Applying FIFO-Queue ACO Algorithm to Broadcast Problem of Wireless Sensor Networks

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Abstract

Minimum-energy Broadcast Problem in wireless sensor networks is categorized as an NP-complete problem in which one sensor node sends packets to all other nodes in network under the condition of minimizing the total power dissipation of all nodes in sending. In this paper, we investigate an application of FIFO-queue Ant Colony Optimization (ACO) algorithm to this problem. Experimental results show that FIFO-queue ACO can find better solutions than other algorithms.

1 Introduction

Wireless Sensor Network (WSN) is a system for dynamic environmental monitoring. A large number of so-called sensor nodes (hereafter, nodes), each of which is responsible for collecting measurements and for interacting with other nodes, form a network in self-organized ways. Communications among nodes are performed cooperatively for relaying measurements obtained by nodes to the host computer at outside of the network as well as for distributing commands from the host computer to nodes; almost all the nodes do not need to communicate to the host computer directly. WSN can be formed easily and rapidly, because there are no wires for communication. For this reason, WSNs are favorable for monitoring dangerous areas, such as disaster areas. Nodes are driven only by their built-in batteries, thereby they determine the lifetime of a WSN.

It is important to reduce the power consumptions of nodes from the viewpoint of the cost-effectiveness for WSNs. The task of broadcasting, i.e., a node (or the host computer) sends commands to all the nodes, is important for operating a WSN and is the most power-consuming task. This task can be formulated to a combinatorial optimization problem, known as Minimum-energy Broadcast Problem (MBP) [1]. MBP is an NP-complete problem where the total power dissipation for all the nodes should be minimized under the condition that all the nodes receive a packet of data from a node.

It is shown that an Ant Colony System (ACS) [2] approach is effective for finding good solutions for MBP [3]. ACS is a particular class of Ant Colony Optimization (ACO) meta-heuristics [4], which are inspired by observations of biological ants' behaviors. On ACS, several agents make candidates of the solution according to the best candidate in the past, choose the best candidate among them, and preserve it. The cycles of 'make candidates'–'evaluate'–'preserve' lead the candidates to gradually improved. However, it is prone to fall into one of local minima in the search space because this strategy utilizes the only one candidate in the past cycles.

In this paper, we propose a method to cope with MBP by applying a FIFO-queue ACO algorithm [5]. FIFO-queue ACO is also a class of ACO meta-heuristics. Several candidates in the past cycles are put in the queue with a certain length that works in a first-in-first-out (FIFO) manner and are available for making candidates. This approach corresponds to a kind of multiple-point search methods and is expected to avoid local minima. We show the effectiveness of our proposed method, by comparing with ACS and Broadcast Incremental Procedure (BIP) that is an approach mainly used for MBP, through computer simulations. The performance is evaluated by the total power dissipations with respect to the number of nodes in the network. Before describing the ACS and FIFO-queue procedure for MBP in sensor networks, first we assume the network model.

2 Minimum-energy Broadcast Problem

We assume a WSN that consists of fixed N-nodes. Any node can be used as a relay node to bring a packet to other nodes in the network. All nodes have omnidirectional antennas, so that if the node i transmits to node j, nodes closer to i than j will also receive. The power consumption for node i sending a packet to node j, P_{ij}, is defined as:

$$P_{ij} = [(x_i - x_j)^2 + (y_i - y_j)^2]^{\alpha/2} \qquad (1)$$

where (x_i, y_i) $(1 \leq i \leq N)$ are the coordinates of the nodes in the network, and $\alpha(2 \leq \alpha \leq 4)$ is the channel loss exponent. Minimum-energy Broadcast Problem (MBP) is a problem to find the minimum power dissipation for all the nodes when a source node sends a packet to all other nodes in the network. This is categorized as NP-complete because the solution space expands exponentially with respect to linear increase in the number of nodes in the network.

