On Design of Mobile Agent Routing Algorithm for Information Gain Maximization in Wireless Sensor Networks

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***Abstract*— Mobile agent routing for data aggregation in wireless sensor networks may considerably decrease the data traffic among sensor nodes. Finding an appropriate route which leads to the highest aggregation ratio is a major challenge in these networks. Complexities on the design of a mobile agent routing algorithm are related to the precise selection of source nodes and their visiting sequence during mobile agent migration. In this paper, the improvement of mobile agent routing for the dynamic model designed by Xu and Qi is proposed. Xu-Qi's model is developed to solve the problem of target tracking application using the mobile agent migration. The pattern of source nodes selection is based on the cost function, the trade-off between increasing the information gain and decreasing the energy consumption. In this paper, a method is proposed to expand the cost function; our method improves the impact of both information gain and power efficiency in source nodes selection; also, it increases the accuracy of aggregated data. The scope of wireless sensor networks covered by this paper is suitable for many applications. Simulation results in NS2 show that for networks with different number of nodes, the proposed method has less delay and energy consumption compared to Xu-Qi's model.**

Keywords- wireless sensor networks; data aggregation; mobile agent; dynamic routing; information gain

I. INTRODUCTION

A WSN *(Wireless Sensor Network)* typically consists of hundreds or even thousands of sensor nodes scattered in a geographical region to perform sensing, processing, and communication tasks. The sensor nodes have limited resources, such as battery power, processing capacity, memory, and network bandwidth. The data collected by sensor nodes are transmitted to the unlimited resource PE *(processing element)* or sink, where a higher degree of processing is performed. In the dense networks, sensor nodes are geographically close to each other. Therefore, nearby nodes may sense the environmental data with negligible differences. If all sensed data are transmitted to the PE, the network bandwidth utilization will be unnecessarily increased. In order to eliminate the redundant data, an aggregation scheme is used [1]. Data aggregation scheme can be classified in two categories: CS *(Client-Server)* and MA *(Mobile-Agent)* based [2]. Data aggregation schemes can be integrated with routing concepts. The *data-centric routing* aims to find the route with the highest ratio of data aggregation.

In traditional CS scheme, all data packets are passed to the PE for further processing. The packets enter the PE arrival queue and wait for their turn to be processed. Due to the asynchronous data processing and congestion taken place on arrival queue, delay and packet loss rate may be increased. This scheme is not scalable for large-scale wireless sensor networks, where node density is high. Therefore, as increasing nodes number in the network, energy and bandwidth consumption will be increased.

In the new MA scheme, a different processing model is employed. MA is a piece of software code that is initially dispatched by the PE and subsequently moves among source nodes to collect data. The sensor nodes that will be visited along the route by an MA are known as the source nodes. Structure of the MA consists of four main components: The *identification*, which identifies an MA specially; *processing code*, which is used to process sensed data locally; *route*, which is a set of source nodes and their visiting sequence during mobile agent migration; *data space*, which carries aggregated results. When the MA arrives at the source node: First, it takes a local processing on the sensed data; then, it aggregates the data from source nodes that have already been visited; finally, it stores aggregation results in its own data space. After the MA leaves the current source node, it migrates to another one. Eventually, MA will return to the PE. Transmitting collected data through an MA packet to a PE may consume less energy and bandwidth in WSNs [3].

The route design problem means selecting a sequence of source nodes which will be visited by MA. The node selection process should lead to increase in the energy-time efficiency and data aggregation ratio. The routing problem can be divided into two categories: the *static*, and the *dynamic* routing [4]. In the static scheme, the entire topology information is needed. PE uses it to construct an efficient route for MA migration. The main drawback of this scheme is that it is not scalable. In the dynamic scheme, a node is selected as the next source node locally; The MA based route is specified autonomously and through migration from one node to another one. Therefore, MA can dynamically adapt itself to any variable environmental conditions.

The rest of this paper is organized as follows: In Section 2, the related work on mobile agent routing for data aggregation is presented. In Section 3, the assumptions and problem statement are described. The problem solution approach is explained in Section 4, including the trade-offs in the route selection. In Section 5, the details of proposed algorithm are discussed. The high performance of our

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proposed method is approved by simulation results in Section 6. The paper is concluded in Section 7.

II. Related Work

In this section, we intend to review some algorithms which have been proposed to find appropriate MA routes in WSNs.

