Lifetime optimization in Multi- Sink Environment using the Hybrid PSO based LEACH algorithm in WSN's.

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Abstract:

WSN is a large network consists of a group of spatially distributed autonomous sensors interconnected by means of wireless communication channels to monitor physical or environmental conditions, such as temperature, sound, pressure, etc. To decrease the delay in data transmission and to minimize the energy consumption, clustering is mainly used in multi sinks environment in WSNs. An evolutionary algorithm to minimize the energy consumption in multi sink environment is presented in this paper. A popular clustering technique is Low Energy Adaptive Clustering Hierarchy(LEACH), random clustering has been replaced by PSO.A number of sinks/ Base stations (BS) are deployed in large scale and Meta-heuristic particle swarm optimization algorithm is used to select the Cluster Head (CH). A new hybrid Particle swarm optimization is proposed to improve the performance. Simulation results show the improvement in energy conservation and number of nodes alive in multi-sink environment.

Keywords : WSN, LEACH, Cluster Head Selection, meta heuristic algorithms, Particle Swarm Optimization, Multi-Sink.

Introduction :

A Wireless sensor network (WSN) consists of wireless Sensor Nodes or motes, which are devices equipped with a processor, a radio interface, an analog-to-digital converter, sensors, memory and a power supply. The processor provides the mote management functions and performs data processing. The sensors attached to the mote are capable of sensing temperature, humidity, light, etc. Wireless sensor network becomes a vital topic with the rapid development that is susceptible to a wide range of attacks due to deployment in the hostile environment. Wireless sensor networks have revolutionized the recent years of development by creating significant impact throughout the society by various civilian and military applications [1,2]. All Sensor nodes sends the sensing data to the base station via other nodes like cluster head nodes. Here Energy efficiency is an important factor of wireless sensor networks. So as to minimize the energy consumption clustering, cluster head selection and multi-sink environment plays major role. Clustering is an familiar approach where all the sensor nodes grouped into clusters. Each cluster will have Cluster head (CH) and it receives the data from the non cluster members and forwards to base station (BS) which is nearer to the CH. The cluster head selection will be done by the meta-heuristic algorithm like Particle Swarm Optimization (PSO).

Related Works :

Satyanarayana.M and Kuda Nageswararao [3] specified various techniques on Optimizing Cluster-Head selection in Wireless Sensor Networks using Hybrid Meta heuristic algorithms. Nayak and Anurag Devulapalli [4] utilized fuzzy logic based clustering technique to reduce the energy consumption rate further. In this method, size of cluster is optimized through Fuzzy inference engine (Mamdani's rule). The appropriate selection of CHs reduces the energy consumption and enhances the life of network. Gong et al. [5] designed a routing protocol ETARP (i.e., Energy Efficient Trust-Aware Routing Protocol for Wireless Sensor Networks) to reduce the energy consumption and increase the security during communication among nodes in WSNs. The selection of route between sensor nodes is based on utility theory. Shi et al. [6] addressed the issue of mobile sinks like route maintenance in WSNs by introducing dynamic layered routing protocol. The distribution frequencies and scopes of routing updates are minimized using the combination of dynamic anchor selection and dynamic
layered Voronoi scoping.

The authors in the paper [8, 9] deal with mobile multiple sinks. Data dissemination to multiple mobile sinks consumes a lot of energy [10]. Many papers [7, 8] have concentrated on positioning of the sink to have optimal energy consumption.

Shankar et al. [11] used hybrid Particle Swarm Optimization (PSO) and Harmony Search Algorithm (HSA) to select CH efficiently utilizing minimum energy. Zahedi et al. [12] presented the problem of uneven distribution of CHs, unbalanced clustering, and their scope to limited applications of WSNs. They used fuzzy c-means clustering algorithm to create balanced clusters and Mamdani fuzzy inference system to select suitable CHs. Fuzzy rules are optimized through swarm intelligence algorithm based on firefly algorithm.

Sabet and Naji [13] implemented the multi-level route-aware clustering (MLRC) technique to save energy in decentralized clustering protocols. The main advantage of this protocol is that it creates a cluster and routing tree, simultaneously, to reduce an unnecessary generation of routing control packets.

