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Adaptive Clustering Based Dynamic Routing of Wireless Sensor Networks via Generalized Ant Colony Optimization

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Abstract

Wireless sensor networks (WSNs) use battery-powered sensor nodes for sensing, thus the energy efficiency is critical to extend the lifespan. The performance depends on the trade-off among energy consumption, latency and reliability. Data aggregation is a fundamental approach to eliminate redundancy and minimize transmission cost so as to save energy. Dynamic clustering based routing is proposed to achieve good performance via adaptive algorithms. The generalized Ant Colony Optimization (ACO) is applied to increase the reliable lifespan of sensor nodes with energy constraints. Each sensor node is modeled as an artificial ant and dynamic routing is modeled as ant foraging. The ant pheromone is released when an energy efficient channel from the source to sink is secured. Route discovery, data aggregation and information loss are modeled as the processes of pheromone diffusion, accumulation and evaporation. Each sensor node estimates the residual energy and dynamically calculates probabilities to select an optimal channel to extend the lifespan of WSNs.

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Keywords: Wireless Sensor Networks; Ant Colony Optimization; Data Aggregation; Adaptive Rule; Clustering Based Dynamic Routing.

1. Introduction

Contrary to classical networks, the structure of wireless sensor networks encompasses numerous small or tiny battery powered autonomous devices, serving as the sensor nodes. Each node relies on the wireless channels for transmitting and receiving data with other nodes.

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Adaptive protocols are needed since the WSNs differ in the network densities, from sparse to dense deployments. The combination of computing, sensing and communication technologies makes it possible for compact design. With dense deployment, broadcasting by flooding leads to information redundancy. It gives rise to applications of adaptive routing schemes [1]. WSNs encounter typical challenges, such as interference, security, scalability and handoffs. With respect to an example of wireless cellular networks, despite of the fact that voice and data transmission speed is gradually increasing, optimal distribution of energy consumption remains a tough challenge. The power control strategy based on Signal to Interference plus Noise Ratio (SINR) balancing is necessary to minimize energy consumption and optimize power control in cellular networks to achieve best energy distribution. The energy of the sensor nodes mainly consists of transmission energy and overhead energy, while the transmission energy is subject to attenuation and fading with respect to distance and frequency, which also differs between single-path and multi-path propagation [2]. Optimization of transmission energy consumption is designed to maximize the network lifetime with each single layer. Simplifications are made to decouple layers and maximize the network lifetime. The approach is extended to cross-layer optimization of time division multiple access WSNs with an arbitrary degree of accuracy and efficiency. Numerical examples illustrate benefits of the cross-layer design [3]. Energy efficiency is critical to extend network lifetime. The energy wasted by redundant sensors can be reduced by sensor mode switching, but frequent alteration has negative effect on reliability. Ant colony optimization is proposed to obtain the maximum reliable sensor working periods. The minimum sensor working period is restricted before mode changing. The proposed algorithm enhances scheduling reliability of WSNs [4]. WSN data aggregation is an important technique for data collection which improves the energy efficiency, alleviates data redundancy and reduces congestive routing traffic in message transmission. Ant colony aggregation is also proposed to provide an intrinsic way of exploring the search space to optimize settings for optimal data aggregation. The algorithm yields longer maximum lifetime and better scalability with the same hop-count delay [5]. An artificial ant colony is applied to the distributed sensor wakeup control in WSNs to accomplish both surveillance and target tracking. Communication, invalidation and fusion of target information are modeled as pheromone diffusion, loss, and accumulation. The advantages include that no requirement of cluster leaders, robustness to false alarms, and no need of actual node position [6]. The ACO for data aggregation consists of 3 phases of initialization, transmission and operation. In transmission, each sensor node estimates the remaining energy and pheromone amount of neighbors to dynamically select the next hop. After transmissions, the pheromones are adjusted in terms of global and local merits for evaporating or depositing. It shows high superiority on efficiency in energy constrained WSNs. It also benefits to the network lifetime, computation complexity and success ratio of one hop transmission [7]. Sensor nodes in dense networks generate redundant information, so data aggregation should be conducted to save energy. Packets of diverse applications are unlikely aggregated by heterogenous sensors, thus static routing protocols are substituted by dynamic routing protocols, since the spatial isolation caused by static routing is unfavorable to data aggregation. Attribute-aware data aggregation is introduced to enhance efficiency. Inspired by potential in physics and pheromone in ant colony, dynamic routing is elaborated where the packets of same attribute are made spatially convergent. It is also scalable with respect to network size and adaptable to mobile tracking mobile [8]. A novel clustering based data collection scheme is applied with direct sink access to evaluate performance in terms of energy consumption, latency, and robustness. With joint effect of clustering and data correlation, cluster heads use low overhead and simple medium access control. Since data are collected periodically where the packet arrival is not a continuous random process, the framework is based on transient analysis rather than steady state analysis. Extensive simulations with various protocol parameters show that is is fairly accurate across a wide range of parameters. Despite the trade-off between energy consumption and latency, both can be substantially reduced by proper clustering design [9]. In this work, adaptive schemes using generalized Ant Colony Optimization will be applied to clustering based dynamic routing of WSNs.

