WSN Protocols based on Genetic Algorithm: A Survey

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Abstract-A wireless sensor network (WSN) is a network of wireless computing sensor nodes which are used to sense environmental conditions like motion, sound, etc in an area. These networks collect the information from the environment and send it to the sink node. The main constraint in these networks is the energy of the nodes. As these sensors have limited battery life, routing protocol should be designed appropriately so that minimal energy is used. Long communication distances between the sensors and the sink in the WSN drain the energy of the sensors and reduce the lifetime of the network. By clustering a sensor network we can help minimize the total communication distance, thus increasing the network lifetime and reducing energy consumption. The genetic algorithm is used to select the cluster heads for the WSN and hence create the energy efficient clusters for transmission of data in the wireless sensor network. In this paper, we present a recent survey of various fitness functions used genetic algorithm protocols. Specifically, we will show the fitness parameters and fitness functions for each protocol. Furthermore, a comparison of these protocols in terms of advantages, disadvantages and the Cluster Head selection criteria are provided.

Keywords: Wireless Sensor Network, LEACH, Genetic Algorithm, Fitness Function

I. Introduction

Low power. But they have limited battery. Energy is the main factor that affects the performance of a wireless sensor network is a network of small wireless sensor network. [11] Hence, data routing computing [2]. Thus the routing protocols implementing local collaboration are desirable [3,4]. Sensor networks have devices called sensor nodes [1]. These protocols should be designed properly as the sensor nodes are used to send data over the area where are deployed. Sensor nodes should be of low cost and channel bandwidth is limited which has to be shared applications in various fields like military, environmental, medical, etc. On the basis of the

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application, the network may be deployed randomly or deterministically. [10]

In all our selected protocols, the WSNs have: fixed base station and homogeneous nodes. An optimum routing method is desired with maximum network lifetime and the shortest path selection for data transfer [5,6].

In Direct Transmission (DT) method [13] , the sensor nodes send their data directly to the Base Station. Therefore, in this method, the far away nodes will die very quickly because most of their energy is used in transferring the data over the distance. In another method, Minimum Transmission energy (MTE) protocol, multi-hop transfer is used. [14,15] The data packets are transmitted from one node to its nearest node and so on towards the Base Station. Hence, the nodes close to the BS die quickly as they are used for the relay of lots of data of the far away nodes.

Cluster based approaches are found to be most appropriate for the applications with continuous data transfer. For example, Heinzelman et al. [7] have studied the LEACH protocol, which is a hierarchical and self-organized cluster-based approach.

II. Leach

LEACH stands for Low Energy Adaptive Clustering Hierarchy protocol [8]. It is the most popular clustering algorithm used in WSNs. In LEACH we have a fixed Base Station (BS) located far from the nodes and all the nodes have same initial energies. [12] The sensor nodes monitor the area at a fixed rate.pooo In LEACH, clusters of nodes are made, and in each cluster, a Cluster Head (CH) is elected to which the nodes of the cluster send their data. The different CHs send the cumulative data packets to the BS.

LEACH works in two phases, setup phase and steady phase. In setup phase, every node selects a random number between 0 and 1 and computes a threshold formula T(n). In the steady phase, the nodes transfer data to their associated CH and the CHs collect all the data on the basis of TDMA schedule. The redundant data is removed and outcome is sent to the BS. After a specific period of time, the next round starts with the setup and steady phases.[10]

III. Genetic Algorithm

Genetic algorithm is mainly an optimization technique based on natural selection and evolution. During each generation, it maintains a population of individuals where each individual is a coded form and is called a chromosome. Each chromosome is evaluated by the fitness function. Next new population is generated from present one through selection, crossover and mutation [16, 17].

A chromosome is a collection of genes. Here, in WSN, a chromosome denotes a particular arrangement of nodes in routing chain for the given network. In Figure 1, the gene index represents the position of nodes in that chain and the gene value provides that node's identification number (ID). Thus, in this representation each chromosome encodes an ordered sequence of nodes [18].