Hoang et al., [14] suggested the Harmony Search Algorithm (HSA) to reduce the intra-cluster distance and increase the energy efficiency of the system. The protocol is a music based metaheuristic optimization technique and is similar to the music improvisation procedure wherein musicians polish the pitch till a better harmony is obtained. HSA was compared with the familiar cluster-based algorithm developed for WSNs known as LEACH, heuristic optimization algorithms like PSO and GA. HSA was also compared with the conventional K-means as well as Fuzzy C-Means (FCM) clustering protocols. The experiment shows positive outputs where the search algorithm is capable of optimizing the power efficacy of the network and also improve network lifespan. Particle Swarm Optimization(PSO) based LEACH Protocol

Nanda and Panda [15] reconsidered all major nature based metaheuristic algorithms used until recently for partition clustering. Further, key issues involved during formulation of various metaheuristics such as clustering problem and other important application areas are discussed.

Dhivya and Sundarambal [16] suggested a meta-heuristic optimization method named Cuckoo Search (CS) .It is employed in sensor networks to aggregate data. In this method the least energy nodes are combined as subordinate chains (or) clusters to sense data and high energy nodes as CH to communicate to the BS. The modified CS was suggested to achieve improved network performance and to incorporate reasonable energy dissipation. In this method optimum number of clusters is formed with nominal energy consumption. The possibility of the method was obvious with the simulation results when compared with other traditional cluster based routing methods.

3. Low Energy Adaptive Clustering Hierarchy (LEACH)

LEACH algorithm divides wireless sensor network into several clusters. The algorithm introduces a random clustering scheme for wireless sensor network (Heinzelman et al 2000). It is a dynamic clustering routing method where nodes are selected as cluster head randomly based on a threshold value calculated using Equation 2.1. Main techniques of LEACH protocol include algorithms for distributing cluster forming, adaptive cluster forming, and cluster header position changing. The technique of distributing cluster forming ensures self-organization of most target nodes. The adaptive cluster forming and cluster header position changing algorithms ensure to share the energy dissipation fairly among all nodes and prolong the lifetime of the whole system in the end.

In LEACH, the nodes organize themselves into local clusters, with one node acting as the CH. All non-cluster head nodes must transmit their data to the cluster head, while the cluster head node must receive data from all the cluster members, perform signal processing functions on the data e.g. data aggregation and transmit data to the remote base station. Therefore being a cluster head node is much more energy intensive than being a non-cluster head node. In the scenario where all nodes are energy limited, if the cluster heads were chosen a priori and fixed throughout the system lifetime, the cluster head sensor nodes would quickly use up their limited energy, such method is known as static clustering method. Once the cluster head runs out of energy, it is no longer operational. Thus, when a cluster head node dies (e.g. uses up all its battery energy) all the nodes that belong to the cluster lose communication ability.

Thus, LEACH incorporates randomized rotation of the high energy cluster head position such that it rotates among the sensors in order to avoid draining the battery of any one sensor in the network. In this way the energy load associated with being a cluster head is evenly distributed among the nodes. Media access in LEACH was chosen to reduce energy dissipation in the non-cluster head nodes. Since the cluster head node knows all the cluster members, it can create a TDMA schedule that tells each node exactly when to transmit its data. This allows the nodes to remain in the sleep state with internal modules powered down, as long as possible. In addition using a TDMA schedule for data transfer prevents intra cluster collisions. The operation of LEACH is divided into rounds. Each round begins with a set up phase when the clusters are organized followed by a steady state phase where several frames of data are transferred from the nodes to the cluster head and on to the base station. The nodes must all be time synchronized in order to start the set up phase at the same time. In order to minimize the set up overhead, the steady state phase is long compared to the set up phase.