2. Adaptive Clustering Based Dynamic Routing in Wireless Sensor Networks (WSNs)

With rapid technology advancement in Micro-Electro-Mechanical Systems (MEMs), dense WSNs could be widely deployed with hundreds or thousands of micro sensors, so suitable routing is necessary for extending the lifespan of low cost, low power and super compact sensor nodes and micro sensor nodes. Hierarchical routing protocols are designed to partition WSNs into clusters, where artificial intelligence has been applied for dynamic routing via generalized Ant Colony Optimization. The quality of service (QoS) metric should also be defined to elect the cluster heads, whose criteria cover both the residual energy and connectivity (distance, hop count to sink). The total number of clusters is subject to slight change along with the time which depends on the threshold defined, and change of cluster heads will be scheduled as infrequently as possible. The source node is the node that can provide required information to the network. Initially each source node could claim to be the cluster head covering a cluster with all N hop count neighboring sensor nodes. All sensor nodes will be grouped into clusters. Inside a cluster, the covered node with the highest amount of QoS metric is voted as the cluster head. All sensor nodes are assumed to have an equal amount of initial energy. Starting from the next round, each unvisited source node can still claim to be the cluster head of a cluster covering all N hop count neighboring sensor nodes. When the energy of any cluster head node is depleted, those nodes fail in communicating with the sink turn out to be dead nodes. Thus reelection will be scheduled, the source node with the highest amount of QoS metric is voted as the new cluster head. It is possible that the cluster head has been generated, replaced or completely depleted. The number of dead nodes should be recorded as time goes on which in fact represents reliability and expected lifespan of sensor networks. If the source does not receive a response within a time period, it backs off exponentially before trying to send a route request again.

Cluster structure changes slightly in presence of gradual revisions of network topology. All sensor nodes that are within the N hop count communication range of the cluster head belong to this cluster. For any sensor nodes within the communication range of at least two cluster heads, it is also referred to as a gateway node. Upon data aggregation, the cluster head collects the cluster information and sends a summary to neighboring cluster heads via gateway. Any cluster head keeps information of every sensor nodes of the cluster in a topological table. The table provides gateway assess with the neighboring cluster list, distance list, and hop count list to reach neighboring clusters, other clusters and sink node cluster. Through data transmission, sensor nodes transmit information to the cluster head node so that the cluster head can aggregate all information. The gateway sends information to neighboring cluster heads step by step till the destination cluster head is reached. Eventually all data will be sent to the sink node. Data aggregation is critical to prolong the lifespan of WSNs. When the size of WSNs increases, extra amount of data flow involves so those sensor nodes near the sink node essentially dissipate energy more rapidly than other nodes less visited or unvisited. Since sensor nodes near the sink will use up energy more rapidly than sensor nodes far away from the sink, which turn out to be dead nodes, the reconstruction of cluster has to be made where the nodes close to the sink will be revoked. In order to increase energy efficiency of routing, the QoS metric is defined on a basis of distance between neighboring sensor nodes, average hop count to the sink node, and residual energy of the sensor node.

The hierarchical routing contains both proactive and reactive routing protocols, covering initially proactive routing and subsequently reactive flooding on covered nodes rather than packet propagation throughout the entire network. In proactive routing protocols, all sensor nodes keep updating existing tables to maintain the concurrent information of WSNs. Once network topology changes, update information on clusters and cluster heads will be propagated throughout the network. When any connection is broken, the message is sent back to generate local recover mechanism. When the next hop is unreachable, the sensor node will seek for other alternative neighboring nodes that help to reach upcoming hops. If a solution is reached, the packet will be sent out over the newly selected channel. Dynamic routing protocol has two major phases of route discovery and route maintenance. When a cluster head sends a packet to a sink node, it must identity the availability of the existing route so that the packet can be sent in a straightforward way, otherwise it will initiate the route discovery via directional flooding by sending a route request packet with information of the cluster head, sink node and identification index. A route request packet contains the sequence of hops counted from the cluster head to destination. When destination receives the route request packet, positive feedback information is sent back as a route response. If an abnormal transmission condition occurs, the sensor node will generate a route error packet accordingly, so that the corresponding hop is removed and the alternative route is applied.