3 Ant Colony Optimization Meta-heuristic

Biological ants can find short paths between their nest and food placed at a distance. This is performed by indirect communications among them by the use of their pheromones. This behavior of ant colonies has motivated the design of Ant Colony Optimization (ACO) Meta-heuristic. The ACO Meta-heuristic has been applied to several combinatorial optimization problem for which the construction of a solution can be described as a path in a decision graph. An ACO Meta-heuristic is an iterative search process where in every iteration each of M (artificial) ants constructs one candidate for the solution by following a path through the decision graph. In their constructions, which edge in a graph should be chosen depends on pheromone information, which is modified by the candidates made by former ants. The pheromone information τ_{ij} represents the effectiveness in sending packets from node i to node j. The pheromone information is stored in a so called pheromone matrix where element τ_{ij}, indicate how good it seems to send packet from node i to node j, for $i, j \in [1 : N] = \{1, ..., N\}$. Ants tend to choose an edge in a graph with relatively high value of pheromone information.

In every generation each of m ants construct one solution that describes a sequence of broadcasting. Starting at a source node an ant selects the next transmission using pheromone information as well as heuristic information. The heuristic information, denoted by η_{ij}, is static information that wouldn't change. The heuristic value is $\eta_{ij} = 1/P_{ij}$.

Let R and NR be a set of nodes that have received data and a set of nodes that have not yet respectively. Each of ants start to make a candidate from $R = \{Source\}, NR = \{\text{other } N-1 \text{ nodes}\}$. An ant makes a transmission to choose a sender node i from R and a receiver node j from NR with probability q_0 so that this transmission maximizes $\tau_{ij} \cdot \eta_{ij}^{\beta}$, where $\beta = \{\beta_A, \beta_B\}$ is a parameter for each ant; otherwise a transmission is determined by choosing nodes i and j according to the probability distribution described as

$$p_{ij} = \frac{\tau_{ij} \cdot \eta_{ij}^{\beta}}{\sum_{k \in R, l \in NR} \tau_{kl} \cdot \eta_{kl}^{\beta}}. \qquad (2)$$

It repeats to select a sender and a receiver by these manners until all node have received data, i.e., $NR = \{\phi\}$. A parameter β determines the characteristic of an ant. An Ant with a large β tends to choose transmissions with low power consumptions, while one with a small β may take transmissions that need high power consumptions. In our experiments, each of ants have either β_A or β_B as the value of β where $\beta_A \geq \beta_B$ for enriching the diversity of candidates.

After all the ants make candidates for a solution of MBP, each of these candidates is evaluated by calculating the total power dissipation of it. The pheromone information τ_{ij} is then updated by the quality of these candidates. The τ_{ij} is increased (decreased) when the transmission from node i to node j is included in the candidate with a good(worse) evaluation. After modifications of pheromone information, ants start to make candidates again.

We have shown the general scheme of ACO Meta-heuristic. The updating of pheromone information are most important in ACOs, because the actions of ants deeply depend on these information and irrelevant modifications for them lead ants to one of local minima, not to the global minimum in the search space. For this reason, several scheme for updating pheromone information have been proposed, such as Ant Colony System (ACS)[3] and FIFO-queue ACO[5]. In the following we will describe them with focusing on updating scheme.

3.1 Ant Colony System

In ACS, there are two rules for updating pheromone information τ_{ij}, which represents *evaporation* and *deposit* of pheromone. The rule of evaporation makes the ants not to choose the same transmission as previously selected one, and it is expressed by

$$\tau_{ij} \leftarrow \rho\tau_0 + (1-\rho)\tau_{ij}, \quad \forall (i,j) \in T_k \qquad (3)$$

where $0 < \rho < 1$ is the evaporation constant that determines inheritance of the past transmissions, τ_0 is the initial value of pheromone, and T_k is a set of transmissions made by ant k. This rule is applied at each time of each of ants making a candidate.

After all the ants make candidates and evaluation for them are finished, the deposit rule is applied. Let *best* be the index of the candidate with the best evaluation out of all the candidates in the past, the deposite rule is represented as follows:

$$\tau_{ij} \leftarrow \rho / Y_{best} + (1-\rho)\tau_{ij}, \quad \forall (i,j) \in T_{best} \tag{4}$$

where Y_{best} and T_{best} are the total power dissipation and the set of transmissions, respectively, for the best candidate. By using this rule, the value of τ_{ij} increases where the transmission from node i to node j is contained in the best candidate, and hence searching the solution is performed around the best candidate in the past.

