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Ant Colony Based Mobile Sink Routing Algorithm for Wireless Sensor Network

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Abstract: Wireless Sensor Networks (WSN) are networks usually comprised of a large number of nodes with sensing and routing capabilities. Routing is usually implemented for the transport of the sensed data to sinks. Most of the considered scenarios in previous works deal with sensor nodes that do no move and are un-replaceable. This study explores the idea of exploiting the mobility of data collection points (sinks) for the purpose of increasing the lifetime of a wireless sensor network. The proposed method is based on ant colony optimization algorithm. Mobile sink routing problem is NP-hard and it will take a long time to solve a problem if the wireless sensor network is huge. Ant colony optimization algorithm is a metaheuristic which has been widely used in optimization problems. Experimental results proved that not only maximum wireless sensor network life time reached but also execution time is declined.

Key words: Wireless sensor network, mobile sink routing, ant colony optimization, lifetime

INTRODUCTION

A wireless sensor network is made up of a large number of inexpensive and smart devices that are networked via low power wireless communications. All nodes in a wireless sensor network are classified into two types:

- Sensor node
- Sink node

Since,each sensor node has a small communication range, each sensor node relays the sensed events to a sink node (Kim *et al*., 2005). As the number of sink nodes is increased, the path length from sensor node to sink node is decreased and the lifetime of the sensor nodes is increased. However, the number of sink node is constrained financially because the cost of the sink node is more expensive than the sensor node.

Sparse and disconnected networks can be better handled with mobile sinks (Hamida and Chelius, 2008). Mobile sinks could obtain sensor data from isolated portions of the network which might otherwise be inaccessible in a static sink case, thus enhancing the connectivity of the network. Acquiry of data from loosely connected portions of the network can be achieved be mobile sink routing protocol with much less effort than the conventional static sink routing protocols which spend excessive resources to cope with such topology (Chatzigiannakis *et al*., 2008). Sink mobility also reduce the number if hops on data routes, especially in delay-tolerant application where data aggregation nodes are utilized which wait and disseminate data when the sink gets closer at a cost of increased delays. Shorter data dissemination path lead to increased throughput and reliability together with decreased energy consumption. Other advantages of sink mobility include security benefits mobile sinks (Fig. 1). The problem of mobile sink routing is a promising research field with unique challenges. In this study, a comprehensive and effective solution will be proposed.

Related works: WSN studies with mobile sinks can roughly be grouped in two main classes:

- The ones concentrating on the coordination of the network so that the extra overhead due to the mobile sink (s) is compensated
- Those that focus on the determination of efficient mobile sink locations

Studies belonging to the first class consider a given (constant or random) trajectory of the sink and propose data communication and propagation protocols aiming to improve some performance metrics of the network such as the energy, throughput, accuracy, message latency and message loss rate. This type of studies generally does not involve the determination of efficient sink trajectories.

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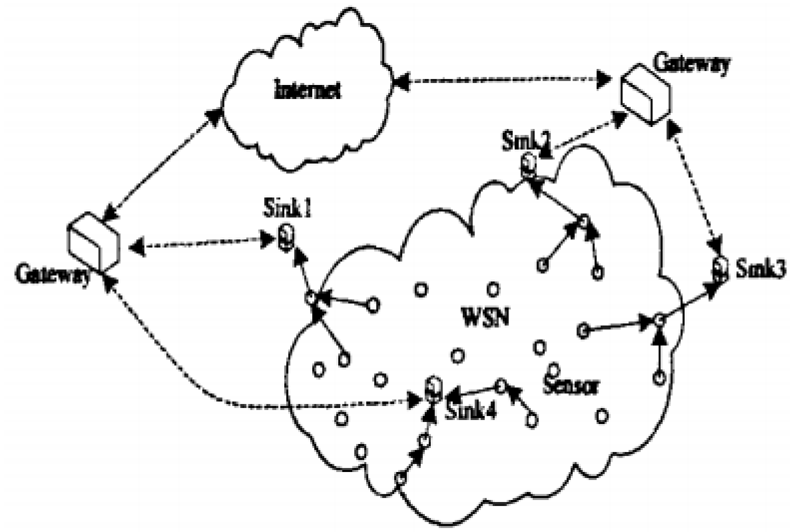

Fig. 1: Structure of wireless sensor networks with mobile sinks

Studies in the second class pay attention to the explicit decisions about sink moves. Furthermore, most of them provide mathematical optimization models that optimize some WSN performance metrics such as:

- The network lifetime
- The total energy spent
- Total cost for given data propagation protocols

In other words, the route (s) of the sink (s) are optimally determined with respect to the WSN performance metric chosen by the network designer. The models either employ an a priori data propagation mechanism such as the shortest path or they optimally determine the data routes from sensors to the sinks.

