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ENERGY OPTIMIZATION IN WIRELESS SENSOR NETWORK USING NSGA-II

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ABSTRACT

The rapid growth in wireless technology is enabling the variety of advances in wireless sensor networks (WSNs). By providing the sensing capabilities and efficient wireless communication, WSNs are becoming important factor in day to day life. WSNs have many commercial, industrial and telecommunication applications. The efficient use of available energy is one of the major issues in wireless sensor network. The battery life of sensor nodes should be long enough to decrease the maintenance cost. The multi-objective evolutionary algorithms (MOEAs) are used for solving two or more objective problems. In this paper, we suggest non-dominated sorting of solutions of multi-objective problems using multi-objective evolutionary algorithm (MOEA), called as non-dominated sorting genetic algorithm II (NSGA-II). The primary objective of this paper is prolonging the lifetime of wireless sensor networks. The energy consumption in the network is optimized such that lifetime of network is increased. The simulation results show that NSGA-II provides better solution to select cluster head. The comparison of NSGA-II with well-known energy efficient algorithm LEACH shows, the proposed system can increase the network lifetime four to five times more than LEACH.

Keywords: clustering, multi-objective optimization, NSGA-II, wireless sensor network.

1. INTRODUCTION

The recent development in wireless communication has proven the importance of wireless sensor network in many fields like military applications, industry monitoring, health, home etc. The wireless sensor network is made up of large number of low-cost, ultra small, autonomous and multifunctional sensor nodes. The sensor node consists of different components like one or more sensors, data processing unit and transceiver [1]. The sensor network consists of many sensor nodes and these sensor nodes are densely deployed in observation area. The nodes sense the physical quantity (e.g. pressure, temperature, sound, vibration, light, motion etc.), process the data and transmit/receive information to base station (BS) or sink.

The sensor node is having battery unit for the process of collecting the information and sending it to base station. The lifetime of wireless sensor networks is mainly depends upon the energy consumed during transmission of data. For each packet transmission sensor node loses some energy. Thus after some transmission time node will lose its energy completely and it will die. The relation between energy of sensor nodes and communication distance is inversely proportional. Thus for long distance communication between sensor node and base station more energy is consumed. The energy sources used for communication are limited. Hence efficient and effective use of available resources is one of the major challenges.

To prolong the lifespan of a wireless sensor network, sensor nodes are scheduled to sleep dynamically using Sleep Scheduling (SS) mechanism. Instead of "being awake" all the time, every node has chance to "sleep" by using Sleep Scheduling mechanism [14].

Multi-objective optimization (MOO) has been applied in many fields of science and engineering, economics, logistics. In MOO, optimal decision needs to be taken in presence of trade-off between two or more conflicting objectives. Achieving the optimal value for one objective requires compromise on one or more other objectives. The solution needs to be chosen such that, there must be some trade-offs among all objectives. One way to handle such problems is 'Pareto-optimality' [3]. In this approach, instead of single solution we have set of optimal solutions known as 'Pareto-optimal solutions'. The pareto-optimal solution is also called 'non-inferior solution' or 'non-dominated solution' because no other solution is dominated [3].

Many multi-objective evolutionary algorithms (MOEA) are suggested to solve the multi-objective problems. We used non-dominated sorting genetic algorithm-II (NSGA-II) to solve multi-objective problems. We considered seven different energy related problems in WSNs. These objective functions are designed as multi-objective problem.

In the Direct Transmission (DT) method, all sensor nodes directly communicate with base station. So each node individually sends the collected information to BS. In this method the nodes which are at larger distance from base station will drain their energy faster than the nodes which are nearer to base station. Therefore this approach is efficiently suitable for smaller observation area, where communication distance between sensor nodes and BS is less.

The efficient way of energy consumption is making clusters of sensor nodes. The formation of set of similar nodes is called as clustering. All the available nodes are divided in some number of groups. These groups are called as clusters [13]. Each cluster will have cluster head (CH) and cluster members. Cluster head (CH) is the cluster administer. It will collect all the data from cluster members within its cluster, process it and send to base station as shown in Figure-1. Nodes belonging in a cluster can execute different functions from other nodes.