3. WSNs Energy Dissipation Models

Communication of WSNs takes place between the source node and sink node. Each source node generates a data packet to reach the intermediate sensor nodes and eventually the sink sensor node via routing. The data packets are transmitted through active sensor nodes while other sensor nodes stay idle upon communication. It is possible that some data packets could be merged into one packet on the way to destination. The energy model must cover transmission path loss energy, sensing energy, receiving energy and computing energy dissipation at sensor nodes. Fading and attenuation are neglected in simplified models. It is also assumed that the packet loss has no effect on actual energy dissipation for sending or receiving a packet. Routing decisions are made with respect to least energy routing topologies at diverse transmission power levels. For example, a direct link from the source node to sink node represents simplest connection. When multi-hop transmission is applied, a group of intermediate nodes must be introduced, giving rise to a raise in the hop count between the source nodes and sink node as well as additional path energy dissipation. Since the network lifespan depends on the length of time for the first battery to be drained out among all nodes, lifespan is shortened due to excessive path energy dissipation. Assuming the energy dissipation is dominated by wireless communication instead of computation. Energy consumption for sending and receiving a packet of size s is expressed as (1).

$$E_{CO}(d, s)=(E_{TR\_ELE}+E_{AMP}+E_{RE\_ELE})\times s = (E_{TR\_ELE}+\gamma\times d^{\lambda}+E_{RE\_ELE}) \times s \tag{1}$$

where $E_{CO}(d, s)$ is total energy consumption for sending and receiving a data packet of the size s [Bit]; E_{TR_ELE} [J/Bit] is the overhead energy of transmitter electronics that accounts for both analogue and digital signal processing (e.g., phase lock, modulation, digital coding and filtering); E_{AMP} [J/Bit] is the transmission energy consumed in power amplifiers which is a function of the distance; E_{RE_ELE} [J/Bit] is the overhead energy of receiver electronics that accounts for both digital and analogue signal processing (e.g., digital decoding, demodulation); d [m] is the Euclidean distance for signal transmission between two sensor nodes; γ [J/Bit*m^{λ}] is the coefficient for transmission amplifying; λ is path loss exponent. For power loss of single path propagation, free space channel model is applied where λ is equal to 2. For power loss of multiple path propagation, multipath fading channel model is applied where λ is equal to 4. Now define E_{IN} and $E_{RS}(d, s)$ as the initial energy and residual energy of the sensor node, then the residual energy is determined by (2).

$$E_{RS}(d,s)= E_{IN}-E_{CO}(d,s)=E_{IN} -(E_{TR\_ELE} +\gamma\times d^{\lambda}+E_{RE\_ELE})\times s \tag{2}$$

The sensor node residual energy monotonically decreases along with time. When any path is excessively applied, the associated residual energy decreases dramatically under exceptional energy consumption, path switching should be triggered. Dynamic routing is implemented using adaptive aggregation.

