

Research Article

A Novel Enhanced Coverage Optimization Algorithm for Effectively Solving Energy Optimization Problem in WSN

¹M. Senthil Kumar and ²Ashish Chaturvedi

¹Department of Electronics and Communication Engineering, V.B.S. Purvanchal University, Jaunpur, Uttar Pradesh, India

²Arni School of Computer Science and Applications, Arni University, Indora (Kathgarh), Himachal Pradesh, India

Abstract: In Wireless Sensor Networks (WSN), Efficient-Energy Coverage (EEC) is one of the important issues for considering the (WSNs) implementation. In this study, we have developed the new algorithm ECO (Enhanced Coverage Optimization) for solving the EEC problem effectively. The proposed algorithm uses three types of major work for effectively solving the problem. One of the three pheromones is the local pheromone, which helps an ant organize its coverage set with fewer sensors. The other two pheromones are global pheromones, one of which is used to optimize the number of required active sensors per Point of Interest (PoI) and the other is used to form a sensor set that has as many senses as an ant has selected the number of active sensors by using the former pheromone. This study also introduces one technique that leads to a more realistic approach to solving the EEC problem that is to utilize the probabilistic sensor detection model. The main goal of ECO is Efficient Coverage on target area with minimum energy consumption and increased network's lifetime.

Keywords: Ant Colony Optimization (ACO), energy efficient coverage, three types of pheromones, Point of Interest (PoI), probabilistic sensor detection

INTRODUCTION

Wireless Sensor Networks (WSNs) have attracted significant attention over the past few years. A growing list of civil and military applications can employ WSNs for increased effectiveness; especially in hostile and remote areas. Examples include disaster management, border protection, combat field surveillance. In these applications, a large number of sensors are expected, requiring careful architecture and management of the network.

The Wireless Sensor Network (WSN) is a class of wireless networks in which sensor nodes collect process and transmit data acquired from the physical environment to an external base station directly or, if required, uses other wireless sensor nodes to forward data to an external base station (Li *et al.*, 2010). The transmitted data is then presented to the system by the gateway connection. The ideal wireless sensor is networked and scalable, consumes very little power, is smart and software programmable, capable of fast data acquisition, reliable and accurate over the long term, costs less to purchase and install and requires no real maintenance. WSN applications are used to monitor the surrounding environment in a wide range of areas, for example, medical, security, military and agricultural industries.

A Wireless Sensor Network (WSN) is a complex structure consisting of a large number of sensor nodes distributed over a target region. Each sensor has limited computational and storage capacity, a restricted sense and communication radios and a finite power supply. These constraints have led researchers to find better ways of using the sensor nodes looking for a reduction of energy consumption, while maintaining an acceptable coverage threshold. The increasingly cheaper and better technology, along with a wide range of applications, has played an important role in the growing popularity of WSNs. There are primarily four techniques used by efficient power management algorithms:

- Long term scheduling, which uses a successive activation of disjoint covers (sets of sensors).
- Short term scheduling, which selectively activates nodes based on their individual battery status
- Routing selection, which establishes the shortest path for data transmission.
- Rate allocation, which reduces the amount of data to be coded and transmitted by exploiting its correlation. These techniques, or any combination of them, could be implemented using either a distributed or centralized method.

Corresponding Author: M. Senthil Kumar, Department of Electronics and Communication Engineering, V.B.S. Purvanchal University, Jaunpur, Uttar Pradesh, India

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A sensor node can only be equipped with a limited energy supply in all application scenarios. Energy is consumed during computation and communication among the nodes. The Sensor node lifetime shows a very strong dependency on battery lifetime (Luntovskyy *et al.*, 2010). Selecting the optimum sensors and wireless communications link requires knowledge of the application and problem definition. Battery life, sensor update rates and size are all major design considerations. Examples of low data rate sensors include temperature, humidity and peak strain captured passively. Examples of high data rate sensors include strain, acceleration and vibration.