In [5], authors proposed two simple heuristic algorithms, LCF *(Local Closest First)* and GCF *(Global Closest First)*, to design a route for MA migration. In LCF, the node with the shortest distance to the current source is selected as the next node, while in GCF, the shortest distance to PE is considered. These algorithms are static and centralized. Since the entire network topology information is needed, these algorithms are not scalable. Also, the route selection is only depended on the spatial distance of source nodes, but not on energy consumption.

Authors of [6] proposed two static routing algorithms, IEMF *(Itinerary Energy Minimum for First-source-selection)* and IEMA *(Itinerary Energy Minimum Algorithm)*. The list of N source nodes which will be visited by the MA has been specified in PE. Using the round robin method in IEMF, each node is temporarily replaced as the first source node, and then the LCF algorithm will be applied to route among the other *N-1* source nodes. Therefore, N routes are designated among which only one route with minimum communication cost will be selected. Communication cost is formulated by considering energy consumption and data aggregation models. Consequently, the performance of the LCF algorithm is improved by taking into account the energy constraint in MA routing. The IEMA is the iterative version of the IEMF, where the IEMF is used to determine the next source node in each hop. Thus, IEMA selects the order of the remaining source nodes besides the first one. Although both algorithms find an energy efficient route for MA, these are still based on the non scalable LCF algorithm.

In [7], Y. Xu and H. Qi proposed an algorithm for the dynamic MA migration in the target tracking application. In this algorithm, an MA is dispatched in the network with Gaussian distributed sensor nodes to follow a moving target at different times. MA migrates to nodes which can obtain more accurate information about the target location by consuming the lower migration energy. Hence, a cost function is defined to decide about selecting the source nodes. Cost function is a trade-off between the energy expenditure on MA migration and benefit of high information gain. The neighbors of current source are known as the next node candidates, among which one node with minimum cost value is selected as the next source. Information gain model is used to compare the data accuracy collected by nodes. By collecting the more accurate data about the target, the node will have a greater probability for selection as the next source. In order to gain the maximum information about the target; the MA should migrate to the nodes with higher signal strength. The closer a sensor node is to the target, the higher signal energy and information gain would be achieved. Here, a zero mean Gaussian function is used to model the relationship between the information gain of candidate node k at time t, $I_k(t)$, and target distance as [7]:

$$I_k(t) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{\left\| \widehat{x(t)} - x_k \right\|^2}{2\sigma^2}}, \tag{1}$$

where σ is the standard deviation, $\left\| \widehat{x(t)} - x_k \right\|$ is the distance of the node k from the target at time t, x_k is the location of node k, and $\widehat{x(t)}$ is the target location at time t which can be estimated by trilateration localization algorithm.

In [8], the heuristic TBID *(Tree-Based Itinerary Design)* algorithm is presented to find near-optimal routes for multiple MAs. The algorithm is executed statically at the PE. The area around the PE is divided into concentric zones to construct the MA routes from the inner zones to the outer ones. The number of routes is assigned to MAs is equal to the maximum number of first-zone nodes. At each round of algorithm runs, the lowest costly node will be attached to a tree. The objective is to minimize the total energy cost of routes. Although this algorithm is designed for static routing, the use of proper data structures can adapt it to the dynamic network conditions.

In this paper, a data-centric routing algorithm based on MA is proposed. The algorithm is an improvement of MA routing for the dynamic model designed by Xu and Qi in [7]. Xu-Qi's model is developed for target tracking application in WSNs. The source nodes are determined by the minimum value of the cost function, the trade-off between the information gain and energy consumption. At each hop along the route, selection of the next source node is performed among neighbors of current source. Hence, two consecutive source nodes may gain the similar information. The improvements of our algorithm for route selection include:

- Our algorithm is not limited to special applications.
- The possibility of visiting the more selective nodes is decreased due to their lower remaining energy.
- The algorithm seeks the nodes which consume the lower power for transmitting an MA to the next hop.
- If none of the current node neighbors obtain the higher information gain, then MA can migrate to the nearest 2^n-hop nodes $(n \geq 1)$ by consuming the minimum transmission energy.
- The higher aggregation ratio can be achieved by traversing the smaller number of source nodes.
- Our algorithm has less end-to-end delay and energy consumption.

Finally, we evaluate the solution performance in terms of both energy and delay to verify the practicality of our algorithm.

III. Assumptions And Problem Statement

In this section, we will define the purpose of our research along with main assumptions in this paper.