Gu considered a single mobile sink that is routed through a constant path repeated periodically. Sensors are assumed to have limited buffer sizes and the length of the sink path should be short enough so that the buffers of the sensors are not filled up between the sink visits. Researchers try to find such a path for the sink which ensures no data loss. They group the sensors according to their data collection rates and locations.

Somasundara *et al.* (2007) also analyzed the same problem but their solution approach is somewhat non-standard; they handle the problem as a single machine flow shop scheduling problem by taking the sink as the machine and the sensors as the jobs waiting to be processed by the sink.

Vincze *et al.* (2006) concentrated mainly on the energy usage of the sensors. They assign negative or positive charges to sensors and sinks by comparing the residual energy levels of the sensors and then apply the Coulomb's rule in a repetitive manner until the sink locations converge.

Nesamony *et al.* (2006) proposed a mathematical optimization model which assumes a mobile sink traveling within the network area to collect the data from the sensors in a single-hop fashion. A shortest sink route that passes through each sensor's transmission range is sought in the study.

Yun *et al.* (2013) also considered the queue-based delay tolerant model given in Yun and Xia (2010) and propose a decomposition algorithm for its solution. Hence, a distributed setting is implemented by that solution procedure.

Keskin *et al.* (2014) provided a mathematical model which integrates WSN design decisions of sensor places, activity schedules, data routes, trajectory of the mobile sink (s) and then present two heuristic methods for the solution of the model.

Rersearchers of Tunca *et al.* (2014) presented a survey of the existing distributed mobile sink routing protocols. The main focus of this study is about design and challenges associated with the problem.

Ant colony optimization: Biologically inspired computing is a field of study which is related to biology, computer science and mathematics. It uses computers to model nature and parallel study of nature to improve the usage of computers. Bio inspired computing is a major part of natural computation. It takes bottom-up and decentralized approach. Bio-inspired techniques involve the methods of specifying a set of simple rules, a set of simple organisms which follows those rules and a iterative method applies to those rules (Binitha and Sathya, 2012). Bio-Inspired Algorithms can be divided into two classes, namely, evolutionary algorithms and

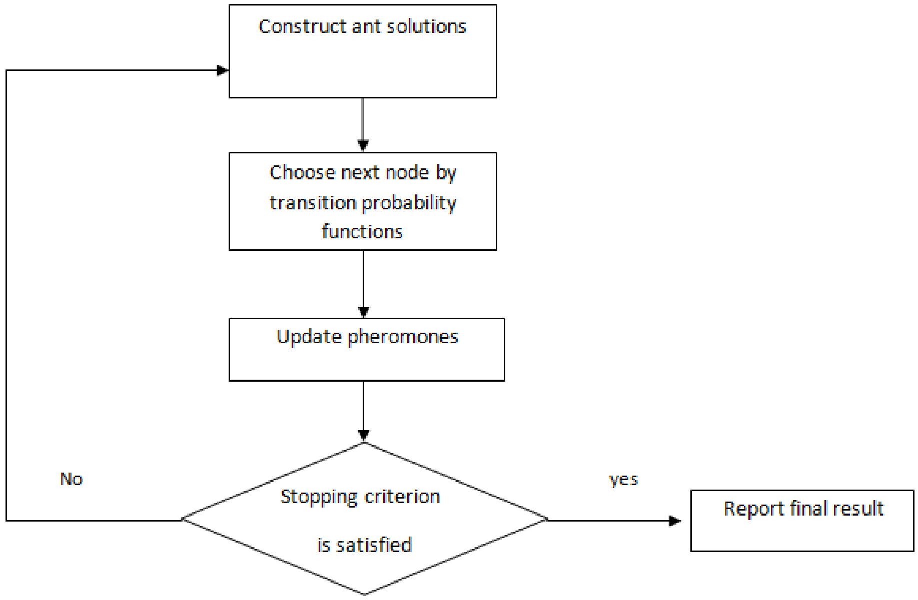

Fig. 2: Flowchart of ant colony optimization algorithm

swarm based algorithms which are inspired by the natural evolution and collective behavior in animals, respectively.