Many techniques have been proposed to conserve energy and prolong the network's lifetime (Noah *et al.*, 2010; Anastasi *et al.*, 2009). Among them, scheduling methods, which reduce energy consumption by planning the activities of the devices, have been shown to be effective (Lin *et al.*, 2010). These activity scheduling methods need to have devices densely deployed in an interest area. Then, only part, or a subset of the devices accomplishes the sensing task, while the other devices can be scheduled into a sleep state to save energy. By scheduling the devices' activities from active to sleep, or vice versa, this method needs only a subset of the devices for monitoring an area of interest at any time. Therefore, the lifetime of the WSN is prolonged. To achieve a longer lifetime, it is important to find the maximum number of disjoint subsets of devices in the scheduling method. Many scheduling algorithms have been proposed to solve the EEC problem.

RELATED METHODOLOGY

The main objective of the sensor network is to cover the region. The random deployment of sensors to cover a given square-shaped area, where the circles represent the sensing range, each point of the area is monitored by at least one sensor (Ming *et al.*, 2010). According to the sensor network architecture, two assumptions are made:

- All the sensor nodes are static once deployed and each one knows its own location which can achieve by using some location system.
- Every sensor independently in their sensing activities and schedules itself for or sleep intervals.

For a centralized approach to work effectively, targets must have fixed locations as well as the deployed sensors. This unchangeable structure of the network permits long term scheduling to take place only once in a central computing unit, where information about all sensor's location is gathered just after deployment to solve the EDSC problem. When a solution to the problem is available, it is transmitted to each sensor in the form of an index representing its membership to a cover that is used as the number of battery periods a sensor has to wait before turning

itself to active mode. Clearly, the biggest disadvantage of centralized algorithms is that their functionality relies on the network's ability to transmit data from every single node to the central computing unit and vice versa. In probabilistic disc model (Chen *et al.*, 2010) takes into account the uncertainty of the signal detection process and assumes that the detection probability is a continually decreasing function of the distance. Therefore, it is more realistic to presume that a sensor node can detect the occurrence of an event with a certain probability if the distance between the sensor and a PoI is greater than the sensing radius in the Boolean disc model.

Heinzelman *et al.* (2002) developed a cluster based routing scheme called Low Energy adaptive cluster in hierarchy. In LEACH the role of the cluster head is periodically transferred among the nodes in the network in order to distribute the energy consumption. The performance of LEACH is based on rounds. Then, a cluster head is elected in each round. In this election, the number of nodes that have not been cluster heads and the percentage of cluster heads are used. Once the cluster head is defined in the setup phase, it establishes a TDMA schedule for the transmissions in its cluster this scheduling allows nodes to switch off their interfaces when they are not going to be employed. The cluster head is the router to the sink and it is also responsible for the data aggregation. As the cluster head controls the sensors located in a close area, the data aggregation performed by this leader permits to remove redundancy. A centralized version of this protocol is LEACH-C (Lindsey and Raghavendra, 2002). This scheme is also based on time rounds which are divided into the setup phase and the steady-phase. In the setup phase, sensors inform the base station about their positions and about their energy level. With this information, the base station decides the structure of clusters and their corresponding cluster heads. Since the base station possesses a complete knowledge of the status of the network, the cluster structure resulting from LEACH-C is considered an optimization of the results of LEACH.

The conventional ACO algorithm is based on the behavior of real ants. When a group of ants set out from their nest to search for a food source, they use a special kind of chemical to communicate with each other. The chemical is referred to as the pheromone. Once the ants discover a path to a food source, they deposit pheromone on the path. By sensing pheromone on the ground, ants can follow the path to food source discovered by other ants. As this process continues, most of the ants tend to choose the shortest path to food as there have been a huge amount of pheromones accumulated on this path (Selcuk and Karaboga, 2009). As time goes on, pheromones evaporate, opening up new possibilities and ants cooperate to choose a path with heavily laid pheromones. The ACO algorithm has a parallel architecture and a positive feedback loop mechanism.