3.1 Determining cluster head nodes

Initially, when clusters are being created, each node decides whether or not to become a cluster head for the current round. This decision is based on the suggested percentage ‘p’ of cluster heads for the network (determined a priori) and the number of times the node has been a cluster head so far. This decision is made by the node n choosing a random number between 0 and 1. If the number is less than a threshold T(n), the node becomes a cluster head for the current round (HaimingYang BiplabSikdar 2007). The threshold is set as in Equation 2.1.

$$T(n)=\begin{cases}\dfrac{P}{1-P\left(r \bmod \left(\dfrac{1}{p}\right)\right)} & \text{if } n\in G \\ 0 & \text{otherwise}\end{cases} \qquad (2.1)$$

Where, p is desired percentage of cluster heads, r is the current round, G is the set of nodes that have not been cluster heads in the last rounds

Using this threshold, each node will be a cluster head at some point within rounds. During round 0 (r = 0), each node has a probability 'p' of becoming a cluster head. The nodes that are cluster heads in round 0 cannot be cluster heads for the next rounds. Thus the probability that the remaining nodes are cluster heads must be increased, since there are fewer nodes that are eligible to become CHs. After -1 rounds, T = 1 for any nodes that have not yet been cluster heads, and after rounds, all nodes are once again eligible to become cluster heads. Future versions of this work will include an energy-based threshold to account for non-uniform energy nodes. In this case, it is assumed that all nodes begin with the same amount of energy and being a cluster head removes approximately the same amount of energy for each node. However LEACH was one of the best approaches for cluster head selection and energy balancing, but still it has certain limitations as describe in the next section. LEACH is a completely distributed approach and requires no global information of network. There are many variants and modification of LEACH developed, which form LEACH family. Some of the modified LEACH (Fan & Song 2007) discussed in the various existing works are Two-Levels Hierarchy for Low-Energy Adaptive (TL-LEACH) (Loscri et al 2005), Energy-LEACH (E-LEACH) (Fan & Song 2007), Centralized Low Energy Adaptive Clustering Hierarchy (CLEACH) (Heinzelman et al 2002), Vice-LEACH (V-LEACH) (Yassein et al 2009), Low Energy Adaptive Clustering Hierarchy Fuzzy Logic (LEACH-FL) (Ran et al 2010), Weighted Low Energy Aggregation Clustering Hierarchy (W-LEACH), (Abdulsalam & Kamel 2010) and Threshold-based LEACH protocol (T-LEACH) (Hong et al 2009).

3.2 Limitation of LEACH algorithm

Though, the energy consumption is distributed among all the sensor nodes, so many limitations of LEACH are found as follows:

There is a possibility of none of the sensor node in the network selecting itself as a cluster head during some rounds.

There is a possibility of concentration of all the selected cluster heads in only a part of the network.

- The even distribution of the cluster heads is not guaranteed.
- The clusters are not guaranteed to be of equal sizes.
- A balanced cluster head distribution is not guaranteed.
- Cluster head selection is not energy adaptive.
- Cluster formation, during each round, consumes energy of all the sensor nodes.

Nodes near the cluster boundary are expected to consume more energy as compared to other sensor nodes.

Most of these limitations seem to be encouraged by the basic cluster head selection strategy, of generation of a random number and its comparison with a calculated probabilistic threshold by all the sensor nodes, used in LEACH. The possibility of the random numbers to be generated being either greater or smaller to their respective calculated thresholds may cause none or all of the eligible sensor nodes to select themselves as cluster heads, during some data gathering rounds. In such scenario, all nodes acting as forced cluster heads are required to transmit their sensed and processed data, directly to the distant base station and result in their more energy consumption which, as its consequence, reduces the network lifetime (Younis et al 2003).

4. MULTI-SINK in WSN

The proposed work expects to lessen the energy consumption by deploying multiple sinks . Table 1 shows comparison of various parameters of WSN with single sink and multiple sinks. Energy Consumption in single sink WSN is higher because lots of energy is wasted in sending the data from multiple sensing nodes to the single sink. Moreover there is congestion close to the sink. Energy consumption is lower in multiple sinks because traffic will be shared among multiple sinks. The data from the multiple sensing nodes need not travel long distances as the sink is close by. The congestion at one single sink is also avoided. The end to end delay is high in single sink where as quite low in multiple sink.