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The hybridization of well-known algorithm for optimal cluster head selection exhibits high throughput, residual energy and improved lifetime [15]. In order to obtain a global search with faster convergence, a hybrid of HAS and PSO algorithm is proposed for energy efficient cluster head selection. The high search efficiency of HAS and dynamic capability of PSO that improves the life time of sensor nodes [16].

Clustering allows aggregation of data received from its cluster members and sends the aggregated data to BS. Clustering reduces the number of nodes taking part in transmission also it limits data transmission. Clustering is powerful tool for reducing the communication distance and optimizing the energy consumption in sensor networks. In our work, we used non-dominated sorting genetic algorithm-II (NSGA-II) for clustering. The NSGA-II algorithm is performed at base station (BS) which gives number of non-dominated solutions. BS chooses the best solution to select cluster head.

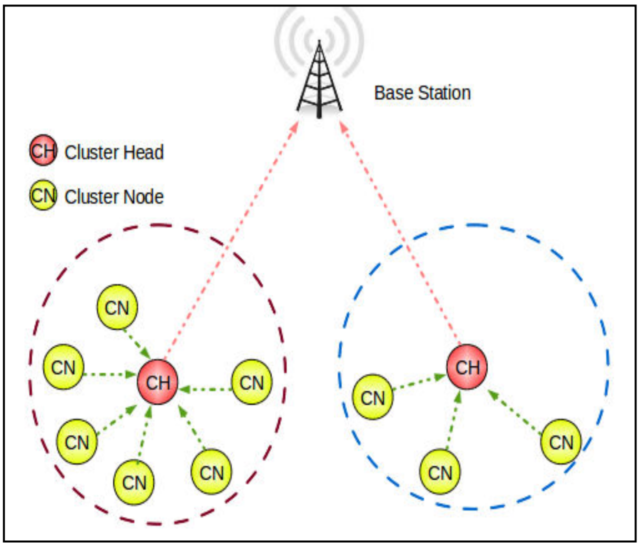

Figure-1. Clustering in WSN.

2. RELATED WORK

Hussain *et al*. proposed intelligent technique for cluster formation and management using genetic algorithm (GA) [5]. GA is performed at base station to select cluster head. Different fitness parameters are considered to form fitness function. The weighted sum method is used to make multi-objective problem as a single objective. All the fitness parameters are multiplied with different weighing coefficients.

Jin *et al*. proposed an energy efficient algorithm based on genetic algorithm (GA) to solve the energy optimization problem [6]. The genetic algorithm is used to provide solution for clustering the network into number of independent clusters. Clustering helps to reduce communication distance between sensor nodes and cluster head, cluster head and sink.

Xue *et al*. described a multi-objective differential evolutionary (MODE) algorithm to solve different objectives including latency, channel capacity and energy [8]. However, in this paper routing problems in wireless sensor network are considered as multiple objective problems. Communication delay and energy consumption are optimized. By considering latency and energy, optimal routes between sensor nodes are found.

Attea *et al.* considered the coverage optimization problem for wireless mobile sensor networks (MSN) [9]. In this paper, the locations of mobile sensors are re-decided so that data is routed to BS more efficiently. Non-dominated sorting genetic algorithm-II (NSGA-II) is used to create set of Pareto-optimal solutions which are non-dominated solutions. The BS will select one for clustering with high coverage efficiency.

Konstantinidis *et al.* proposed multi-objective evolutionary algorithm for power assignment problem in WSN [11]. The paper provides optimal solution to determine transmit power levels of sensor nodes.

Javadi *et al*. addresses clustering of homogeneous wireless sensor network using multi-objective two-nested genetic algorithm (M2NGA) [12]. In this paper two vectors for energy consumption and delay are evaluated. The proposed M2NGA method is compared with other GA based clustering methods.

3. MULTI-OBJECTIVE OPTIMIZATION

The multi-objective optimization (MOO) is an array of multiple criteria decision making. The process consists of mathematical optimization problems. Problems involving more than one objective function to be optimized simultaneously. Optimal decision needs to be taken in presence of trade of between two or more conflicting objectives. In MOO there just not exist single solutions that simultaneously optimize each objective. But there exists number of Pareto-optimal solutions, and the solution is called non-dominated with greater efficiency.