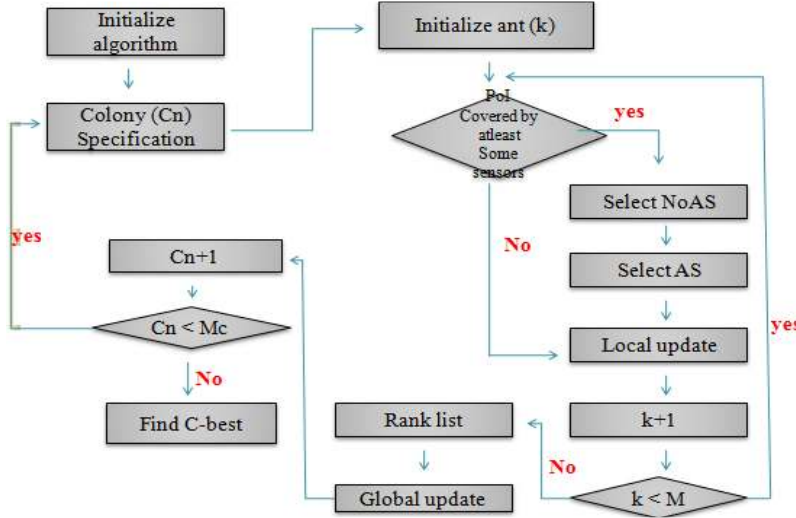


Fig. 1: Flowchart of the proposed algorithm

PROPOSED ENERGY COVERAGE OPTIMIZATION ALGORITHM

The main objective of the proposed COA algorithm is efficient coverage of target areas with minimum energy consumption and also increased network's lifetime. Here, we are using one technique that is to utilize the probabilistic sensor detection model lead to a more realistic approach to solving the EEC problem.

The proposed system COA uses three types of pheromones to find the solution efficiently. One of the three pheromones is the local pheromone, which helps an ant organize its coverage set with fewer sensors. The other two pheromones are global pheromones, one of which is used to optimize the number of required active sensors per Point of Interest (PoI) and the other is used to form a sensor set that has as many senses as an ant has selected the number of active sensors by using the former pheromone.

The proposed algorithm can be viewed as the following procedures:

- **Initialization of the algorithm:** Collect the position information of sensors and PoIs. And also all pheromone values and parameters are initialized
- **Initialization of ants:** Initialized the number of ants M , which compose a colony and the also initialized the number of colonies M_c , which is the repeated count within a time slot
- **Selection:** Select the number of active sensors p_{NOAS} and also select the active sensors p_{AS} using roulette wheel selection
- **Local pheromone updating:** Local pheromone τ_{SS}^k is updated at the end of each ant k 's travel for PoI j .
- **Rank list:** Ant k organizes a subset c_{jk} is stored as the set c_k . Each set that is made by M ants is saved on the Rank List cell

- **Global pheromones updating:** Global pheromone trail amount τ_{NoAS} and τ_{AS} are updated, if Rank list M is completed
- **Find C_{best} :** The set with minimum cost among M is individually saved at C_{best} . To update C_{best} , repeat the same process M_c times.

The flowchart of this algorithm is given by Fig. 1. These procedures are described in details below.

Initialization of the algorithm: In the first stage, we collect position information of the sensors and the PoIs. After loading, we find and store a set of S_{cover} sensors which cover each PoI 'j'. The set S_{cover} is a $T \times N$ matrix that consists of the following elements:

$$S_{cover,ji} = \begin{cases} 1, & \text{if sensor } i \text{ covers } POI \ j \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

And also we initialized local pheromone and two global pheromones. This matrix (1) is used to initialize the global pheromone field τ_{AS} (for organizing the Active Sensors (AS)) per PoI at the initial stage, for every time slot as follows:

$$\tau_{AS,ji} = S_{cover,ji} \times Residual\ Energy_i(ts) \quad (2)$$

where $Residual\ Energy_i(ts)$ is the residual energy of the sensor 'I' at time slot (ts).