Swarm intelligence appears in biological swarms of certain insect species. It gives rise to complex and often intelligent behavior through complex interaction of thousands of autonomous swarm members. Interaction is based on primitive instincts with no supervision. The end result is accomplishment of very complex forms of social behavior and fulfillment of a number of optimization and other tasks. The main principle behind these interactions is called stigmergy or communication through the environment. An example is pheromone laying on trails followed by ants in ant colony optimization algorithm. Ant colony optimization algorithm is a metaheuristic (Dorigo *et al*., 2006) algorithm which is inspired by foraging behavior of ants. Pheromone is a potent form of hormone that can be sensed by ants as they travel along trails. It attracts ants and therefore ants tend to follow trails that have high pheromone concentrations. Ants attracted by the pheromone will lay more pheromone on the same trail, causing even more ants to be attracted. Ant colony optimization algorithm has advantages like:

- Scalability; population of the agents can be adapted according to the network size. Scalability is also promoted by local and distributed agent interactions.
- Fault tolerance; ant colony optimization processes do not rely on a centralized control mechanism. Therefore the loss of a few nodes or links does not result in catastrophic failure but rather leads to graceful, scalable degradation
- Adaptation; agents can change, die or reproduce, according to network changes
- Modularity; agents act independently of other network layers

Figure 2 shows flowchart of ant colony optimization algorithm.

MATERIALS AND METHODS

Proposed algorithm: The sensor network is modeled as a graph G(V, E) where V is the set of all the nodes in the square grid and E is the set of all links (i, j) where i and j are neighboring nodes. The V_s is a list which contains sink nodes. The sink can only be located at one node position in the grid. The sink keeps moving among grid positions until the maximum network lifetime is reached which occurs when one sensor node's residual energy drops below a predefined threshold. For calculating power consumption of sensor nodes in network, following formula is used:

$$P_{(i,j)} = E_{elec} + E_{amp} d(i,j)^{\gamma}$$

d(i, j) is the range of transmission for node (i) in network. α is the factor for path's importance in WSN. The ϒ has the value between one and five $(1<\Upsilon>5)$. The E_{amp} is power consumption of transmitter and E_{elec} is circuit's power consumption.

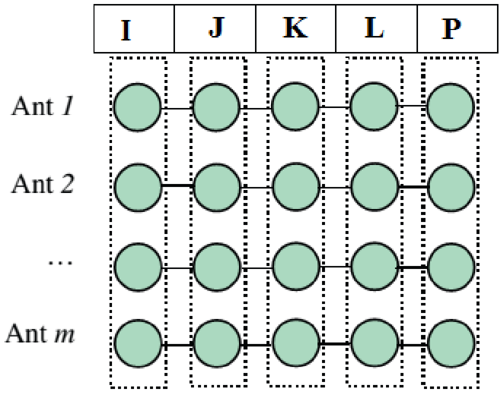

Fig. 3: Position of ants in the first step of ant colony optimization algorithm

In this architecture, each node must connect to head cluster which needs the least energy consumption. The energy which is needed to connect sensor to head cluster is calculated by:

$$\min: \sum_{j\in V_M}\left[\sum_{j\in V_s}\left[P_{(i,j)}\right]\right]$$

because, E_{amp} and E_{elec} are roughly the same. Equation 2 can be considered as follow:

$$\min: \sum_{j\in V_M}\left[\sum_{j\in V_S}\left[d^{\gamma}_{(i,j)}\right]\right]$$

In this study, a novel ant colony base mobile sink routing algorithm is presented. Ant colony optimization algorithm is a metaheuristic [22] algorithm which is inspired by foraging behavior of ants. Pheromone is a potent form of hormone that can be sensed by ants as they travel along trails. It attracts ants and therefore ants tend to follow trails that have high pheromone concentrations. Ants attracted by the pheromone will lay more pheromone on the same trail, causing even more ants to be attracted. We used this behavior to apply mobile sink routing in WSN. The algorithm starts from a population of ants which have random positions in network. Also a primary pheromone is assigned to each ant (τ_0). Figure 3 describes the beginning part of algorithm. Second step in ant colony optimization algorithm is evaluation. The amount of pheromone shows how appropriate the solution is. Evaluation (fitness) function is described by Eq. 5:

$$p^a_{ij}(t)=\begin{cases}\dfrac{\left[\tau_{ij}(t)^{\alpha}[\eta_{ij}]^{\beta}\right]}{\sum_{l\in N^a_i}[\tau_{il}(t)]^{\alpha}[\eta_{ij}]^{\beta}} & \text{if } \exists\, j\in N^a_i\\ 0 & \text{otherwise}\end{cases}$$