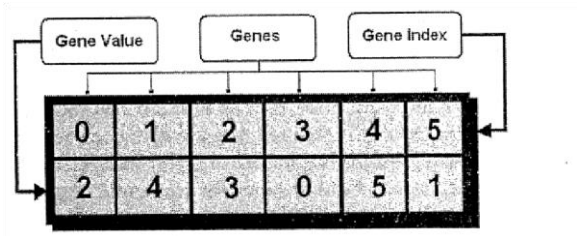

Figure 1: A chromosome containing 6 genes, The Gene Index and the Gene Values are shown [18]

GA evaluates individuals based on a fitness function to select the best population. In wireless sensor networks, a genetic algorithm (GA) is used to optimize the number of clusters and sensor connections for a network and hence to maximize network lifetime. The fitness value determines the fate of each chromosome; better the fitness value, better the chances of survival. The major components of genetic approach are explained below:

1. Population Initialization: A population consists of a group of individuals called chromosomes

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that represent a complete set of nodes denoted by sequences of 0s and 1s. The first step in GA is initialization of population with randomly generated set of individuals. The new population for next rounds is then generated by two methods: steady-state GA and generational GA. The steady-state GA replaces one or two members of the population; whereas the generational GA replaces all of them at each generation of evolution. The resulting generation will have some of the individuals from the previous population while others evolve as a result of crossover and mutation.

2. Fitness: An individual's ability to pass on its genetic material is its fitness to survive and further reproduce. In a GA, fitness of each chromosome is evaluated by the fitness function. [20] The chances of survival are more for population with higher fitness value as calculated by fitness function.

3. Selection: The selection process determines the chromosomes from the current population to be mated (or crossover-ed) to create new generation. These newly generated chromosomes will join the existing population and the combined population will be basis for the next selection process. There are several methods for selection process, such as: "Roulette wheel selection" – in this the parents are selected according to their fitness; the fitter the chromosomes are, the more are their chances to be selected; "Tournament selection" – in which two chromosomes are selected at random from population. First, for a predefined probability p, the more fit of these two is selected and with the probability (1-p) the chromosome with less fitness is selected.[19]

4. Crossover: The word 'crossover' defines the recombination of component materials due to mating. It is the process of reproduction responsible for transfer of genetic material. The outcome of crossover largely depends on the selected chromosomes from the population. Crossover acts on two parents. [17] The one-point crossover is simplest crossover in which a point is chosen at random and the two parent chromosomes exchange information after that point. An example of such crossover is shown in Figure 2.

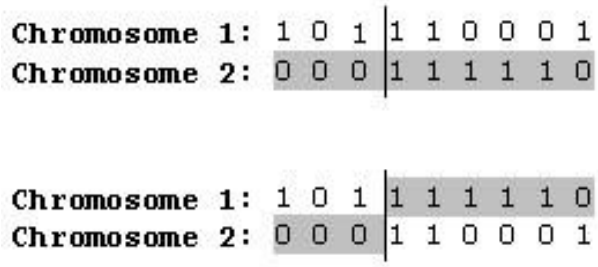

Figure 2: Crossover [26]

In Figure 2, the bit sequences of first chromosome after the crossover point are copied to the second chromosome and vice versa. Crossover is done according to crossover rate, also called crossover probability. Generally the crossover rate is high, with the value being 0.80 to 0.95.

5. Mutation: The population formed after crossover will have traits of the parents only, i.e. no new traits have been intertwined. Mutation process allows new genetic patterns to be introduced in the population produced by crossover mutation introduces a new sequence of genes but there is no guarantee that the mutated population will fit. The mutated chromosome is selected if it has high fitness value else it is dropped. Like crossover, mutation rate is applied to control how mutation occurs in GA. But this mutation probability is very low, of the order of 0.005 to 0.01. In GAs, the probability of mutation can be implemented either on a 'per-bit' basis - if the mutation rate is

   0.001, each bit in a chromosome has 0.1 percent chance of being mutated; or on a 'perchromosome' basis - the mutation rate of 0.001 means there is a 0.1 percent chance of a

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chromosome being mutated. Mutation is a unary operator that affects only a single chromosome.

	Offspring 1	Offspring 2
Original	1100110110001110	1001001100000110
Mutated	1100110010001110	1001001100000110

Figure 3: Mutation[17]

Figure 3 above is an example of mutation on per-bit basis. Mutation affects only a single chromosome and a randomly selected bit of that chromosome will be changed from 0 to 1, or vice versa.