A. Network Model

A wireless sensor network is modeled as a graph $G(V, E)$, where V is the set of static sensor nodes, $V=\{v_1, v_2, \ldots, v_n\}$, and E is the set of bidirectional links e_{ij} between nodes, $E = \{e_{ij} = \{v_i, v_j\} \mid v_i, v_j \in V, i \neq j\}$. The network consists of N

sensor nodes that are scattered in a rectangular field A with Gaussian distribution. The PE is denoted by v_0, considered as both the start and end points of MA migration route. It is supposed that except for the PE, all sensor nodes are resource-constrained especially in terms of energy and bandwidth. The sensor nodes are aware of their remaining energy and geographical location in the form of (x, y) coordinates. The sensor nodes have maximum transmission range R, where they can recognize their neighbor nodes in every time intervals. Each sensor node broadcasts a list including the amount of remaining energy, the geographical location, and the number of times which it was visited by MA. It is supposed that the current source node being met by MA is denoted by v_i. The candidates of next source node are shown with v_j, as one of them will be selected as the next hop of MA. The data aggregation operation is performed by MA during moving among the source nodes. The MA packet only passes through the intermediate nodes between current and next source nodes. Mobile agent migration in a wireless sensor network is illustrated in Fig. 1.

B. *Problem Statement*

In this paper, we study the MA as a processing component which aggregates the collected data by the source nodes in the WSN. The scope of the network is not limited to special applications. The MA is dispatched by the PE to aggregate the data sensed by source nodes during migrating from one node to another. After completing the mission, it returns to the PE.

The problem is to design a dynamic and informative route for MA migration by considering the following parameters:

- Increasing the network lifetime by taking into account of the remaining energy level of each node as well as the required power for transmitting an MA.
- Improving the accuracy of aggregated data by selecting the source nodes with maximum information gain.
- Decreasing the end-to-end delay of MA migration when it is dispatched until it is returned.

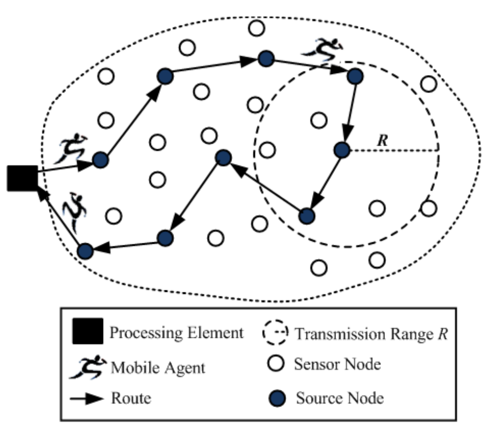

Figure 1. The mobile agent migration in the wireless sensor network to aggregate the sensed data of source nodes along the route.

IV. Solution Approach

To design an efficient route for MA migration in the network, it is important to select the source nodes which have minimum migration cost. To decide whether a node could be chosen as the next source, a cost function is defined. This function consists of the following components.

A. *Information Gain, $I_j(x, y)$*

It is supposed that the sensor nodes are scattered by Gaussian distribution in the field A. Once a source node v_i senses data, all its nearby neighbors may collect the same data with small differences. In result, instead of migrating to the adjacent nodes, MA could migrate to farther nodes to achieve higher degree of information gain. Therefore, the information gain is directly related to the nodes distance. In order to demonstrate the relationship between the information gain and the nodes distance, the inverse Gaussian function in two-dimension would be used as:

$$I_j(x, y) = \left(\sigma^2\sqrt{2\pi}\right)e^{\left(\frac{d_{ij}^2}{2\sigma^2}\right)}, \tag{2}$$

where σ is the standard deviation and the value of mean is selected as zero, d_{ij} is the distance between nodes v_i and v_j which is calculated as:

$$d_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2}, \tag{3}$$

where $\left(x_i, y_i\right)$ and $\left(x_j, y_j\right)$ are the coordinates of nodes v_i and v_j in the network.

B. *Migration Energy, E_{ij}*

The energy cost for sending an MA from node v_i to v_j equals to sum of the transmitting energy e_{tx}^{ij}, the receiving energy e_{rx}^{ij}, and the energy consumption in their intermediate nodes along the route. Also, it is supposed that the needed energy for the data processing is the same for each node in the network.

The amount of energy for transmitting and receiving an MA is measured as [6]:

$$e_{tx}^{ij} = c_{tx} \times S_{tx} + O_{tx}, \tag{4}$$

$$e_{rx}^{ij} = c_{rx} \times S_{rx} + O_{rx}, \tag{5}$$

where c_{tx} and c_{rx} are the energy consumption per bit for both transmitting and receiving an MA packet, S_{tx} and S_{rx} are the size of MA packet which is transmitted and received respectively, O_{tx} and O_{rx} are the constant components of the channel usage overhead.