4. Adaptive Clustering Based Dynamic Routing Via Generalized Ant Colony Optimization (ACO)

The ACO algorithm simulates the natural behavior of ant foraging. The moving ants are trying to locate the pheromones deposited on the way between food resources and nests. Collective intelligence of artificial ants is modeled as a practical combinatorial optimization problem. An individual ant shares information with other ants by depositing pheromones and interacting between ants and environment. In this case, the colony of ants functions as the cooperative agents in order to perform necessary tasks such as selecting the shortest trail to reach the sources of food. The pheromones also evaporate along with the time so that new possibilities come up when ants cooperate again to select the path with high amount of pheromones. Based on the pheromone trails and heuristic information, multiple routing preferences are available with certain probabilities, the whole colonies of ants will be modeled as societies of moving agents. The artificial ants cooperate and record information such as positions and qualities from existing options. Best trail information is reached via communication and comparison. The purpose of covering heuristic information is to inspire ants to reach candidate search regions via collective interaction among ants. The updated learning rule is determined by the amount of pheromone accumulated, which serves as an iterative feedback mechanism. This learning process also represents the natural phenomenon that ants are seeking for food randomly between the colony and food sources. Pheromone trails to food sources visited by some ants are more likely to be followed by other upcoming ants. On the other hand, the amount of pheromone will be reinforced if other ants also locate food successfully. The updating rule of foraging is in favor of the trails with high amount of pheromone and short distance. The larger distance for ants to commute, the longer time for pheromones to evaporate. Excessive accumulation can be avoided due to pheromone evaporation, so that convergence to global rather than local optimization is reached. Both reinforcing and evaporation processes have strong impact on the pheromone density, while constraints should be set up for exploration and exploitation process. Via positive feedback, the optimal trail information is accepted by all ants eventually. Ant colony aggregation represents a stigmergy system where the ants exchange information mutually by depositing pheromones so that the shortest trail to the source is reached. The initial cluster heads are elected by comparing the residual energy E_{RS} of all sensor nodes within neighborhood of N hop count distance. All source sensor nodes are candidates among whom those with the highest residue energy are voted as the cluster heads of a cluster within neighborhood of N hop count distance. The total number of clusters is subject to slight change in the subsequent update procedures. However, frequent changes of cluster heads ought to be avoided. Then two updating rules will be applied by computing probabilities in the routing table in terms of the amount of pheromone and visibility function. The pheromone is a major component to determine probabilities in the routing table. The first step in ACO is the trail selection between neighboring clusters. When an individual ant walks from cluster head i to cluster head j, the probability in the selection rule for a single ant is defined as (3).

$$p_{i,j}=(\tau_{i,j})^{\alpha}(\eta_{i,j})^{\beta} / \sum[(\tau_{i,j})^{\alpha}(\eta_{i,j})^{\beta}] \tag{3}$$

where $\tau_{i,j}$ represents the amount of pheromone on the trail from cluster head i to cluster head j; $\eta_{i,j}$ is the trail visibility function equal to the reciprocal of the energy distance between two cluster heads i and j; α is a parameter to adjust the impact of the amount of pheromone $\tau_{i,j}$; β is a parameter to adjust the impact of the heuristic visibility function $\eta_{i,j}$. The chosen trail is expected to have large visibility. The heuristic visibility and energy distance metrics are defined as (4), where factors of the geometrical Euclidean distance, overhead energy of transmitter electronics and transmission energy dissipated in power amplifiers are all considered.

$$\eta_{i,j} = 1 / E_{DIS}(i, j);\ E_{DIS}(i, j)=(E_{TR\_ELE} + E_{AMP}) \times s = (E_{TR\_ELE} +\gamma\times\|d_{ij}\|_2^{\lambda})\times s \tag{4}$$

where $E_{DIS}(i, j)$ represents the energy distance metric between cluster head i and cluster head j, $\|.\|_2$ represents the Euclidean distance, $E_{TR\ ELE}$ and E_{AMP} represent the overhead energy of transmitter electronics and transmission energy, respectively; γ is a coefficient for amplifying and s is the pack size. Thresholding is applied for binary decision making if a newly generated random number is acceptable or not. (3) does not apply if the generated random number is less than the threshold. In this case, $p_{i,j}$ is assigned as one when the cluster head j was unvisited recently, which favors transition probability maximization; otherwise $p_{i,j}$ is assigned as zero when the cluster head j was visited. Both local update and global update rules will be applied in the pheromone update step, where the local update is solely applied to any individual artificial ant, but global update is applied when ants in the whole colony have made trips successfully. The local update is independent of the interaction within the colony, while the global update contains information on interaction within the colony. The local pheromone update rule is defined as (5).

$$\tau_{i,j}(t+1) = (1-\rho)\tau_{i,j}(t) + \Delta\tau_{i,j} \qquad (5)$$

where ρ is the rate of pheromone evaporation ($0<\rho<1$); $\tau_{i,j}$ is the pheromone amount on the trail between the cluster head i and cluster head j, which is equal to the total energy dissipation at the current round for communication between cluster head i and cluster head j; $\Delta\tau_{i,j}$ is the amount of pheromone being deposited; $\Delta\tau_{i,j} = \eta_{i,j}$ when the ant travels on a trail between cluster head i and cluster head j. Evaporation of pheromone is necessary so as to avoid excessive accumulation. For those cluster heads not chosen by artificial ants, the amount of pheromone decreases exponentially, which conforms to the fact that if any WSN sensor node does not receive a reply within certain period of time, the sensor node has to back off exponentially before another route request will be sent again. To prevent searching procedures from stagnation, constraint minimal amount of pheromone is specified which represents the least necessary amount of the residue energy of the sensor nodes. The pheromone amount s simultaneously affected by two processes of evaporation and deposition. The global pheromone update rule is defined as (6).

$$\tau_{i,j}(t+1) = (1-\rho)\tau_{i,j}(t) + \rho(E_{RS} / E_{IN}) \qquad (6)$$

where ρ is the rate of pheromone evaporation; $\tau_{i,j}$ is the amount of pheromone; E_{RS} and E_{IN} are initial energy and residue energy, respectively. The local update and global update will both applied to the ACO problem to achieve a balance between exploration and exploitation. In this case, global optimization can be reached via adaptive clustering based dynamic routing.