3.2 FIFO-queue ACO

FIFO-queue ACO algorithm is one of extension from ACS algorithm. The key idea of updating pheromone information is to introduce *queue* that can store several candidates and works First-In-First-Out (FIFO) manner. These candidates are also used for updating τ_{ij}.

Let $T_k(t)$ be the candidate made by ant k and $T_{min}(t)$ be the best candidate at the iteration t. Ants make the candidates $T_k(t)$ for each iteration, $T_{min}(t)$ is chosen so that it has the least power consumption, and it is then put in the queue. This queue has a certain capacity so that up to certain number (say, K) of candidates can be stored, and it is empty at $t = 0$. When it contains K candidates and a new candidate come in the queue, the candidate that was put in at the earliest ($T_{min}(t-K)$) is removed. The updating of τ_{ij} are performed on the addition of new candidate ($T_{min}(t)$) and on the removal of oldest candidate in the queue ($T_{min}(t-K)$), these are defined as follows:

$$\tau_{ij} \leftarrow \tau_{ij} - (1-w_e)(\tau_{max} - \tau_0)/K, \quad \forall (i,j) \in T_{min}(t-K), \tag{5}$$

$$\tau_{ij} \leftarrow \tau_{ij} + (1-w_e)(\tau_{max} - \tau_0)/K, \quad \forall (i,j) \in T_{min}(t). \tag{6}$$

These rules mean that the τ_{ij}s of the candidate on the removal from the queue decrease and those on the addition to the queue increase.

The updating rule for the best candidate (deposit rule) is also introduced in FIFO-queue ACO, but it is different from that in ACS. The updating is performed only when the best candidate is changed, while in ACS it is done for each iteration. Let T_{old} be the best candidate for all the candidates until the iteration $t-1$. When $T_{min}(t)$ has the lower power consumption than T_{old}, the following updates of τ_{ij} are applied:

$$\tau_{ij} \leftarrow \tau_0 - w_e(\tau_{max} - \tau_0), \quad \forall (i,j) \in T_{min} \tag{7}$$

$$\tau_{ij} \leftarrow \tau_0 + w_e(\tau_{max} - \tau_0), \quad \forall (i,j) \in T_k(t) \tag{8}$$

where $w_e (0 \le w_e \le 1)$ is a parameter that controls the degree of pheromones to be placed at updating $T_{min}(t)$ and τ_{max} is the maximum value of τ_{ij}.

4 Experimental results

In this section we explore the improved performance of our proposed scheme through different scales of MBP. For comparing the performance, we also apply the same task to ACS and Broadcast Incremental Power (BIP) algorithm that is a standard algorithm for solving MBPs.

We prepare the networks with 10, 25, 50, 75, 100 nodes. Nodes are placed randomly at (x_m, y_m) in the network, where $0 \le \{x_m, y_m\} \le 10$ holds. The source node is randomly selected out of these nodes. We generate 20 different configurations for the network with each number of nodes.

We adopt the total power dissipation for a network as the metric for evaluating the performance. To facilitate the comparison of these algorithms over a range of configurations of networks, we introduce *normalized power* for each network configuration. Let $C_i(n)$ be the total power dissipation with respect to the network configuration n and in the case of using the algorithm i, where i takes ACS, BIP, or FIFO-queue, the normalized power $C_i^{/}(n)$ is then defined as