In our paper we considered seven different objective functions. These seven objective functions are described in [13].

Objective 1: Minimizing the total energy consumed by non-cluster head nodes sending message to their own CHs is given by,

$$z_1 = \sum E_{nonCH-CH} \tag{1}$$

Objective 2: Minimizing the total energy of non-CH nodes is given by,

$$z_2 = \sum E_{nonCH} \tag{2}$$

Objective 3: Maximizing the total energy of CHs is given by,

$$z_3 = \frac{1}{E_{CH}} \tag{3}$$

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Objective 4: Minimizing energy of CH to transmit the elements of its cluster is given by,

$$z_5 = \max(E_{CH-nonCH}) \quad (4)$$

Objective 5: Maximizing the number of non-CH nodes is given by,

$$z_4 = \frac{1}{N} \quad (5)$$

Objective 6: Minimizing the total energy consumed by CHs in order to transmit the packet collected within them to BS is given by,

$$z_6 = \sum E_{CH-BS} \quad (6)$$

Objective 7: Minimizing the total energy required for non-CH nodes to communicate with Sink directlyis given by,

$$z_7 = \sum E_{nonCH-BS} \quad (7)$$

In above equations $E_{nonCH-CH}$ is the energy required to send packets from non-cluster head to cluster head. E_{nonCH} and E_{CH} are total energy of non-cluster head and cluster head respectively. $E_{CH-nonCH}$ is the energy required to send packets from cluster head to non-cluster head. N shows the number of non-cluster head nodes. E_{CH-BS} is the energy required to send packets aggregated by cluster head to base station. $E_{nonCH-BS}$ is energy required by non-cluster head node to send packets to the base station.

In our work, we use first order radio energy model suggested in [4]. The energy required by transmit amplifier to transmit information is proportional to square of the distance between two nodes. Using first order radio model, the energy consumed by transmitter circuitry for transmission of k-bit packet to the distance d is $E_{TX}(k,d)$ and is given by,

$$E_{TX}(k,d) = k * E_e + k * \in_{amp} * d^2 \quad (8)$$

$$E_{TX}(k,d) = k * E_e + k * \in_{amp} * d^4 \quad (9)$$

Equation (8) and (9) are for short and long distance transmission from one node to other. Here short distance is referred to a distance from cluster members to the cluster head (CH) and long distance is referred to cluster head (CH) to sink (BS). Similarly, to receive this message radio model uses equation (10) given by,

$$E_{RX}(k,d) = k * E_e \quad (10)$$

In the above equation $E_{RX}(k,d)$ is the energy consumed by receiver circuitry for k-bit packet to distance d. E_e is the energy required for transmitter as well as receiver circuitry. $\in_{amp}$ gives energy dissipation for transmit amplifier. The values for parameters used in energy model equations are given in Table-1.

Table-1. List of parameters used for energy model.

Operation	Energy Dissipated
Transmitter Circuitry (E_e)	50 nJ/bit
Receiver Circuitry (E_e)	
Transmit Amplifier (ε_{amp})	100 pJ/bit/m^2

4. NSGA-II BACKGROUND

To overcome the drawbacks of NSGA such as lack of elitism and computational complexity NSGA-II is introduced in [2]. The important steps involved in NSGA-II are as follows:

Step 1: Initialize population

The initial population size can be selected randomly depending upon the dimension of variables. We considered the population of individuals as 50.

Step 2: Non-dominated sorting

The cost values for objectives given in equations 1-7 are calculated. For individual i to become non-dominated solution, no other individual should be dominated. The rank values are assigned to each individual. All the individuals are sorted according to ranks and crowding distances [13].

Step 3: Genetic operation

In this step, two parents are randomly selected from individuals. From these two parents two new children are generated which are called ‘offsprings’. These offsprings are produced using crossover and mutation operations.