Determining the Number of Active Sensors (NoAS) is an axiomatic fact that the fewer the number of active sensors per PoI, the length is the lifetime of the WSN. Initialize the global pheromone field using a Gaussian function which is based on the following equation:

$$\tau_{NoAS,jm}(0) = \begin{cases} \frac{1}{\sigma\sqrt{2\pi}} e^{-(m-\mu_j)^2/2\sigma^2} & , \text{if } m \leq n_j(3) \\ 0, & \text{otherwise} \end{cases}$$

where n_j is the number of sensors covered at PoI and $m = 1 \dots n_j$. This function has a constant σ and the mean μ_j used in Eq. (3) is zero at the beginning of the proposed algorithm but increases with the number of times that the first ant of the first colony fails to organize the sensor set, which met the condition is, PoI in the region is mostly covered by at least some sensors. The repeated failure of this ant under the initialized τ_{NOAS} means that the current distribution with the mean is μ_j insufficient to determine the number of active sensors at PoI. Thus, there is a higher chance to organize the efficient set of the sensors for all of the ants.

Selection: The Selection process is based on Roulette wheel selection. In Roulette wheel selection, each individual is selected with a probability proportional to its fitness value. Thus, weak solutions are eliminated and strong solutions are considered to form the next iteration.

To find a covering sensor set at PoI 'j', ant 'k' first determines the number of active sensors, n_j^k , using the global pheromone field τ_{NOAS} . Then, ant chooses with a probability determined in accordance with the intensity of pheromone. The selection probability of the n_j^k for ant 'k' is as follows:

$$P_{NOAS}(n_j^k) = \begin{cases} \frac{\tau_{NOAS, jn_j^k}(t)}{\sum_{m=1}^{n_j} \tau_{NOAS, jm}(t)}, & \text{if } n_j^k \leq n_j \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

where, n_j is the number of sensors covered at PoI. Eventually, ant k determines n_j^k through roulette wheel selection (or the fitness proportionate selection) using the above probabilities.

The selection probability of the sensor $s_{i,j}^k$ for ant 'k', when ant 'k' plays the roulette wheel selection is as follows:

$$p_{AS}(s_{i,j}^k) = \begin{cases} \frac{\tau_{AS, ji}(t) + \tau_{SS, i}^k(t)}{\sum_{m \in \text{allowed}_m} (\tau_{AS, jm}(t) + \tau_{SS, m}^k(t))}, & \text{if } \text{allowed}_m \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

where, $\text{allowed} = S_{cover}(j) - \{\text{tabu}_j^k\}$, or this is the set of remainder sensors, except that the first one is selected among sensors, except that the first one is selected among sensors, is the local pheromone, which has effects in the third loop, i.e., while ant travels alone. In contrast, the global pheromone fields, τ_{NOAS} and, τ_{AS} which have influence in one time slot, i.e., the time it takes to complete the travel of the colonies.

Local pheromone updating: After finishing ant k's selection, this pheromone field is initialized and is then

used by the ant k+1. This field is updated whenever ant 'k' decides on the sensors that cover the PoI 'j'. The selected sensor gets the value Q_{ji} every time it is selected by ant 'k', as follows:

$$\tau_{SS, i}^k(t+1) = \tau_{SS, i}^k(t) + \Delta\tau_{SS, ji}^k \quad (6)$$

The local pheromone $\tau_{SS, i}^k$ is updated at the end of ant k's travel for the PoI 'j'. Thus, this equation describes the policy of the pheromone update at t+1 which is the point when ant 'k' has organized the subset s_j^k to cover the PoI 'j' if 't' is the point of the previous update. $\Delta\tau_{SS, ji}^k$ is the amount of pheromone trail added on the element of vector τ_{SS}^k for sensor 'i' chosen by ant 'k' at the PoI 'j' and where $\Delta\tau_{SS, ji}^k$ is the amount of the updated pheromone trail and is given as follows:

$$\Delta\tau_{SS, ji}^k = \begin{cases} Q_{ji}, & \text{if ant k selects sensors} \\ 0, & \text{otherwise} \end{cases} \quad (7)$$

Rank list maintenance: Ant organizes a subset c_{jk} that covers the PoI 'i' through the roulette method. The subset is generated and stored as the set c_k , which is selected by ant k and is the union set of c_{jk} . Each set that is made by 'M' ants is saved on the Rank List cell. The tour of a colony ends here. When the colony finished. Cost from the Eq. (7) with the M sets collected by the previous colonies, until the (cn-1) th iteration (or colony) and the new M sets are made by the current cn th colony. Then, we have to arrange the total 2M sets in increasing numerical order. Among them, we cut M sets in order and store them in the Rank List again.