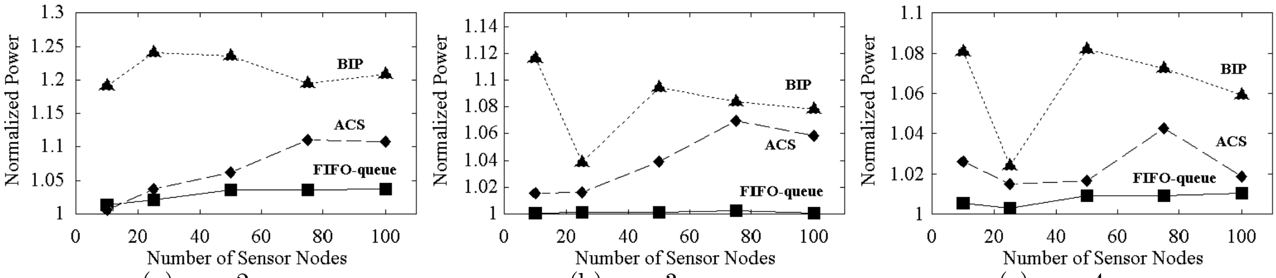
$$C_i^{/}(n) = C_i(n)/C_{best}(n). \tag{9}$$

where $C_{best}(n)$ denotes the lowest power dissipation for the network configuration n, i.e., $C_{best}(n) = \min(C_{\mathrm{ACS}}(n), C_{\mathrm{BIP}}(n), C_{\mathrm{FIFO-queue}}(n))$. The calculation of $C_i^{/}(n)$ for each configuration is performed by the average for 20 simulations where the random sequences are different each other.

The parameters of ACS algorithm we use in this experiment are shown in Table 1, where T_{MAX} denotes the maximum iteration for this algorithm, and M_A and M_B are the number of ants that take the value of β as β_A and β_B respectively. Note that the parameters β_B and q_0 are modified during the simulation.

For FIFO-queue ACO algorithm, we apply the parameters as $\tau_{MAX} = 1.0$, $K = 1$, and $q_0 = 0.5$, for all the configurations. The initial value of pheromone τ_0 is set to $1/N$. The conditions of T_{MAX}, β_A, and β_B are the same as those in Table.1.

The normalized powers of ACS, BIP, and FIFO-queue ACO with respect to the number of nodes are shown in Fig.1. Figures 1(a), 1(b), and 1(c) are the results in the case that the parameter of propagation loss exponent α are 2, 3, and 4, respectively. This α indicates the difficulty in communications in



(a) $\alpha = 2$ (b) $\alpha = 3$ (c) $\alpha = 4$

Figure 1: Normalized power with respect to the number of nodes

Table 1: Parameters used in ACS.

	number of nodes				
	10	25	50	75	100
T_{MAX}	50	100	100	100	200
M_A	5	7	13	19	25
M_B	5	6	12	18	25
τ_0	10^{-2}	$5 \cdot 10^{-3}$	$5 \cdot 10^{-3}$	10^{-3}	$5 \cdot 10^{-4}$
ρ	0.2				
β_A	2.0				
β_B	$2/\alpha^2$ for $t \leq 0.5 \cdot T_{MAX}$ $2/\alpha$ for $0.5 \cdot T_{MAX} < t \leq 0.75 \cdot T_{MAX}$ 2 for $0.75 \cdot T_{MAX} < t$				
q_0	0.3 for $t \leq 0.5 \cdot T_{MAX}$ 0.6 for $0.5 \cdot T_{MAX} < t \leq 0.75 \cdot T_{MAX}$ 0.9 for $0.75 \cdot T_{MAX} < t$				

a long range. From the definition of normalized power (Eq.(9)), smaller value of $C_i^{/}(n)$ means more improved performance. From these results we see that FIFO-queue ACO(solid lines) can achieve lower power dissipations than ACS and BIP for almost all cases. The values of $C^{/}_{FIFO-queue}(n)$s are steady with respect to the number of nodes, while those for ACS and BIP change widely. This shows the stability of FIFO-queue ACO algorithm.

5 Conclusion

We propose a method of applying FIFO-queue ACO algorithm to MBP in this paper. In our method, a queue for storing candidates in the past iterations is introduced for enriching the diversity of candidates, in order not to converge the local minima in search space. The improved performance of the proposed method, as compared to the previously proposed algorithms such as ACS and BIP, is also investigated. From the numerical results, we find that our proposed method can aquire better solutions, from the viewpoint of the total power dissipation, than other algorithms.

However, there are two challenging issues for further improvement of our method: the computational time required for our method and the application to the multicast communications rather than broadcast communications. These issues remain for future work.

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