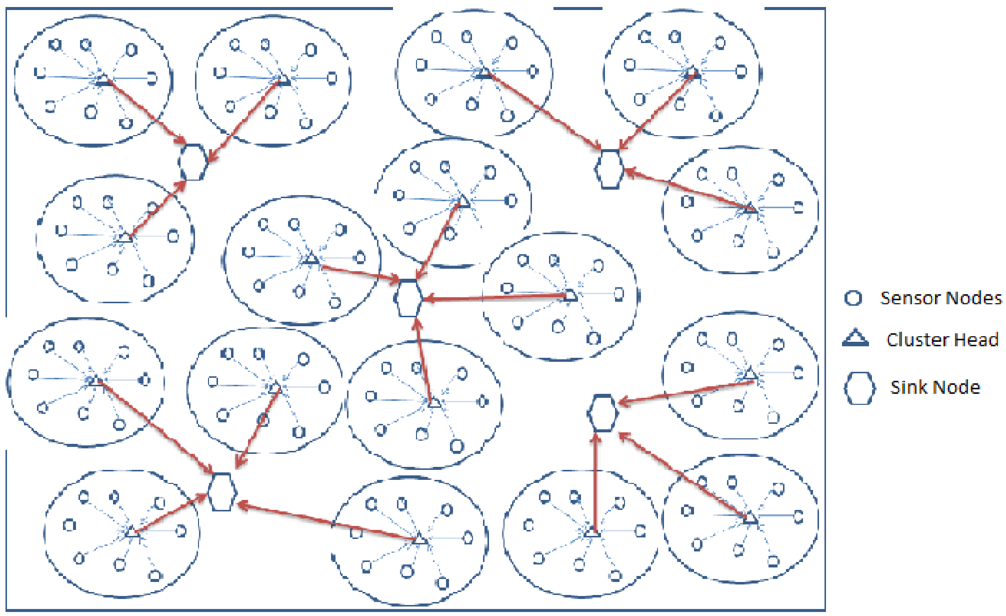


Fig1: Multi-Sink Environment in Wireless sensor networks.

Table 1: Comparisons between single sink and multiple sink in WSN

Parameter	Single Sink	Multiple Sink
Energy Consumption	Higher	Lower
End to end delay	Higher	Lower
Connectivity	Lower	Higher
Data Delivery	Lower	Higher
Scalability	Lower	Higher
Data Aggregation	Required	Not Required
Cost	Lower	Higher

There is lower connectivity between nodes in case of single sink. Some of the nodes which are far off from the sensor, do not form the part of the network. But, in the case of multiple sinks, higher connectivity is ensured as the sinks are close to the nodes. The possibility of outliers is also reduced. There is lower data delivery due to congestion in single sink where as in multiple sinks, as the data collecting nodes are high, traffic will be distributed among different sinks so more data can be successfully delivered to the sinks Sensor nodes have limited transmission range so with single sink, nodes closer to the sink, have to forward lots of packets including the ones from other nodes as well. So the chances to such nodes dying out are increased causing a communication link failure. Whereas, in case of multiple sinks, large scale network can be handled because there is no congestion on a single node closer to the sink. Every node is transmitting data directly to the sink. In single sink the data captured at every CH needs to be aggregated by the CH and then sent to the sink. Lots of energy is consumed in data aggregation. Whereas, in the case of multiple sinks, data need not to be aggregated by the sinks and the energy consumed in data aggregation is saved.

5. Particle Swarm Optimization

Inspired by the flocking and schooling patterns of birds and fish, Particle Swarm Optimization (PSO) was invented by Russell Eberhart and James Kennedy in 1995. Originally, these two started out developing computer software simulations of birds flocking around food sources, then later realized how well their algorithms worked on optimization problems. the birds behavior was first simulated on computer by Craig Reynolds [17], and further studied by the Frank Heppner [18]. PSO is a population based search strategy that finds optimal solutions using a set of flying birds with velocities that are adjusted dynamically according to their requirement.. The term --*particle* refers to population members, which are specified as the swarm positions in the n-dimensional search space. The secret of the PSO success lies in the experience-sharing behavior in which the experience of each particle will continuously communicated to part or the whole swarm, leading the swarm motion.