In our work, we use one-point crossover, where two parents (chromosomes) will exchange some of their part with each other at crossover point as shown in Figures (2) and (4). The crossover rate is the probability of how many parents are selected for the crossover operation.

$$n_c = round(p_c * \frac{n_{pop}}{2}); n_m = round(p_m * n_{pop}) \quad (11)$$

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Two parents before crossover are:

Parent 1	1	1	1	0	1	0	1	0
Parent 2	1	1	0	0	1	1	1	0

Crossover Point

Two offsprings generated after crossover are:

Offspring 1	1	1	1	0	1	1	1	0
Offspring 2	1	1	0	0	1	0	1	0

Figure-2. Crossover.

Another method to produce offspring is mutation. Only one chromosome is selected to do mutation on it. As shown in Fig, one bit is randomly flipped in the parent individual. Mutation rate is the probability of how many bits will be flipped in the chromosomes.

Parent before mutation

Parent	1	1	1	0	1	0	1	0

Offspring	1	1	0	0	1	0	1	0

Offspring after mutation

Figure-3. Mutation.

Number of offspring generated by crossover and mutation operation is given by equation (11) respectively [13].

Step 4: Selection

The cost values for each offspring generated by crossover and mutation is calculated. The individuals generated after crossover and mutation are put together with initial population $n_{pop}+n_c+n_m$. Again the non-dominated sorting operation is carried out with these individuals and ranks of the individuals are evaluated. When the sorting is done individuals with same number as initial populations are selected and others are rejected. The flowchart of this algorithm is shown in Figure-4.

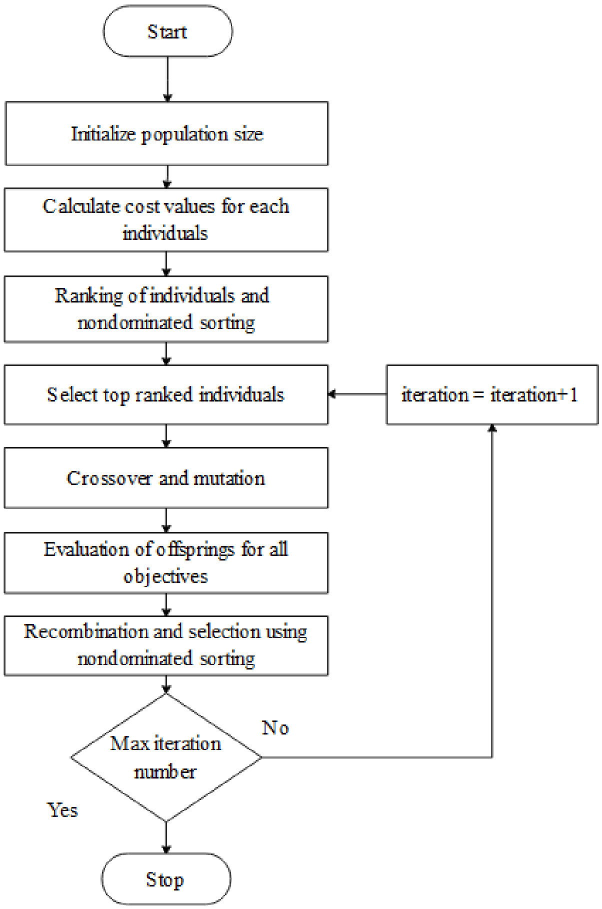

Figure-4. Flowchart of NSGA-II.

5. CLUSTER TOPOLOGY FOR SIMULATION SCENARIO

The assumptions for the simulation scenario are: BS has all the nodes location and energy information also it uses equations (8), (9) and (10) as energy model. The lengths of the packets from BS to nodes and vice versa are 2000bits. The network topology is again selected by BS at the end of each round N. Also in each round R, the CHs send time division multiple access (TDMA) information to the nodes in its cluster. Each node informs BS about their energy continuously by putting energy information into the information packet. Cluster heads aggregate the packets collected within clusters and they transmit the data to BS. The data aggregation energy at BS is 5nJ. For NSGA-II algorithm the parameters are given in Table-2. First to select network topology the BS runs NSGA-II algorithm.

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Table-2. List of parameters used in NSGA-II.