The intermediate nodes between the two source nodes can only forward the incoming MA packet. The average number of intermediate nodes which are located between the nodes v_i and v_j along the route is calculated as $\left\lceil \frac{d_{ij}}{R} \right\rceil$. Therefore, the energy spent by each intermediate node in transmitting and receiving of an MA packet is equal to e_{tx}^{ij} and e_{rx}^{ij}, respectively [6]. In result, the forwarding energy consumed by all these nodes will be calculated by $\left\lceil \frac{d_{ij}}{R} \right\rceil \times \left(e_{tx}^{ij} + e_{rx}^{ij}\right)$.

The total energy for sending an MA from node v_i to v_j is measured as:

$$E_{ij} = \left(e_{tx}^{ij} + e_{rx}^{ij}\right) \times \left(1 + \left\lceil \frac{d_{ij}}{R} \right\rceil\right) \tag{6}$$

where E_{ij} is the sum of the transmitting energy of node v_i, the receiving energy of node v_j, and the energy consumption of their intermediate nodes.

C. Remaining Energy, e_j

A candidate node v_j will be designated as the next source, if its remaining energy is higher than the other nodes. Due to the prolonging network lifetime, a candidate node with the lower energy level would not be selected.

D. Transmission Power, P_j

As pointed out in (2), a candidate node v_j which is farther from the current source may gain the more precise information. In contrast, a farther node may entail more power consumption to send out an MA. Hence, a trade-off between the information gain and the transmission power is defined. We use the number of neighbors around a candidate node v_j as an approximation of its transmission power. Once a candidate node with the more neighbors is selected as the next source, it usually can consume less transmission power during its next hop. The transmission power P_j is inversely related to the number of v_j's neighbors, N_{neigh}^{j}, shown as $P_j \approx \frac{1}{N_{neigh}^{j}}$.

E. Migration Cost, C_{ij}

Decision of selecting the best candidate node as the next hop is made by the cost function, C_{ij}. Cost function C_{ij} indicates the migration cost spent to transfer an MA from current node v_i to candidate node v_j. The cost function is the trade-off between increasing the benefits and decreasing the losses as follows. Cost function tries to increase the information gain and network lifetime as well as to decrease the energy consumption on MA migration. Therefore, it increases the probability of selecting the lowest-cost node among the candidate nodes. The cost function C_{ij} for transferring an MA from v_i to v_j can be defined as:

$$C_{ij} = \alpha\left(1 - \frac{I_j(x,y)}{I_{max}}\right) + \beta(N_{visit}+1)\left(1 - \frac{e_j}{e_{max}}\right)$$

$$+\gamma \frac{E_{ij}}{E_{max}} + (1-\alpha)\frac{P_j}{P_{max}} \tag{7}$$

$$0 \le \alpha, \beta, \gamma \le 1, \quad N_{visit} \ge 0,$$

where $I_j(x, y)$ is the information gain of a candidate node v_j, I_{max} is the maximum information gain of nodes, E_{ij} is the energy consumption for transferring an MA from node v_i to v_j, E_{max} is the maximum transmission energy for sending MA from one node to another, e_j is the remaining energy of node v_j, e_{max} is the same initial energy of nodes, and N_{visit} is the number of times that node v_j has already been visited by MA; Numerous selection of node v_j as the next source will cause its more energy loss and reduction of the network lifetime. Therefore, the number of times that a node can be visited by an MA is limited. α, β and γ are the weighed factors, P_j is the power consumed to transmit an MA from node v_j to its next hop, and P_{max} is the maximum power to transmit an MA in the network; P_{max} is inversely proportional to the maximum number of a node neighbors, $P_{max} \approx \frac{1}{N_{max}}$, where N_{max} is calculated as [9]:

$$N_{max} = (N-1) \times \frac{\pi R^2}{A} , \tag{8}$$

where N is the number of scattered sensor nodes in the network, R is the maximum transmission range of nodes, and A is the area of network. The cost consumption on the MA migration is decreased by increasing the number of node neighbors. Thus, the possibility of selecting that node as the next source would be increased.

V. ALGORITHM DESCRIPTION

Data will be aggregated in the selected source nodes. Other intermediate nodes will forward the MA packet. When a node is selected as the next source, the value of its information gain will be stored in MA packet as the latest.