5. Case Studies on Adaptive Clustering Based Dynamic Routing Via ACO

Since WSNs differ significantly in network densities, both sparse and dense deployment cases should be taken into account. Within an area of one square mile, 100 and 256 sensor nodes are randomly placed to represent two different cases. The overhead energy of transmitter electronics ETR_ELE is selected to be 50nJ/Bit. The overhead energy of receiver electronics ERE_ELE is selected to be 50nJ/Bit. The transmission amplifying coefficient γ is selected to be 100J//Bit*m2. The threshold is selected to be 0.5. Path loss exponent λ is equal to 2 and the rate of pheromone evaporation is equal to 0.25. The initial sensor node energy E_{IN} is selected as 1J. The packet size s is 1024 Bits. For the dense sensor deployment case, simulation results of initial round, as well as 10, 100, and 1000 rounds are recorded for data analysis. For the sparse sensor deployment case, simulation results at initial round, as well as 10, 100, and 500 rounds are recorded for data analysis. In simulations, symbols of source nodes, covered nodes, cluster heads, sink nodes and dead nodes are listed in Fig. 1. The lifespan curves of sensor nodes in dense and sparse WSNs dynamic routing are shown in Fig. 2. The iterative routing process in the dense deployment case is shown in Figs. 3-4 and the iterative routing process in the sparse deployment case is shown in Figs. 5-6.

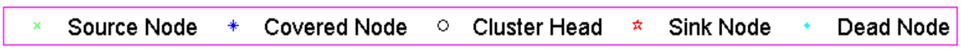

Fig. 1. Symbols in WSNs Dynamic Routing Via ACO

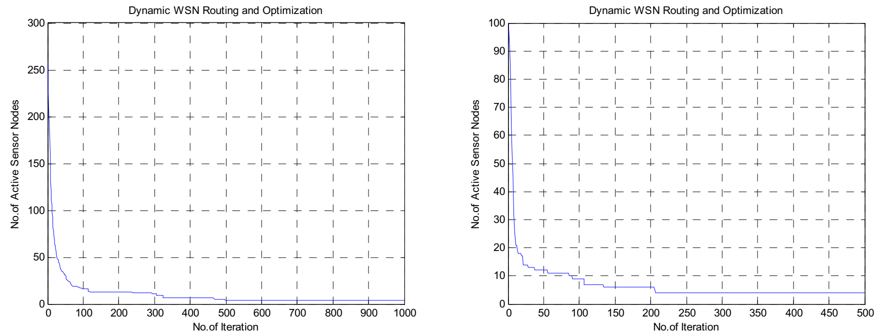

Fig. 2. Lifespan Curves of Sensor Nodes in Dynamic Routing (a) Dense WSNs; (b) Sparse WSNs

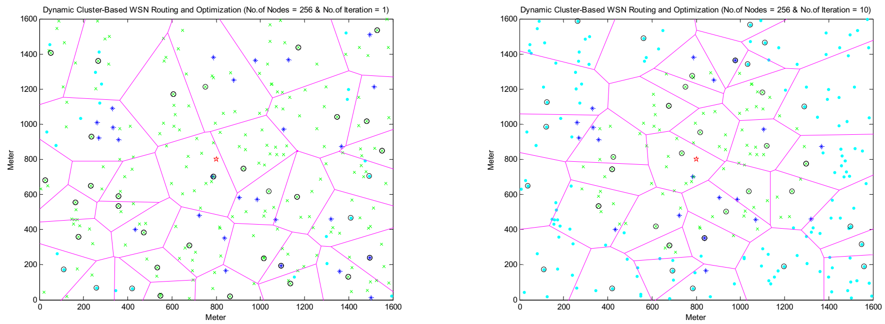

Fig. 3. Dense WSNs Dynamic Routing Via ACO – Initial Stage (a) Round 1; (b) Round 10