Parameter	Values
Iteration number	150
Population number	50
Crossover probability (p_c)	0.9
Mutation Probability (p_m)	0.1

For the simulation of LEACH algorithm, we considered 100x100m^2 area as the observation area and 100 nodes are randomly deployed in that network area. Packet length is considered to be 2000bits. The probability to become cluster head for sensor node is p=0.05 and p=0.1. The results area plotted considering both the probabilities.

6. RESULTS AND ANALYSIS

The performance of LEACH and NSGA-II is evaluated and graphs obtained from simulation are compared. The resulted graphs of simulation are shown in Figures 5-7.

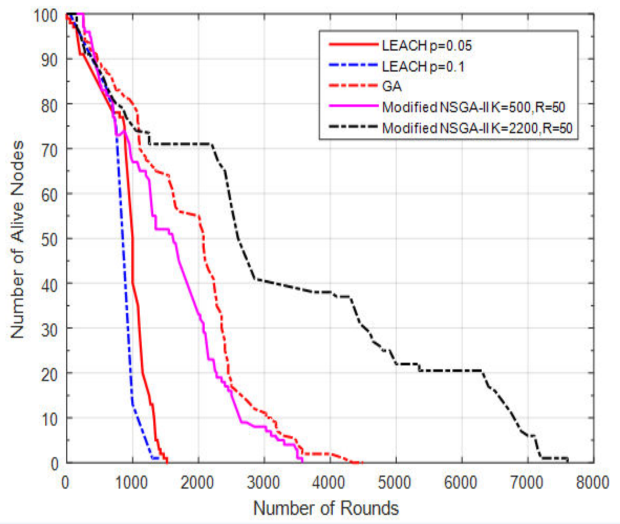

Figure-5. Comparison of lifetime of NSGA-II and LEACH.

The numbers of alive nodes after successive rounds are shown in Figure-5. The network lifetime of two algorithms NSGA-II and LEACH is compared and result is shown in Figure-5. As the topology update period changes K=500 and K=2200, the network lifetime also changes. For LEACH, no nodes are alive after 1500 rounds where more than 50 nodes are alive at the same round for NSGA-II. All the nodes die after 7000 rounds for NSGA-II with topology update K=2200.

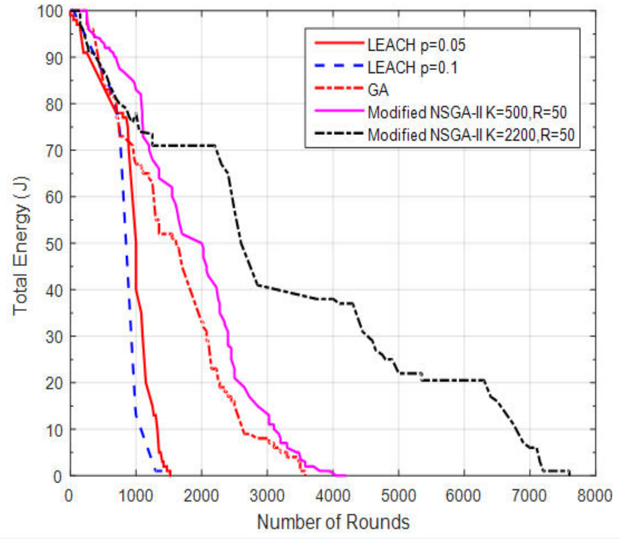

Figure-6. Total energy of all nodes.

As shown in Figure-6 the results obtained with NSGA-II are better than LEACH for energy optimization. The energy of all the nodes goes on reducing with number of rounds. For the LEACH, all the nodes completely lose their energy after 1500 rounds where 71J energy is still available for NSGA-II algorithm. For the topology update K=2200 all nodes have more energy than topology update K=500. For NSGA-II with K=2200 the energy of all the nodes drops to zero after 7000 rounds.