5.1 Overview of PSO

PSO consists of predefined number of particles (swarm) i.e n. Each particle has the position $X_{i,d}$ and the velocity $V_{i,d}$, $1 \leq d \leq D$ in the d^{th} dimension fo search space. During each iteration each particle finds the personal best called P_{best} and the global best called G_{best}.. To find the global best solution, it uses the personal best and global best to update the velocity $V_{i,d}$ and the position $X_{i,d}$ using the following equations

$$V_{i,d}(t+1) = \omega \times V_{i,d}(t) + c_1 \times \chi_1 \times \left(X_{Pbest\ i,d} - X_{i,d}\right) + c_2 \times \chi_2 \times \left(X_{Gbest\ d} - X_{i,d}\right) \quad (1)$$

$$X_{i,d}(t+1) = X_{i,d}(t) + V_{i,d}(t+1) \quad (2)$$

where $0 < \omega < 1$ is the inertia weight, c1, c2, $0 \leq c1, c2 \leq 2$ are the acceleration coefficients. The updating process is repeated until it is reached to an acceptable value of G_{best}. After getting new updated position, the particle evaluates the fitness function and updates P_{best} as well as G_{best} as follows:

$$Pbest_i = \begin{cases} P_i, & \text{if } (\text{Fitness}(P_i) < \text{Fitness}(\ Pbest_i) \\ Pbest_i, & \text{otherwise} \end{cases} \quad (3)$$

$$Gbest = \begin{cases} Pbest_i, & if\ (Fitness(Pbest_i) < Fitness(Gbest)) \\ Gbest, & otherwise \end{cases} \quad (4)$$

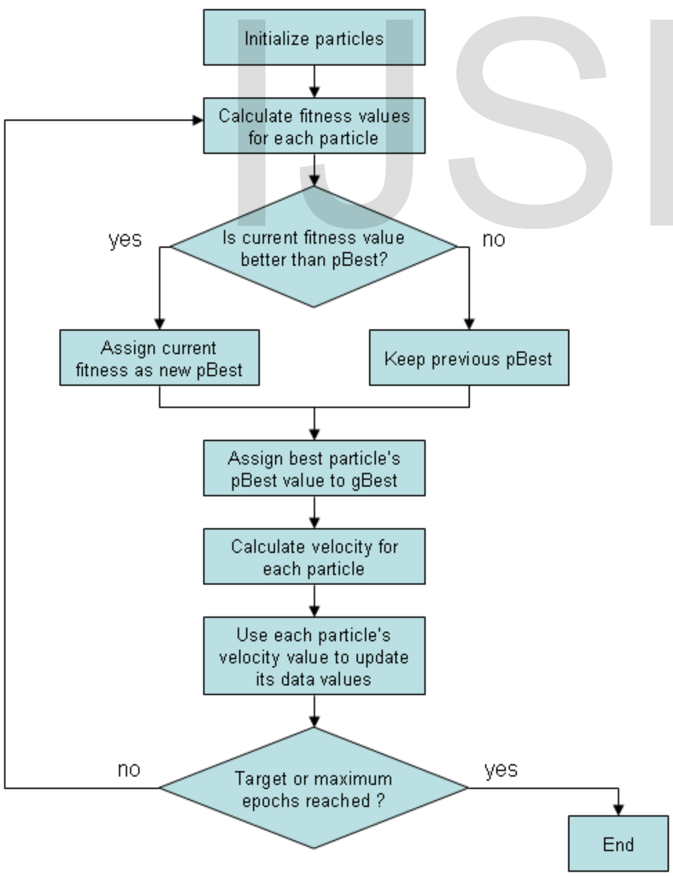
The energy consumption of the node depends on the amount of the data and distance to be sent. In this model, energy consumption of a node is proportional to $d^2$when the propagation distance (d) less than the threshold distance d_0 otherwise it is proportional to d^4. The total energy consumption of each node in the network for transmitting the l-bit data packet is given by the following equations.