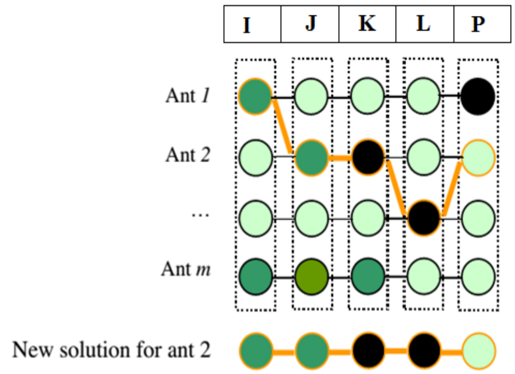

Fig. 4: Path selection in proposed ant colony optimization algorithm

The $\tau_{ij}(t)$ is the amount of pheromone on the edge of between node i and j in (t) iteration. N_i^{α} contains a set of nodes which are neighbors to node i. The α, β are the parameter related to balancing pheromone's value. The next step is updating pheromones. Following equation is used to update each ant's pheromone:

$$\tau_{ij}(t+1)=(1-\rho)\cdot\tau_{ij}(t)+\nabla\tau_{ij}(t)$$

Where:

$$\nabla\tau_{ij}(t)=\begin{cases}Q/F(\underline{x})\,\forall x_{ij}\in\text{candidate group}\\ 0\ \text{otherwise}\end{cases}$$

The Q is a constant. $\tau\nabla_{ij}$ is related to alternation in pheromone's value. The last step is selecting a new path for each ant according to pheromone's value. Figure 4 shows the process of path selection. Path selection is done based on roulette wheel and probability function as follow:

$$p^a_{ij}(t)=\begin{cases}\dfrac{\left[\tau_{ij}(t)^{\alpha}\right]}{\sum_{l\in allowed}[\tau_{il}(t)]^{\alpha}} & \text{if } \forall x_{ij},x_{il}\in \text{allowed}_a\\ 0\ \text{otherwise}\end{cases}$$

Allowed_{α} is a set of candidates for ant$_{\alpha}$ $P^{\alpha}_{ij}(t)$ is probability function of ant$_{\alpha}$ for selecting path between node i and j.

RESULTS AND DISCUSSION

In this study simulation results of proposed algorithm is presented. Implementation of ant colony based mobile sink routing algorithm was developed in MATLAB. MATLAB is a high-level technical computing