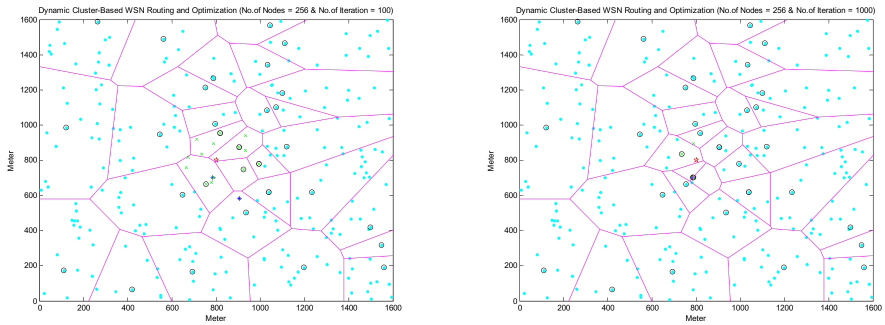

Fig. 4. Dense WSNs Dynamic Routing Via ACO – Middle Stage and Final Stage (a) Round 100; (b) Round 1000

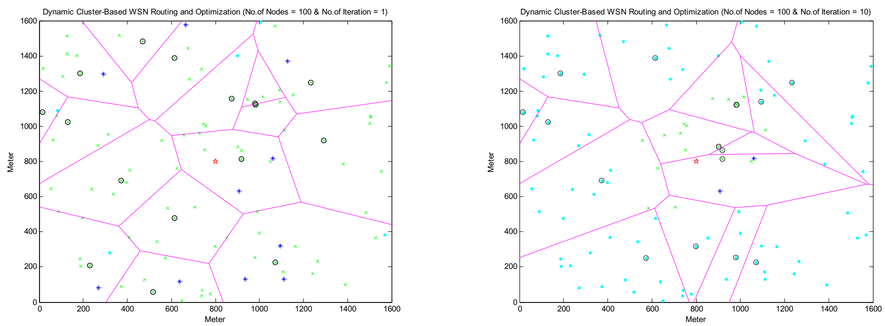

Fig. 5. Sparse WSNs Dynamic Routing Via ACO – Initial Stage (a) Round 1; (b) Round 10

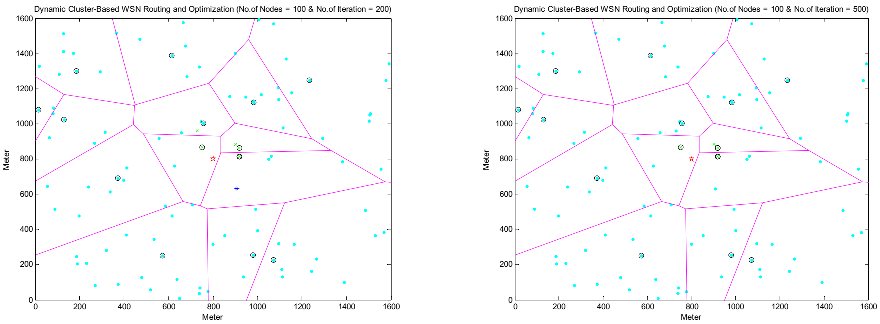

Fig. 6. Sparse WSNs Dynamic Routing Via ACO – Middle Stage and Final Stage (a) Round 100; (b) Round 500

Based on Figs. 1-6, more clusters and cluster heads are needed in dense network than sparse network deployment. For both cases, cluster structure changes more frequently while structure of cluster heads is more stable. Since single sink node rather than multiple sink nodes is applied, more transmission energy is dissipated for remote sensor nodes rather than nearby nodes, some of which turn out to be dead nodes quickly. The two curves on active sensor nodes imply that the total number of these nodes decreases exponentially as time goes on. All results also show that the generalized ACO scheme is well designed for clustering based dynamic routing of WSNs using adaptive updating rules.

6. Conclusions

An adaptive routing protocol for WSNs is presented for data aggregation optimization to alleviate network congestion and eliminate data redundancy to improve energy efficiency. Ant colony optimization routing has provided an essential approach to explore optimal settings for data aggregation and channel selecting. Classical clustering hierarchy protocol is expanded to the low energy dynamic routing via adaptive schemes. Generalized ACO is designed to optimize selections of clusters and cluster heads so as to distribute energy overhead evenly among all sensor nodes for better energy resource harvesting via novel dynamic routing protocol. Simulations are made with respect to energy consumption and connectivity. The critical energy efficiency of WSNs can be improved with a balance between efficient routing and energy consumption.

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