$$E_{TX}(l,d) = \begin{cases} l \times E_{elec} + l \times \varepsilon_{fs} \times d^2, \text{ if } d < d_0 \\ l \times E_{elec} + l \times \varepsilon_{mp} \times d^4, \text{ if } d \geq d_0 \end{cases} \quad (5)$$

where E_{elec} the energy is dissipated per bit to run the transmitter or receiver circuit, amplification energy for free space model ε_{fs} and for multipath model ε_{fs} depends on the transmitter amplifier model and d_0 is the threshold transmission distance. In the same way to receive l-bit of data the energy consumed by the receiver is given by

$$E_{RX}(l) = l \times E_{elec} \quad (6)$$

Flow chart of Particle Swarm Optimization (PSO) :



5.2 PSO Strengths:

- PSO is not only characterized by the fast convergence behavior, but also by its simplicity.
- The PSO has the equations of velocity update, position update, and memory updates are calculated. The implementation of PSO is simple and need few lines of code [19].
- PSO uses memory to store the each particle's best positions and the swarm's global best position, which helps not only to keep track of its own experience, but also helps the superior particle to share its social experience to the other particles.[20]

5.3 PSO Limitations:

- The original PSO assumes that all the particles in the swarm are completely homogenous, and it ignores the internal differences among the birds age, catching skills, and flying experiences.
- It also neglects the relative flying position within the swarm, although it provides an important influence on particles.
- The original PSO fails to locate multiple optima.

6. Proposed Algorithm:

In this paper, the proposed algorithm works in multi sink environment to optimize the energy consumption by selecting the cluster head using particle swarm optimization algorithm by hybridizing with the LEACH clustering technique.

Hybrid PSO Algorithm with LEACH with Multiple Sinks

Algorithm for clustering and CH Selection.

1. All the nodes are deployed in the specified bounded region of 100 X 100mts.
2. All the nodes are initialized with constant value & Assign the 10% of the nodes as the Cluster Heads.
3. All the sink nodes are deployed randomly in the region.
4. calculate the minimum distance CH among all the CHs with each node with each sink
    4.1. Calculate the minimum average intra cluster distance and sink distance.
5. Calculate the parameter to maximize the total energy of CHs using (6).
6. calculate the fitness values to each node and initialize the velocity of each nodes as zero.
7. Assign the lowest value of P_{best} to G_{best}.
8. For r : 1 to maximum number of rounds
9. calculate the velocity and position of each node using PSO algorithm & calculate the nearest cluster head for all the cluster members.
    9.1 Repeat step 4 for finding nearest cluster head for all the normal nodes.
    9.2 Calculate Fitness and update P_{best}
    9.3 Repeat step 8 to calculate G_{best}
    9.4 Mark 10% nodes with minimum P_{best} values as the new CHs and all the other nodes as normal Nodes

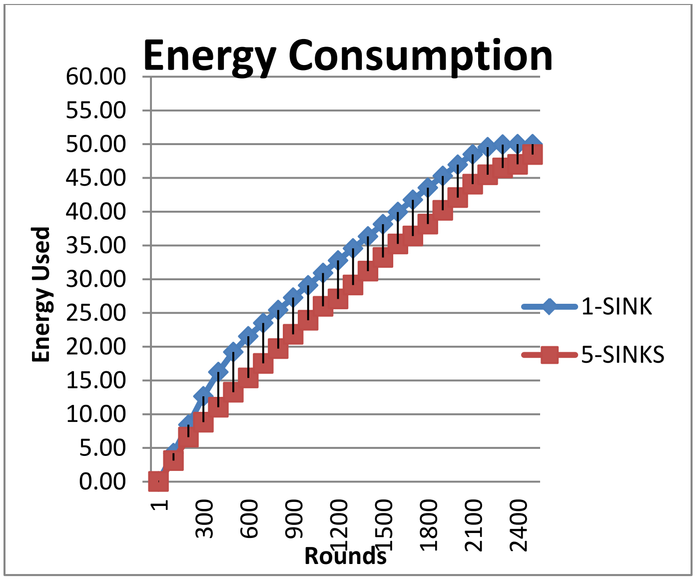
10. calculate the Energy consumption of cluster heads & non cluster heads energy based on distance by applying LEACH algorithm
11. calculating the Total Energy and average energy and number of dead nodes for each round.
12. Repeat the steps [10,11] until the maximum number of iterations reached