Global pheromones updating: After the tour of a colony ends again, the global pheromone trail amount $\tau_{NOAS, jn}$ and $\tau_{AS, ji}$ are updated, using the cost of the sets in RankList (M) if the configuration of the RankList (M) is completed.

The global pheromone trail amount τ_{NOAS} is updated according to the following formula:

$$\tau_{NOAS, jn}(t+M) = (1 - \rho) \cdot \tau_{NOAS, jn}(t) + \Delta\tau_{NOAS, jn} \quad (8)$$

where, ρ is the pheromone decay parameter. The pheromone is evaporated as time goes on. As mentioned above, the global pheromone is updated at the end of travel of a colony that has M ants. Thus, this equation describes the policy of the pheromone update at t+M if t is the point of the previous update and where $\Delta\tau_{NOAS, jn}$ is the added pheromone trail amount at t+M, given as follows:

$$\Delta\tau_{NOAS, jn} = \sum_{k=1}^M \Delta\tau_{NOAS, jn}^k \quad (9)$$

$$\Delta\tau_{NoAS,jn}^k = \begin{cases} \frac{Q_k}{n_j^k}, & \text{if ant } k \text{ selects sensors } n_j^k \text{ at Pol } j \\ 0, & \text{otherwise} \end{cases} \quad (10)$$

Q_k is determined in accordance with the ranking of rank list is as follows:

$$Q_k = \frac{Cost(RankList(1))}{Cost(RankList(k))} \quad (11)$$

Calculation of C-Best: If the number of colonies that accomplish the task is more than M_c , the current time slot is finished and then C_{best} at that time is the optimal cover set of sensors. After that, a new time slot begins and the global pheromone fields and the ranking list are initialized at the beginning. The IACO algorithm finds the optimal cover set of sensors in every time slot, recursively. However, this iteration process goes on until, each PoI must be covered by at least some sensors (i.e., There is no longer satisfied by any of the PoIs, or the network fails to cover any PoIs). The final set C cell is the group of C_{best} and the final solution of the EEC problem. The number of the time slot, TS, also becomes the lifetime of the WSN.

SIMULATION RESULTS AND PERFORMANCE EVALUATION

The performance evaluation is carried out as a simulation study using NS2. We use the following metrics in evaluating the performance of the different multicast routing protocols. The packet delivery ratio is computed as the ratio of total number of unique packets received by the receivers to the total number of packets transmitted by all sources times the number of receivers. Routing overhead is the ratio between the number of control bytes transmitted to the number of data bytes received.

The simulation results of our proposed ECO algorithm are compared to other leading algorithm ACO