6. Population Generation: The nodes of a wireless sensor network are represented as bits of a chromosome. The candidate cluster head nodes (CCHs) are represented by 1s while normal nodes in that chromosome are represented by 0s. The fitness parameters determine the fitness of a chromosome. The chromosome with the best fitness value is selected and its CCHs become the cluster head nodes (CHs). Based on the survival fitness, the future generation transforms using crossover and mutation rates.

IV. An Overview of Algorithms

In this section, we will survey the fitness functions used in different genetic algorithms and display the various parameters used by them in evaluating fitness of population.

4.1. Genetic Algorithm for Hierarchical Wireless Sensor Networks proposed by Sajid Hussain, Abdul Wasey Matin and Obidul Islam [17]

In this algorithm, the base station uses the GA for creation of energy efficient clusters for a given number of transmissions. Here the fitness function F, is a function of the following parameters:

a. Direct Distance (DD) to the base station: sum of distances from all the sensor nodes to the base station.

$$DD = \sum_{i=1}^{m} d_{is} \quad (1)$$

where d_{is} is the distance from the sensor node i to the base station or sink (s).

b. Cluster Distance (CD): the sum of distances from the nodes to the cluster head in a particular cluster and distance from the head to the sink or the BS.

$$C = \sum_{i=1}^{k} d_{ih} + d_{hs} \quad (2)$$

where d_{ih} is the distance from node i to the cluster head h and d_{hs} is the distance from the cluster head h to the BS or sink node s and k is the number of nodes in cluster C.

c. Cluster Distance-Standard Deviation: in case of non uniform spatial distribution of sensor nodes there is a large variation in cluster distances, hence the cluster distances with a deviation(mu) is computed :

$$\mu = \frac{\sum_{i=1}^{h} d_{cluster_i}}{h}$$

$$SD = \sqrt{\sum_{i=1}^{h} (\mu - d_{cluster_i})^2} \quad (3)$$

d. Transfer Energy (E): energy consumed to transfer the aggregated message from the cluster to the base station. for a k cluster ,

$$E = \sum_{j=1}^{k} E_{T_{jh}} + k \times E_R + E_{T_{hs}} \quad (4)$$

e. Number of Transmissions (T): It is assigned by the BS for each data transfer stage. Using the above parameters, the chromosome fitness, F is defined as follows:

$$F = \sum_{i} (w_i \times f_i), \forall f_i \in \{C, DD, E, SD, T\} \quad (5)$$

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The initial fitness parameters can be assigned arbitrary weights, wi. Then, after every generation the best fit chromosome is evaluated and the weights that were assigned to the fitness parameters are updated for the next generation as follows:

$$\Delta fi = fi - fi-1 \quad (6)$$

The Δ f expression represents the change in the fitness parameter value.

$$wi = wi-1 + ci\ \Delta fi \quad (7)$$

where ci = 1/1+e−fi improves the value of weights based on the previous experience. After every generation, the best fit chromosome is evaluated.

4.2. Clustering Protocol for WSN using Genetic Approach proposed by Ali Norouzi, Faezeh Sadat Babamir and Abdul Halim Zaim [24]

In this algorithm, the ratio of total energy consumption to the total distances of nodes is used to calculate the average amount of energy used for every node. A tradeoff between energy consumption and distance parameters is made.

Here the fitness function F, is a function of the following parameters:

1. Direct Distance to Base Station: total distance between whole sensor nodes and the BS is denoted by d_i

$$DDBS = \sum_{i=1}^{m} d_i \quad (8)$$

where m is the number of nodes.

2. Cluster based Distance (CD): the sum of distances between CHs and the BS plus the sum of distances between associated nodes and their CHs.

$$CD = \left(\sum_{i=1}^{n} \left(\sum_{j=1}^{m} d_{ij} \right) + D_{is} \right) \quad (9)$$

where 'n' and 'm' are the number of clusters and corresponding members, respectively. 'd_{ij}' is the distance between a node and its CH, and 'D_{is}' is the distance be-tween the CH and the BS.

3. Cluster based Distance-Standard Deviation (CDSD): It is used for measuring the variation of cluster distances than one average cluster distance.

It depends on the network deployment type: random or deterministic. Here, μ is the average cluster distance and SD gives the cluster distance variation.

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

$$SD = \sqrt{\sum_{i=1}^{n} (\mu - d_c)^2} \quad (10)$$

4. Transfer Energy (E): amount of energy used to transfer the all the data to the base station.

$$E = \sum_{i=1}^{n} \left(\sum_{j=1}^{m} e_{jm} + m * E_R + e_i \right) \quad (11)$$

e_{jm} is the energy necessary to transmit data from a node to the corresponding CH.