7. Simulation Results:

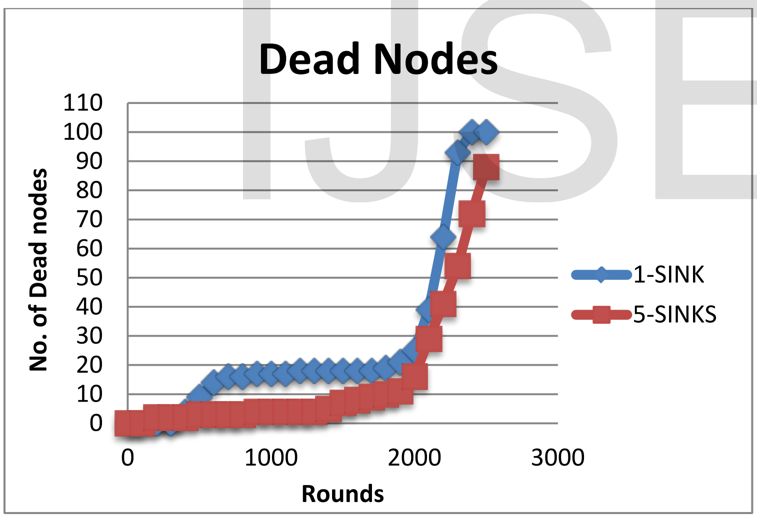
The network scenario is designed and implemented using MATLAB. Here we execute the Hybrid PSO -LEACH method, where PSO method for cluster head selection and the energy consumption in the frame work of LEACH in multi-sink environment. In our 100-nodes(excluding base station/sinks) , 10% alive nodes are cluster heads and the remaining nodes are cluster members, the cluster heads will change for each round. In this section we will evaluate our simulation results in terms of parameters like: dead nodes, alive nodes, energy consumption, and remaining energy and packets transmitted to CH and BS.

Parameter	Value
Network Coverage	100m x 100m
BS's Locations	(25,50), (75,50) ,(50,50) (50,25) (50,75)
Number of Sensor Nodes	100
Initial Energy	50nJ/bit
E_{elec}	50nJ/bit
E_{fs}	10pJ/bit/m2
E_{amp}	0.0013PJ/bit/m4
d_o [d_0= Sqrt(E_{fs}/E_{amp})]	87.70m
E_{DA}	5nJ/bit
Data Packet Size	4096 bits
Control packet size	200 bits

The network scenario is developed based on various parameters like network coverage of (100mts x 100mts), the initial energy allocated for each node is 50nJ(0.5J), and the data packets size of 4096bits and control packet size 200bits. the base stations/ sinks are deployed at the locations of (25,50), (75,50) ,(50,50) (50,25) (50,75).



In figure 2 the Energy Consumption of our proposed PSO-LEACH in multi sink(5) environment. It shows that the multi-sink scenario will give immense results in network life time, which minimizes the energy consumption.



The sensor network lifetime is evaluated in figure 3 in terms of number nodes that manage to remain alive as the network lifetime advances. Our proposed work, PSO-LEACH -multi-sink achieves comparatively better extension to node life time. The reason behind the achievement is the optimized localization of cluster head and multiple sinks are placed in the network nearer to the cluster heads.

8. Conclusion and Future work :

In order to improve the network lifetime several energy-aware cluster based technique with the combination of meta-heuristic algorithms are designed. Particle Swarm Optimization (PSO) is such a method which is known for its easy implementation and fast convergence. In this paper, we have proposed the Hybrid PSO-LEACH-multi-sink algorithm which is best for solving the path problem. Particle Swarm Optimization (PSO) is to select the cluster head and then the nodes transmit the packets from node to CH and from CH to the nearest sink from the multiple sinks.

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