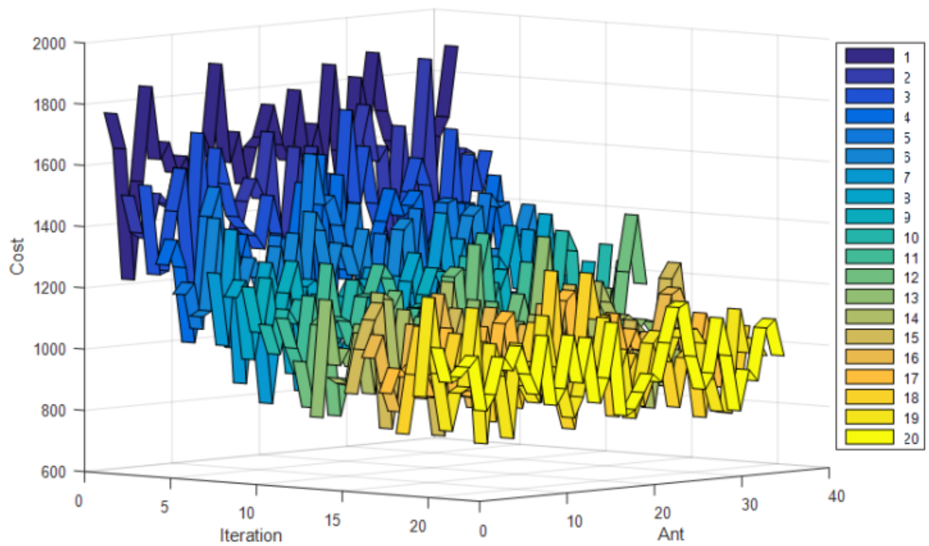

Fig. 5: Diagram of cost per iteration

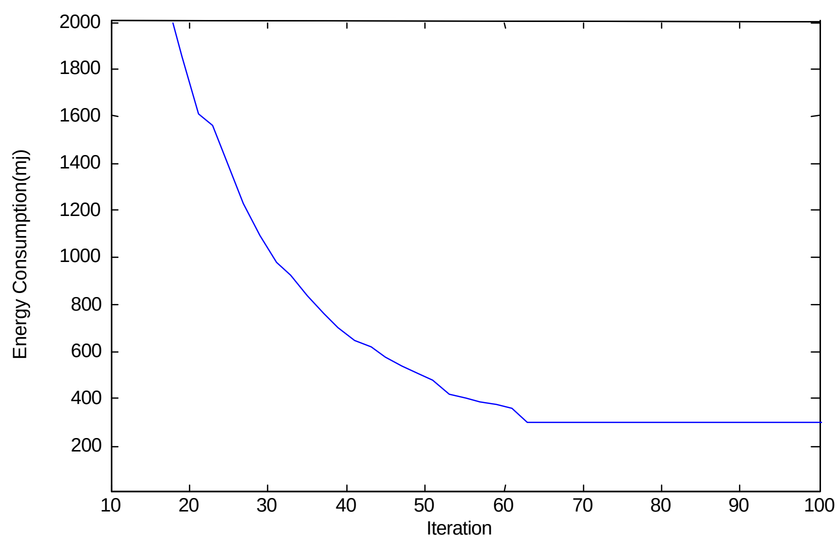

Fig. 6: Energy consumption through different iteration

Table 1: Simulation parameters

Parameters	Values
Simulation environment	100×100 m^2
Sensor range	10 m
α	1
β	1
Iteration	300
No. of ants	50
ρ	0.05
η 1	100 pJ/sec/m
η 2	1 nJ/sec
Size of packet	256 bit

language and interactive environment for algorithm development. For optimization part of algorithm, AMLP Software (Gay, 2015) is used. Simulation environment is considered as 100×100 m^2 and also sensor nodes are static

Figure 5 shows changes in selecting paths for ants through process of ant colony optimization in different iteration. As shown, in first iteration the cost is high for moving mobile sink. The main reason for this problem is lack of pheromone on the path. Through iteration the cost declines till it reaches the minimum value.

Energy consumption of network based on iterations is depicted in Fig. 6. Energy consumption decreases

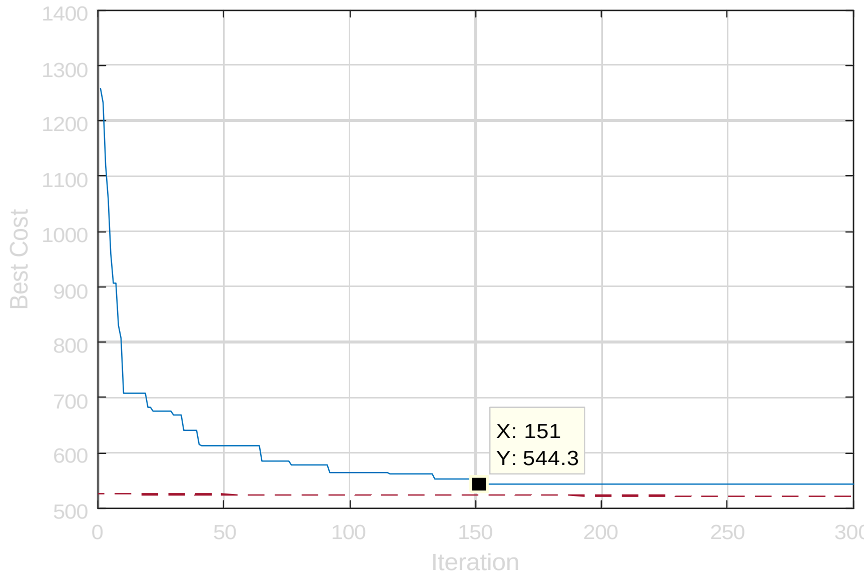

Fig. 7: Value of best cost according to iterations

through iterations. Until it reaches the minimum point. Figure 7 depicts best cost in each iteration in ant colony optimization algorithm.

CONCLUSION

We studied mobile sink routing problem in this study. A novel ant colony based algorithm is proposed to improve network's lifetime. Ant colony optimization algorithm is a metaheuristic which has been widely used in optimization problems. Lifetime improvement is done by decreasing energy consumption of network and finding optimized path. We implementation the presented algorithm in MATLAB. Also, AMLP Software is used for optimization part of algorithm. Experimental results proved that not only the proposed algorithm is accurate but also it improves wireless sensor network's lifetime.

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