5. Number of Transmissions (T): The BS determines number of transmissions for each monitoring period.The fitness function is:

$$F(i) = \left(\frac{e_i * T}{D_a * \#Nodes} \right) * \left(\frac{e_j * T}{D_b * \#CHs} \right)$$
$$: D_a = Width * g_i \Big/ \sqrt{\#Clusters}$$
$$\forall g_i \in \{DDBS, CD, CDSD\}$$
$$[g_i = DDBS] = 1 \because [\#clusters = 1] = 1$$
$$\therefore (D_a = D_b = \#CHs = 1) \quad (12)$$

where "width" is the length of the target environment, and 'D_a' and 'D_b' show the distance between the sensor member nodes-corresponding to a CH and to CHs-BS, respectively. Constants 'e_i' and 'e_j' represent the energy needed to transmit data between member nodes and the CH and from the CH to the BS.

The best value of F(i) obtained by GA, is benchmarked by either width (regarding coverage problem) and e_i and e_j (regarding energy problem).

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4.3. Genetic Based Dynamic Clustering Algorithm proposed by D. Srinivasa Rao and B.J.M. Ravi Kumar [23]

In this algorithm, the cluster heads and the clustering is determined by using the GA in such a way that there is minimum energy consumption in accordance to the network coverage.

The fitness function being used for calculating a fitter chromosome, the residual energy of the nodes is used as the main parameter for the selection of the cluster head. Another parameter considered is the energy to send a message toward the sink node. On reducing the number of cluster heads, there is a considerable effect on decrease in the energy consumption since more energy is used by cluster heads than the normal nodes. Also the lower the communication distance, the lesser energy will be consumed during transmission.

The following is the fitness function used:

$$\text{Fitness} = RE + (X * (SE) + (1 - X) * (N - CH)) \quad 0 <= X <= 1 \qquad (13)$$

RE is the sum of residual energy in the cluster heads;
N is the total number of nodes;
Ch is the number of cluster heads;
SE is calculated as :

$$SE = \sum_{i=1}^{N} (RS_i - (RH_i + HS)) \qquad (14)$$

where RS_i is the sum of energy required for sending a message from normal nodes towards the sink node; RH_i is the sum of required energy for sending a message from regular nodes towards their cluster heads;
HS is the sum of energy required for sending a message from all cluster heads towards the sink node or BS.
The value of X indicates which factor has more importance for consideration: cost incurred by the cluster heads or the required energy (distance related).
In this algorithm, distribution of cluster heads is improved.

4.4. LEACH-GA proposed by Jenn-Long Liu and Chinya V. Ravishankar [25]

In this algorithm, a GA based variant of LEACH has been done to calculate an optimal value of probability for various base station placements. Also, GA is applied only once, before the setup phase of first round.
One more fitness calculation procedure is being used in researches. Here the procedure used is such that every node selects a random number r in the interval [0,1]. If r is smaller than the threshold T(s), based on the user defined probability p_{set} then the node is a candidate cluster head. After that, each node sends its ID, location information, and whether or not it is a CCH to the BS or sink. As the BS receives messages sent by all nodes, it performs GA operations in order to determine the optimal probability, $p_{opt} = k_{opt}/n$, by minimizing the total amount of energy consumption in each round. Hence now the following function can be used for the formulation in GA:

$$f(\vec{x}) = \sum_{c=1}^{k} \sum_{i=1}^{q} (E_{elec} + \varepsilon d^{\alpha}[i, CCH(c)]) \times x_c + \sum_{c=1}^{k} (E_{elec} + E_{DA} + E_{elec} + \varepsilon d^{\alpha}[CCH(c), BS]) \times x_c \qquad (15)$$

where x =[x1, x2, ... , xc , ... , x_k]. The values of x_c are one when it is a CCH, otherwise, it is zero.
The symbol q represents the number of member nodes in a CCH. The optimal probability p_{opt} is determined by the GA by searching the solution space through an evolutionary optimization process incorporating probabilistic transitions and nondeterministic rules, and then applying GA operators.
The parameters $\sum = \sum fs$ and <=2 were used for d≤d0; while, $\sum = \sum_{mp}$ and <=4 were set for d≥d0. Once the optimal probability p_{opt} is found, the BS broadcasts the value of p_{opt} to all nodes. Next are the set up and steady state phases that take place.
The p_{opt} was found to be largest when BS was in the center of the network and decreases as the network moves outward.