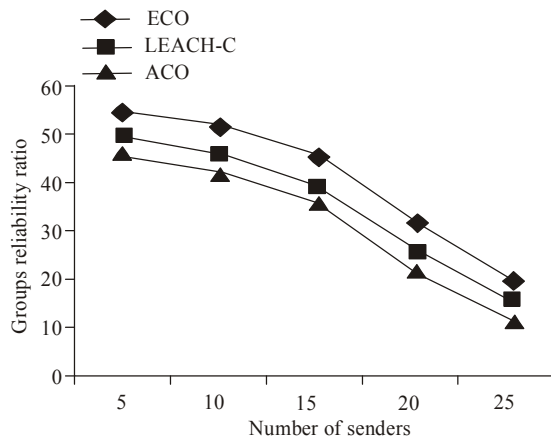


Fig. 2: Packet delivery ratio as a function of traffic load

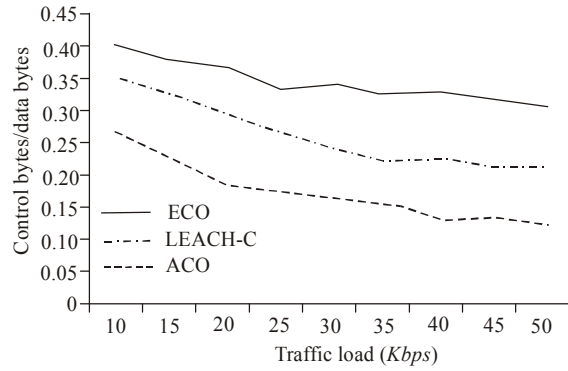


Fig. 3: Routing overhead as a function of traffic load

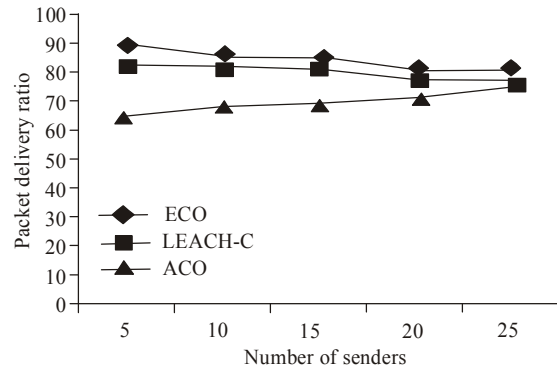


Fig. 4: Packet delivery ratio as a function of number of traffic sources

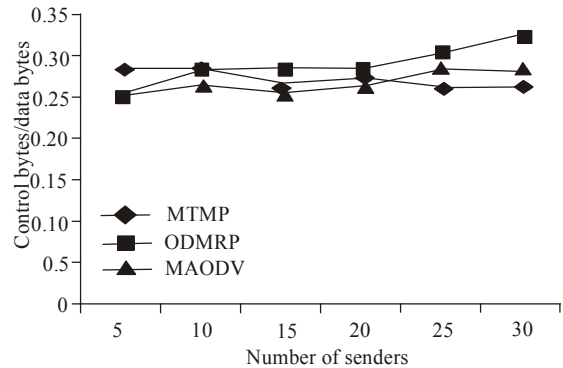


Fig. 5: Routing overhead as a function of traffic sources

and LEACH clustering algorithm (LEACH-C). In these simulations, we use synthetic MANET scenarios, in which we subject the optimization algorithm to a wide range of mobility, traffic load, and multicast group characteristics (i.e., group size and number of sources).

Figure 2 shows the packet delivery ratio as a function of traffic load. It is observed that all optimization algorithm are affected by the increase in network traffic. For the traffic loads considered, ECO algorithm still outperforms ACO and LEACH-C in terms of delivery ratios. The performance of the Proposed ECO algorithm is

much better to ACO and LEACH-C as traffic load increases on account of the great number of redundant transmissions.

Figure 3 depicts the control overhead per data byte delivered as a function of traffic load. It can be seen that Proposed algorithm control overhead remains almost constant with increasing load. The high routing overhead seems to suggest that ECO algorithm can be quite expensive at higher traffic loads and, hence, not scalable with increased traffic loads.

Figure 4 shows the packet delivery ratio as a function of the number of senders. Note that both the Proposed optimization algorithm and ACO packet delivery ratios remain fairly constant with the number of senders; thus, they do not suffer from increased contention except at a higher number of sources, where a slight drop off can be observed and is attributed to data packet loss due to collisions.

Figure 5 depicts how control overhead varies with the number of traffic sources.

CONCLUSION

In this study, a novel ECO algorithm is optimized to solve the EEC problem. The proposed algorithm has new characteristics that are different from conventional ACO algorithms. It uses three types of pheromones to solve the EEC problem efficiently. One is the local pheromone, which helps an ant organize a coverage set with fewer sensors; the others are the global pheromones. One global pheromone is used to optimize the number of required active sensors per PoI and the second global pheromone is used to form a sensor set that has as many sensors as an ant has selected the number of active sensors by using the former pheromone. It also utilizes a reduced number of the user's parameters. To achieve this, it introduced the heterogeneous WSN, which is made by the random selection of the parameters of the probabilistic sensor detection model. So the simulation result shows that the ECO algorithm used to decrease the energy consumption and also increase the network's lifetime.

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