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Wireless Sensor Network Optimization Using ACO Algorithm

A. ULLAH, M. ASHRAF

Department of Electrical Engineering, University of Engineering and Technology, Peshawar, Pakistan

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Abstract: In multiple level hierarchical Wireless Sensor Network, evolutionary algorithms have been applied to find the shortest possible distance from a transmitting head (cluster, intermediate or advanced) to the base station. From evidence and observation, it has been noted that in this methodology sometimes the node responsible for transmitting to the base station would exhaust its total energy and become inactive. To avoid this scenario and make sure that the cluster heads are alive for a considerable amount of time until all or majority of the sensor nodes in the network have died. The following paper describes and implements a methodology by introducing the evolutionary algorithm ACO into the TEEN protocol. The algorithm finds the shortest but at the same time, the most optimal path to the base station from a cluster head such that the total energy loss in transmission is the least in all of the paths found by the ACO. The results have been slightly better than TEEN and corresponding multi0heirarchical heterogeneous implementations such as EAMMH, mod -LEACH, and LEACH.

Keywords: ACO, Wireless Mesh Network, Shortest Path, Hierarchy.

1. <u>INTRODUCTION</u>

wireless sensor network (WSN) is an Α infrastructure that contains tiny, sensing, computational and energy-constrained sensor nodes that are deployed in a field called as the network area. For the improvement of the life time of the WSN efficient energy routing based techniques are implemented. Evolutionary Algorithms, especially Swarm Intelligence (SI) techniques are used to improve the life time of the network in many previous works. Our focus in this thesis is on efficient energy routing improvement by using one of the swarm-intelligence (SI) techniques namely ACO. Many researchers have proposed different algorithms for the optimized design of WSN so that the lifetime of the network can be improved by minimizing the amount of energy consumed in the network due to potential transmission and reception of crucial data sets. (Xu et al. 2004) (Michiardi and Molva 2004).

Increasing demands in the wireless sensor networks for adaptation to network changes such as scalability (Royer and Chai-Keong Toh 1999), routing challenges (Heidemann *et al.* (2001)) and encapsulation of data (Broch *et al.* 1998) and data aggregation (Sun *et al.* 2015) has led to many challenges (Sohrabi *et al.* 2000)(Ephremides 2002) (Xu *et al.* 2004).

1.1 Routing Challenges in WSN

WSN's are classified as homogeneous sensor networks and heterogonous sensor networks based on their nodes classification (Römer *et al.* 2005) (Polastre *et al.* 2005). In the homogeneous type of sensor network, the sensor nodes have same features such as battery power

++Corresponding Author: Email: azy436@gmail.com

capacity, sensing distance, transmission distance, and other functional aspects like constraints on these features, while, in the heterogeneous WSN's, sensor node features are not identical and as a result, they may not perform the same function and work (Akkaya and Younis 2005). In particular cases sensors may not have the identical charge capacity. These are called network resource constraints. So, most of the energy consumed in the node is due to communication on which the lifetime of the sensor network mainly depends, but on the other hand, heterogeneity promises better lifetimes for the network.

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Another big challenge in WSNs is that of scalability. Different techniques have been utilized to be able to maintain the performance of the network when it has been scaled from a small scale to larger number of nodes and more sensors per area. Of those techniques, clustering (Younis and Fahmy) (Heinzelman *et al.* 2002)(Heidemann *et al.* (2001)), location awareness (Intanagonwiwat *et al.* 2003) and hierarchy (Pan *et al.* 2003) (Ye *et al.* 2002) (Gupta and Younis 2003) are notable mentions.

2. <u>MATERIALS AND METHODS</u>

This section briefly explains LEACH and TEEN protocols in perspective of routing and communication mechanisms for lifetime improvement.

2.1 LEACH (Low Energy Adaptive Clustering Hierarchy)

(LEACH) is hierarchical algorithm consisting of nodes that are assumed to be homogeneous and are energy-constrained. The nodes are able to adjust its consumption power thus controlling the distance the sensor can transmit to at the cost of battery power. In this type of hierarchy, the network divides the nodes into set of clusters. (Heidemann *et al.* 2001). The LEACH protocols save information from the nodes and provide it to the BS in hops. There are variations of LEACH protocol in which communication is done in multi hops rather than the inherent behavior of the network to communicate in single hop. The information from every node is primarily transmitted to the head of the clusters, then after that it is transmitted from the local cluster to the base station. Due to its single hop communication technique, LEACH is not scalable. It only works efficiently in small networks. (Fig. 1) shows the communication structure of the LEACH protocol.



Fig.1: Communication structure of LEACH protocol

2.2 TEEN (Threshold-sensitive Energy Efficient Network)

The Threshold-sensitive Energy Efficient sensor Network protocols follow the a,roach of data-centric mechanism. TEEN is a,lied in time-critical network utilization for sensing physical phenomena that occur scarcely. Critical time a,lications are numerous, e.g. Temperature changes in the network area. TEEN protocol has a benefit over other time critical protocols in regards of counter-acting abrupt changes in sensed parameters. This is due to its fuzzy-logic type behavior where two parameters, soft and hard threshold control the behavior of the sensors to changes in the sensed parameters. (Fedor and Collier 2007).