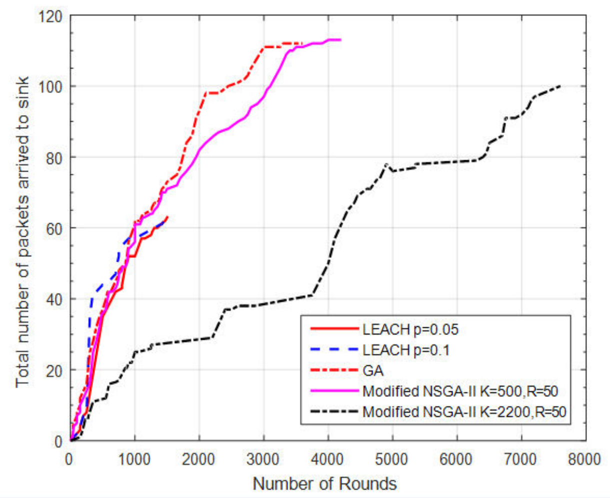

Figure-7. Total number of packets arrived to sink.

The network topology selected by NSGA-II algorithm sends more number of packets to the base station compared to LEACH algorithm. As shown in Figure-7 at 1600 round LEACH algorithm sends approximately 63 packets and NSGA-II with K=500 sends 70 packets whereas NSGA-II with K=2200 sends 25 packets. Even though using NSGA-II very less packets are received by base station at initial rounds, the number of packets goes on increasing with number of rounds.

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LEACH will work till 1600 rounds and NSGA-II with topology update K=500 works good till 3700 rounds.

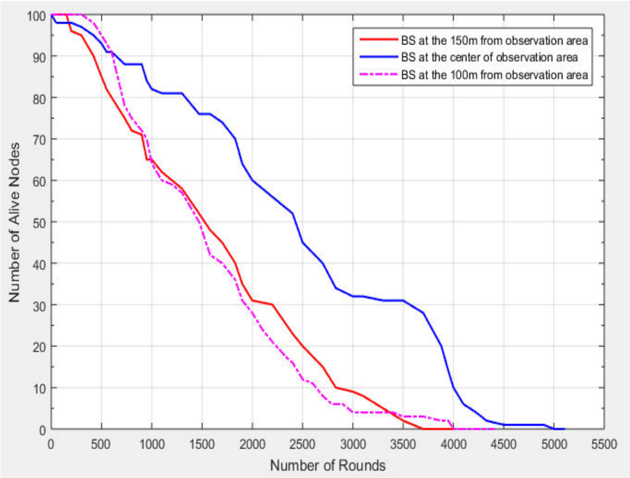

Figure-8. Total energy of all nodes.

The sensor network with different location of base station is considered for plotting results shown in Figure-8 and Figure-9. The algorithm performs better when BS is considered exactly at the center of observation area. At 3000 round, more than 30 nodes are available with network having BS at center whereas less than 10 nodes are available for other network.

As the distance between nodes and BS is increased the energy of all nodes will reduce as shown in Figure-9. The energy of all nodes of network with BS at center will drop to zero after 4700 rounds. For other network the energy of all nodes is available till 3000 rounds. This shows the effect of communication distance on the energy of nodes.

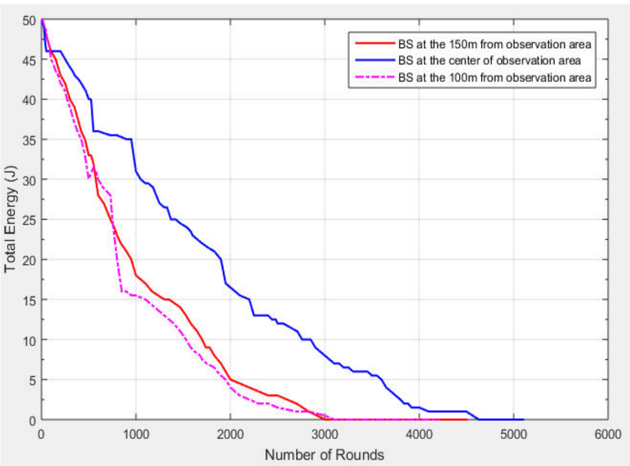

Figure-9. Total energy of all nodes.

