[17].Chih-Hsun Chou, Su-Chen Hsieh, Chui-Jie Qiu," *Hybrid genetic algorithm and fuzzy clustering for bankruptcy prediction",* Applied Soft Computing, Vol.56, pp.98-316,2017.

[18]. K.Vijayakumar, T.Manigandan, "*Nonlinear PID Controller Parameter Optimization using Enhanced Genetic Algorithm for Nonlinear Control System"* Journal of Control Engineering and Applied Informatics, Vol.18, No.2 pp. 3-10, 2016

[19]. S. Piersanti and A. Orlandi, *"Impact of Genetic Algorithm Control Parameters on Chip PDN Decoupling Capacitors Placement,"* in IEEE Transactions on Electromagnetic Compatibility, vol. 60, no. 4, pp. 945-951, Aug. 2018.

[20]. D.J. Reid, *Genetic algorithms in constrained optimization,* Mathematical and Computer Modelling, Vol. 23, No. 5, pp. 87-111, 1996.

[21]. Ying-Hong Liao and Chuen-Tsai Sun, "*An educational genetic algorithms learning tool,"* in IEEE Transactions on Education, vol. 44, no. 2, pp. 20 pp.-, May 2001.

[22]. W. Zhang, Z. Zhang, H. C. Chao, Y. Liu and P. Zhang, *"System-Level Energy Balance for Maximizing Network Lifetime in WSNs,"* in IEEE Access, vol. 5, pp. 20046-20057, 2017.

[23]. S. Yadav and V. Kumar, *"Optimal Clustering in Underwater Wireless Sensor Networks: Acoustic, EM and FSO Communication Compliant Technique,"* in IEEE Access, vol. 5, pp. 12761-12776, 2017.

[24]. *Ai Bo, Thomas Kürner, César Briso Rodríguez, and Hsiao-Chun Wu* "*Radio Wave Propagation and Wireless Channel Modeling"* Hindawi Publishing Corporation. Vol.2013,2013.

[25]. M. B. Nia and Y. Alipouri, *"Speeding Up the Genetic Algorithm Convergence Using Sequential Mutation and Circular Gene Methods,"* Ninth International Conference on Intelligent Systems Design and Applications, Pisa, , pp. 31-36. 2009

[26]. W. B. Heinzelman, A. P. Chandrakasan and H. Balakrishnan, "An application-specific protocol architecture for wireless microsensor networks,"in *IEEE Transactions on Wireless Communications*, vol. 1, no. 4, pp. 660-670, Oct 2002.