The hard threshold is the minimum possible energy that can be used to switch ON or OFF the transmitter so that the sensor node only transmits data to the leader of the cluster where required. Thus, the TEEN reduces the number of transmissions as only the information required at a proper time will be transmitting, so the energy consumption is very much low as compared to its predecessors. Improving this protocol is a hard task as the energy consumption is already the least possible due to the sensors transmitting data only when the sensed data falls in range between hard and soft threshold (Younis *et al.* 2002). (**Fig. 2**) shows the TEEN communication and clustering technique as an illustration.



Fig. 1Communication structure of TEEN protocol

2.3 Ant Colony Optimization Algorithm (ACO)

Swarm intelligence is a class of Swarm Intelligence algorithms where the algorithms mimic the behavior of behavior in the biological organism like fishes, ants and bee's colonies etc. ACO is the one class of swarm intelligence and is a relatively novel meta-heuristic technique (Forster 2007) and has been successfully used in many a,lications especially problems in combinatorial optimization. ACO algorithm models the behavior of real ant colonies in establishing the shortest path between food sources and nests. Ants can communicate with one another through chemicals called pheromones in their immediate environment. The ants release pheromone on the ground while walking from their nest to food and then go back to the nest. The ants move according to the number of pheromones, the richer the pheromone trail on a path is, the more likely it would be followed by other ants. So, a shorter path has a higher amount of pheromone and in probability, ants will tend to choose a shorter path. Through this mechanism, ants will eventually find the shortest path. The main objective of the Ants Colony Optimization algorithm is to find the ideal solution through the mutual cooperation and through the exchange of information between the individual variables called ants in the algorithm (Liu and He 2014).

The main advantage of ACO is that there is no priority in the information, robustness, and sensors organization requirement. ACO is also used in internet problems, assignment problems etc. related to Wireless Sensor Networks (Owen 1988) (Hu *et al.* 2010) (Gong- *et al.* 2011).

Some works done through ACO are Routing Information Protocols (RIP) and Open Short Path First Protocol (OSPF). The OSPF and RIP need to transmit the packets of information over a proper interval to accommodate the change in topology of the network and also change the overall routing table according to the topology change as shown in Fig.3.



2.4 ACO Problem in WSN

The ACO problem can be considered as a graph G=(C,E) where C is a set of Cluster Heads or Nodes and E is a set of all the possible paths between each and every node in the graph. E is also called a set of edges in the graph connecting all the nodes. S is the set of paths in this graph from s starting point to an ending point or node and is considered a solution. For the same starting and ending points there could also exist another path and is also a candidate of the solution set S. The travelling from a starting point to an ending point may be associated with cost, edge length, weightage of the edge or any other parameter mathematically defined in the problem or formulated by assumptions. In our work we have criterion of energy expenditure for communication in the pathway defined by the Solution Set S.

3. <u>IMPLEMENTATION</u>

The ACO algorithm works on the problem space that is devised from the problem function. The problem space can be essentially seen as a planar surface with various locations (CHs). The objective of a randomly set CHs location set is to find the least distance that can be covered by an "ant" if it were to visit each location once only. The location an ant visits in ACO can be called as a "city" and the problem is termed as a TSP – travelling salesman problem. When the ant k is at a CH represented by i, it can go to an unvisited CH represented by j. The probability that the ant will visit a certain CH represented by j is given mathematically as:

$$p_{ij}^{k}(t) = \begin{cases} \left[\tau_{ij}(t)\right]^{\alpha} \left[\eta_{ij}\right]^{\beta} \\ \frac{\sum_{l \in \aleph_{i}^{k}} [\tau_{il}(t)]^{\alpha} [\eta_{il}]^{\beta}}{0 \text{ otherwise}} & \text{if } j \in \aleph_{i}^{k} \end{cases}$$

Here $\eta_{ij} = \frac{1}{d_{ij}}$ and d_{ij} is the distance between

previous CH and next CH represented by i and j respectively. α and β are two variables that stay constant through each different simulation and represent and control the intensity of the pheromone trail or a kind of memory that influences the next path decision and \aleph_{ij} k is local best neighborhood for the given problem in the problem space, or it is the best candidate among all the remaining unvisited CH or locations to become the next location to be visited by the "ant". k represents the ant number in the problem algorithm.