4.5. Genetic Algorithm and Simulated Annealing (GASA) proposed by Vinay Kumar Singh and Vidushi Sharma [21]

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In this algorithm, greedy approach was used. Here, each chromosome represents a valid route from a sensor node to sink. The routing developed in this algorithm is based on respective positons of the nodes in the network.

The lifetime of the network in terms of the number of rounds is used as the parameter for calculation of a fitter individual. Also the distance of the nodes from the sink is considered

$$L_{net} = \frac{E_{initial}}{E_{max}} \quad (16)$$

where L_{net} is the lifetime of the network in terms of the number of rounds; $E_{initial}$ is the node's energy configuration which is same for all rely nodes in the beginning and is known initially and will remain same;

E_{max} is the maximum energy or power dissipated by any node in a chromosome during a round of aggregation of data.

$$fitness = min\,[\alpha.f(C,I) + \beta.(-L_{net})] \quad (17)$$

where L_{net} is defined as above (it is made negative in order to make it a minimization function.); α and β are weighted coefficients of the optimal route(f(C,I)) and expected network lifetime respectively. Also α+ β=1; f(C,I) is the optimal route.

The above fitness function is designed such that it evaluates whether a particular chromosome increases the network lifetime or not. The historically obtained best chromosome (i.e with the maximum fitness Value) is preserved.

4.6. Genetic Algorithm based Energy Efficient adaptive clustering hierarchy Protocol (GAEEP) proposed by Mohammed Abo-Zahhad, Sabah M. Ahmed, Nabil Sabor and Shigenobu Sasaki [22]

Another way or fitness function considers the number of cluster heads and the dissipation energy in communication as the main parameters or factors for its calculation of a fitter chromosome. In this algorithm GA is applied to find the optimum number of CHs based on minimizing the communication consumption energy of all sensor nodes to efficiently maximize the network lifetime and improve stability period.

More are the number of CHs, more energy is consumed as more energy is drained of CHs as compared to non cluster heads. Whereas fewer the CHs greater is the energy efficiency.

The fitness function for GA formulation is:

$$F(X) = w\left(\frac{E_{disp}}{E_{live}}\right) + (1-w)\left(\frac{L}{N_{live}}\right) \quad (18)$$

Where E_{live} is the total energy of all live nodes in sensor field described by:

$$E_{live} = \sum_{j=1}^{N_{live}} E_o(j) = N_{live}\ E_o \quad (19)$$

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V. Performance Comparison Of Genetic Algorithms For Wireless Sensor Network

Factors for comparison	(a) Genetic Algorithm for by Sajid Hussain, Abdul Wasey Matin and Obidul Islam [17]	(b) (GASA) proposed by Vinay Kumar Singh and Vidushi Sharma [21]	(c) (GAEEP) by Mohammed Abo-Zahhad, Sabah M. Ahmed, Nabil Sabor and Shigenobu Sasaki [22]	(d) Clustering Protocol for WSN using Genetic Approach by Ali Norouzi, Faezeh Sadat Babamir and Abdul Halim Zaim [24]	(e) LEACH-GA by Jenn-Long Liu and Chinya V. Ravishankar [25]	(f) Genetic Based Dynamic Clustering Algorithm by D. Srinivasa Rao and B.J.M. Ravi Kumar [23]
Fitness parameters	Direct Distance, Cluster distances, transfer energies, number of packet transmitted	Distance of nodes and estimated lifetime at each round	Sum of energies of all live nodes and dissipation energy	Direct Distance, Cluster distances, transfer energies, number of transmissions	Number of member nodes in CCHs and p_{set} (prescribed probability)	Residual energy and energy required to send a message to sink node
General approach(1)	Cluster based	Greedy approach	Cluster based	Cluster based	Cluster based	Cluster based
Selection technique	Elitist selection	Elitist and tournament selection	Roulette wheel selection	Roulette wheel selection	Not mentioned	Not mentioned
Crossover technique	Single point crossover	2 point crossover	1 point crossover	1 point crossover	1 point crossover	1 point crossover
Network size	100m x 100m	100m x 100m	100m x 100m	100m x 100m	50m x 50m	100m x 100m
No of Nodes	200 nodes	50,100,150, 200,250,300 nodes	100 nodes	200 nodes	100 nodes	100 nodes
Initial energy of each node	2Jm	1J	0.5J	2J	0.5J	1J
Location of sink	200m east of network	center	(50,300)	200m away from network	(25, 250) and (25, 350)	Not mentioned
Packet size	Not mentioned	1000 bits	2000 bits	200 bits	2000 bits	500 bits