7. CONCLUSIONS

In this paper, different energy related objective functions are formulated using multi-objective optimization. The NSGA-II algorithm is used for clustering of sensor nodes. Energy optimization problem is analyzed using non-dominated sorting genetic algorithm-II. Each solution in solution set obtained from NSGA-II is considered as network topology. The performance of LEACH and NSGA-II algorithm is evaluated based on some metrics such as total energy, number of alive nodes and number of packets reached to BS. The networks with different locations of base station are considered to evaluate the effect of distance on energy consumption. The results obtained shows greater efficiency of NSGA-II than LEACH. The numbers of packets reaching to BS are two to three times more than LEACH algorithm. The network lifetime of wireless sensor network is extended and is four to five times more than LEACH.

REFERENCES

[1] Akyildiz I. F., Su W., Sankarasubramaniam Y. & Cayirci E. 2002. A survey on sensor networks. Communications Magazine, IEEE. 40(8): 102-114.

[2] Deb K., Pratap A., Agarwal S. & Meyarivan T. A. M. T. 2002. A fast and elitist multi-objective genetic algorithm: NSGA-II. Evolutionary Computation, IEEE Trans- actions on. 6 (2): 182-19.

[3] Fonseca C. M. and Fleming P. J. 1995a. An Overview of Evolutionary Algorithms in Multi-objective Optimization. Evolutionary Computation. 3(1).

[4] Heinzelman W. R., Chandrakasan A. & Balakrishnan H. 2000, January. Energy-efficient communication protocol for wireless micro sensor networks. In System Sciences, 2000. Proceedings of the 33rd annual Hawaii international conference on (p. 10). IEEE.

[5] Hussain S., Matin A. W.& Islam O. 2007. Genetic algorithm for hierarchical wireless sensor networks. Journal of Networks. 2(5): 87-97.

[6] Jin S., Zhou M. & Wu A. S. 2003, July. Sensor network optimization using a genetic algorithm. In Proceedings of the 7th world multi-conference on systemics, cybernetics and informatics. pp. 109-116.

[7] Srinivas N., Deb K. 1994. Muilti-objective optimization using non-dominated sorting in genetic algorithms. Evol. Comput. 2(3): 221 248.

[8] Xue F., Sanderson A. & Graves R. 2006. Multi-objective routing in wireless sensor networks with a differential evolution algorithm. In Networking, sensing and control, 2006 (ICNSC'06) proceedings of the 2006 IEEE international conference on (pp. 880-885). IEEE.

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[9] Bara'a A. A., Khalil E. A. & Cosar A. 2015. Multi-objective evolutionary routing protocol for efficient coverage in mobile sensor networks. Soft Computing. 19(10): 2983-2995.

[10] Ozdemir S., Bara'a A. A. & Khalil O. A. 2013. Multi-objective evolutionary algorithm based on decomposition for energy efficient coverage in wireless sensor networks. Wireless personal communications. 71 (1): 195-215.

[11] Konstantinidis A., Yang K., Zhang Q. & Zeinalipour-Yazti D. 2010. A multi-objective evolutionary algorithm for the deployment and power assignment problem in wireless sensor networks. Computer Networks. 54(6): 960-976.

[12] Ali Peiravi, Habib Rajabi Mashhadi and S. Hamed Javadi. 2011. An optimal energy-efficient clustering method in wireless sensor networks using multi-objective genetic algorithm. Int. J. Commun. Syst.2013; 26:114-126.

[13] Gokce Hacioglu, Vahid Faryad Aghjeh Kand, Erhan Sesli. 2016. Multi-objective clustering for wireless sensor networks. Expert Systems with Applications. 59: 86-100

[14] Lavanya. N and Shankar. T. 2016. A Review on Energy-Efficient Scheduling Mechanisms in Wireless Sensor Networks. Indian Journal of Science and Technology. 9(32).

[15] T. Shankar, *et al*. 2017.Hybrid approach for optimal cluster head selection in WSN using leach and monkey search algorithms.Journal of Engineering Science & Technology, Taylor's University. 2: 506-517.

[16] T. Shankar, *et al.*2016. Hybrid HAS and PSO algorithm for energy efficient cluster head selection in wireless sensor networks. Swarm and Evolutionary Computation. 30: 1-10.