In each iteration of the algorithm, the algorithm decides the next city or CH location to be visited based solely on the pheromone trail. This is mathematically called as Greedy-ACO. The process repeats for several hundred times The pheromone intensities that are contributed by ant k to an edge between cities (Cluster Heads) i and j is given mathematically as:

$$\Delta \tau_{ij}^{k}(t) = \begin{cases} \frac{Q}{L^{k}(t)} & \text{if } j \in \aleph_{i}^{k} \\ 0 & \text{otherwise} \end{cases}$$

Here Q is a constant and $L^{k}(t)$ is distance travelled by ant k in the current iteration. The pheromone scattering on this trail is updated and added to the previous trail's pheromone by:

Here

$$\tau_{ij}(t+1) = \rho \tau_{ij}(t) + \Delta \tau_{ij}(t)$$

$$\Delta \tau_{ij}(t) = \sum_{k=1}^{m} \Delta \tau_{ij}^{k}(t)$$

Where m is the total number of ants and ρ is a constant representing the rate of evaporation of pheromone. The ACO parameters for the Ant System Type problem formulation are shown in (**Table-1**) below:

Table 1 ACO Parameters used in Simulation Study

Name of parameter	Value / Property
α	1
β	5
ρ	0.5
Ants	50 initially then equal to cluster heads.
Iterations	Equal to round number (3000)

The WSN optimization problem has certain simulation parameters that are standard throughout the research area. The problem formulation and its accompanying ACO embedding algorithm is set with the following parameters shown in (**Table-2**)

Name of parameter	Value / Property
Total number of Nodes	200
Field dimensions	100 x 100 meters
Optimal Election Probability for CH	0.2
Initial Energy of sensors	0.1 Joules
Data aggregation energy	5 nJ
Maximum Rounds	3000
Base Station Coordinates (m)	(150,50)
Rounds per Simulation (min)	500
Free Space Loss Energy	10 pJ
Multipath Loss	1.2 Fj
Transmit Amplifier	50nJ
Receive Amplifier	50 nJ

Table 2 Showing Simulation Setup Parameters

It is evident that the ACO algorithm is used merely for the best possible location of the CH in each level of the architecture to optimize energy consumption and network life time. Moreover, the number of dead sensors nodes per data collection routine will also be decreased. The coding has been derived from TEEN protocol mainly due to its better performance than previous architectures and then ACO is embedded into it.

In summary, the ACO does one of the following two tasks:

1. Based on the given energy values to each CH, it decides the best location for each to efficiently utilize that energy.

2. Based on the given location of each CH, it decides the best values of energy for each CH to properly maintain the network lifetime.

When both techniques are combined, it results in the algorithm as explained by the block diagram shown in Fig.4.



Fig. 4 Flow chart representing the algorithms' workflow

EVALUATION

The algorithm which is a modification of the TEEN protocol by introducing ACO in it is coded in MATLAB 2016 alpha. The simulation results are shown with proper explanations.

4.1 Simulation Field Setup

4.

In the figure 5-1 above, the 200 nodes are spread over a 100x100 meters field in Gaussian random distribution as presented above. The base station is located according to previous researches for coherency. It is at Length x 1.5 and Width x 0.5 coordinates i.e. at coordinates (150,50) meter. The setup is shown in (**Fig. 5**) below:





4.2 Energy Analysis:

The average energy of the remaining alive nodes w.r.t. the round numbers is calculated and plotted in as shown in the following figures. In Fig.6 for our hybrid protocol, the average energy of the remaining nodes drops form 0.1 Joules to 0.070 Joules in 95 rounds.

In the following figure for the LEACH algorithm, the average nodal energy drops from 0.1 to 0.01 Joules in 100 rounds. It means, that the energy consumption per round of communication in LEACH is higher and hence our protocol is comparatively better in sustaining the energy through the rounds.



Fig. 6 Combined graphs for Nodal Deaths vs. round number

Now looking at EAMMH in (**Fig. 7-9**) the average energy of each node in the setup drops from 0.1 Joules to 0.009 Joules in about 95 to 100 rounds. It has been found to be equivalent in energy dissipation to the LEACH protocol.



Comparing EAMMH deaths with our hybrid protocol we see that this only gets around hundred deaths in 500 rounds in contrast to all nodes (200) dead in just around 200 rounds.



Fig. 9 Comparison of Energy consumption w.r.t. round number of EAMMH, TEEN and our hybrid algorithm

In (Fig. 9) we can see that the average energy of the proposed algorithm is slightly better than the TEEN algorithm and far more better than EAMMH and conclusively from LEACH and mod-LEACH due to their same energy signature.

5. CONCLUSION

We proposed the hybrid algorithm by introducing Ant-Colony Optimization Algorithms' type "Ant-System" into a hierarchical 2 level clustering algorithm. This algorithm was derived from the TEEN protocol (Threshold sensitive Energy Efficient sensor Network). We changed the communication technique of the 2nd level hierarchy with the base station to an optimized and routed communication technique after ACO finds the shortest path for communication.

The results were better than some protocols and competitive to some protocols as demonstrated.

Although the ACO technique proved to be suitable for the optimization of energy losses and pathways and improving the lifetime of the network, it fails to do the operation in less amount of time as possible. This means that the algorithm needs refinement and tweaking to attain speed as well as efficiency.

We would recommend the future scholars to study hybrid techniques in WSN, GA implemented for WSN and then this technique and find and research on optimization of the time taken for operation of the simulation as well as the configuration of the problem. TSP, in itself is a computer extensive problem, but more efficient solutions could be found out if certain constraints on the problem space could be introduced and refined.

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