Lifetime and Energy consumption	First dead at 650 rounds
	Last dead at 1175 rounds
	
	Performs better than (d) and (f)
		Average energy consumption graph remains straight at 0.004 J
		
		Performs better than (a), (d), (e) and (f)
			Increased lifetime by 58.996%
			First dead at 1017 rounds
			Last dead at 1175 rounds
			
			Best performance as compared to (a), (b), (d), (e) and (f)
				First dead at 600 rounds
				Last dead at 1700 rounds
				Energy becomes zero at 1900 round
				
				Performs better than (f)
					For (25,250): First dead at 700 rounds
					Last dead at 1100 rounds
					Increased lifetime by 54 %
					
					For (25,350):
					First dead at 450
					Last dead at 800
					Increased lifetime by 110 %
					
					Performs better than (a), (d) and (f)
						First dead at 500 rounds
						Last dead at 1250 rounds
						
						Least performance as compared to (a), (b), (c), (d) and (e)

Applicability	Can be used for grid, cluster and cluster-grid layouts Performs better than LEACH, HCR1 and HCR2	Better performance if number of nodes increased Performs better than clustering and DD	Also works for heterogeneous and dense networks Performs better than LEACH, SEP, ERP, LEACH-GA, ALEACH and DEU protocols	Multiple CHs to manage clusters Performs better than LEACH and LEACH	LEACH-GA method outperforms MTE, DT, and LEACH	Performs better than LEACH

VI. Conclusion

In this paper, we have surveyed various genetic algorithms for wireless sensor networks. The platform used to visualize the working environment of wireless sensor networks is MATLAB 7.8.0. The results show that GAEEP[22] performs best as compared to the other genetic algorithms reviewed. The second best performance is delivered by GASA[21] which is based on non-hierarchical greedy approach. It can also be seen from the table that Genetic Algorithm for by Sajid Hussain, Abdul Wasey Matin and Obidul Islam [17] can be used for grid, cluster and cluster grid layouts. GASA[21] performs even more better if the number of nodes is increased in the same network. GAEEP[22] also works for heterogeneous and dense networks.

References

[1] R. Govindan, J. Heidemann, S. Kumar, and D. Estrin, "Next century challenges: scalable coordination in sensor networks," in ACM/IEEE International Conference on Mobile Computing and Networking, New York, NY, USA, 1999, pp. 263270.

[2]. Chandrakasan, Amirtharajah, Cho, Goodman, Konduri, Kulik, Rabiner, and Wang. Design Considerations for Distributed Microsensor Systems. In IEEE 1999 Custom Integrated Circuits Conference (CICC), pages 279–286, May 1999.

[3]. Clare, Pottie, and Agre. Self-Organizing Distributed Sensor Networks. In SPIE Conference on Unattended Ground Sensor Technologies and Applications, pages 229–237, Apr. 1999.

[4]. M. Dong, K. Yung, and W. Kaiser. Low Power Signal Processing Architectures for Network Microsensors. In Proceedings 1997 International Symposium on Low Power Electronics and Design, pages 173–177, Aug. 1997.

[5]. D. Hall. Mathematical Techniques in Multisensor Data Fusion. Artech House, Boston, MA, 1992.

[6]. L. Klein. Sensor and Data Fusion Concepts and Applications. SPIE Optical Engr Press, WA, 1993.

[7]. C. H. B. Wendi Rabiner Heinzelman, "Energyefficient communication protocol for wireless microsensor networks," in Proc. 33rd Annual Hawaii International Conference on System Sciences, 2000.

[8]. A. Sabarish, M. S. M. Guru, M. A. Dhivya, K. S. Naveen, and S. Vaishnavi, "A survey on clustering protocols in wireless sensor networks," International Journal of Advances in Computing and Information technology, vol. 1, no. 2, 2012.

[9]. Raed M. Bani Hani, Abdalraheem A. Ijjeh, “A Survey on LEACH – Based Energy Aware Protocols for Wireless Sensor Networks,” in Journal of Communications Vol. 8, no.3, March 2013.

[10]. M. Ishizuka and M. Aida, “Performance Study of Node Placement in Sensor Networks,” In Proceedings of 24th International Conference on Distributed Computing Sys-tems Workshops, 23-24 March 2004, pp. 598-603.

[11] F. Akyildiz, W. Su, Y. Sankarasubramaniam and E. Ca- yirci, “Wireless Sensor Networks: A Survey,” Computer Networks, Vol. 38, No. 4, 2001, pp. 393422.

[12]. Wendi Rabiner Heinzelman, Anantha Chandrakasan, and Hari Balakrishnan,” EnergyEfficient Communication Protocol for Wireless Microsensor Networks,” Proceedings of the Hawaii International Conference on System Sciences, January 4-7, 2000, Maui, Hawaii.

[13]. C. Intanagonwiwat., R. Govindan, D. Estrin, J. Heidemann, and F. Silva, “Directed diffusion for wireless sensor networking,” IEEE/ACM Transactions on Networking, vol. 11, issue 1, Feb. 2003, pp. 2-16.

[14]. T. Shepard, “A Channel Access Scheme for Large Dense Packet Radio Networks,” ACM SIGCOMM Computer Communication Review, vol. 26, issue 4, Oct. 1996, pp. 219–230.

[15]. B. Krishnamachari, D. Estrin, and S. Wicker, “Modeling data-centric routing in wireless sensor networks,” Wireless Communications, vol. 1, issue 4, , Oct. 2002, pp. 660-670.

[16]. Shiyuan Jin, Ming Zhou, Annie S. Wu School of EECS University of Central Florida Orlando, FL 32816, “Sensor Network Optimization Using a Genetic Algorithm”.

[17]. Sajid Hussain, Abdul Wasey Matin, Obidul Islam, "Genetic Algorithm for Hierarchical Wireless Sensor Networks" in JOURNAL OF NETWORKS, VOL. 2, NO. 5, SEPTEMBER 2007.

[18]. Ayon Chakraborty, Swarup Kumar Mitr, Mrinal Kanti Naskar, " A Genetic Algorithm inspired Routing Protocol forWireless Sensor Networks", International Journal of Coputational Intelligence Theory and Practice, Vol. 6, N0. 1, June 2011.

[18]. Goldberg, B. Karp, Y. Ke, S. Nath, and S. Seshan, Genetic algorithms in search, optimization, and machine learning. Addison- Wesley, 1989.

[19]. V. Kreinovich, C. Fuentes, and O., "Genetic algorithms- what fitness scaling is optimal?" Cybernetics and Systems, 1933 .

[20]. Vinay Kumar Singh, Vidushi Sharma, "Lifetime Maximization of Wireless Sensor Networks Using Improved Genetic Algorithm Based Approach", International Journal of Computer Applications, Vol. 57, No. 14, November 2012.

[21]. Mohammed Abo-Zahhad, Sabah M. Ahmed, Nabil Sabor and Shigenobu Sasaki, " A New EnergyEfficient Adaptive Clustering Protocol Based on Genetic Algorithm for Improving the Lifetime and the Stable Period of Wireless Sensor Networks", International Journal of Energy, Information and Communications Vol.5, Issue 3 (2014) .

[22]. D.Srinivasa Rao, B.J.M. Ravi Kumar, "Performance Evaluation of Genetic Based Dynamic Clustering Algorithm over LEACH Algorithm for Wireless Sensor Networks", International Journal of Soft Computing and Engineering (IJSCE)

[23]. Ali Norouzi, Faezeh Sadat Babamir, Abdul Halim Zaim, "A New Clustering Protocol for Wireless Sensor Networks Using Genetic Algorithm Approach", Wireless Sensor Network, 2011, 3

[24]. Jenn-Long Liu and Chinya V. Ravishankar, "LEACH-GA: Genetic Algorithm-Based EnergyEfficient Adaptive Clustering Protocol for Wireless Sensor Networks", International Journal of Machine Learning and Computing, Vol.1, No. 1, April 2011

[25].http://www.codeproject.com/KB/recipes/aforge_genetic/crossover.gif