Once MA is dispatched from the PE, it migrates to the nearest node with the minimum cost measured according to the (7). After receiving the MA by the first source node, data will be aggregated. Then, MA tries to find the next source: First, the entire one-hop neighbors will be checked according to the (7) to designate the least costly candidate node; second, the difference of information gain in this candidate node with the current value is calculated. If it is higher than the specific threshold, the MA will be migrated to that node and aggregate data. Otherwise, the MA will migrate to the nearest node two-hop away from the current node for which data is aggregated. Since, the MA has no knowledge of network topology; it first migrates to the nearest one-hop neighbor that hasn't been selected; thereafter, it moves from there to the next closest neighbor. After the MA arrived in the node two-hop away, the threshold condition of the information gain is checked. If condition does not satisfy, the MA will be moved to the nearest node four-hop away of the current node. The process of searching will be continued in all 2^n-hops nodes *($n \geq 1$)*, until a most informative node is selected as the next source. Once, the informative node is found, the MA starts again to aggregate and find the next node in all one-hop neighbors. Finally, MA will return to the PE at the end of the migration. If MA cannot find any next node, it will return back to the PE. Note that in all the above steps, the next node is selected from the non common neighbors of current and previous nodes. The proposed scheme has been suggested for selecting the next node with the highest information gain and the lowest transmission power. A pseudocode description of our scheme is given in Fig. 2.

VI. SIMULATION RESULTS AND DISCUSSION

This section represents the simulation results on the proposed scheme by using NS-2 *(Network Simulator)* [10] as a simulator. The simulation parameters are summarized in Table 1. We consider all types of energy consumptions for both computational and communication costs in our simulations. In simulation results, each data point represents an average of 40 simulation trials. The results include 95% confidence interval for each data point. We first evaluate the impact of using the different values for factor-α on the performance metrics of our scheme. According to (7), α is the weighted factor of information gain with the value ranging from 0 to 1. The evaluated metrics are given below:

- Aggregation Precision Ratio: refers to the precision of aggregated data by MA. If the MA visits all of the nodes in the network, the precision will be one.
- Average End-to-End Delay: refers to the time interval between transferring MA from processing element and its recurrence to this point.

Fig. 3 illustrates the impact of the factor-α on the aggregation precision ratio in our scheme. There is a direct relationship between the information gain and the factor-α. Therefore, increasing the value of factor-α directly enhances the information gain effectiveness on the cost function (7). In result, the data aggregation is performed with more precision.

Fig. 4 shows the average end-to-end delay versus the values of factor-α. Here, are two related points: First, the more information is gained by increasing the factor-α (see Fig. 3); second, the more information is gained in farther nodes of current source in (1). Given these two points, the MA migrates to farther source nodes by increasing the value of factor-α. Therefore, the end-to-end delay will be increased.

We next compare our scheme with Xu-Qi's model, when the number of nodes varies from 100 to 400. The comparison is in terms of average remaining energy and end-to-end delay. The average remaining energy refers to the energy consumption ratio of the nodes at the end of the simulation process after several rounds of MA migrations in the network.

TABLE I. SIMULATION PARAMETERS

Parameter	Value
Terrain Area	2000 m×2000 m
Number of nodes	100 – 400
Transmission Range	115 m
MAC	IEEE 802.11
Simulation time	600 S

Fig. 5 compares the percentage of average remaining energy in our scheme with Xu-Qi's model. Our scheme selects the nodes which consume less power for transmitting the MA along the route; it balances the energy consumption among multi-hop source nodes. Also, the required accuracy of the data aggregation is obtained by visiting the fewer number of source nodes. Hence, our scheme can save up to 52% energy compared to the work in [7].

Fig. 6 shows the average end-to-end delay of MA migration in our scheme comparing with the existing one. Increasing the number of nodes in the network, the end-to-end delay will be increased. However, our scheme has lower delay than the existing model. The reason is that our scheme can find the most informative route by traversing the less number of source nodes; thus, MA takes less time to return to PE. Our scheme can reduce the average end-to-end delay by 13%.

The simulation results verify the practicality of our algorithm. The results show that our algorithm improves the Xu-Qi's model in terms of aggregation precision, energy consumption and end-to-end delay.

```
In PE (v0) :
  find first source node according to (7)
  set last gain to the current gain
  can_fusion =1; hop_count =1; hop_jump =1;
In Sensor Node (vi, i ≠ 0) :
  if can_fusion = 1 then {
    find next node according to (7)
    diff = current gain – last gain;
    if diff ≥ threshold then {
      select this node as next source
      set last gain to the current gain
      can_fusion =1; hop_count =1; hop_jump =1;
    }
    else {
      find the nearest neighbor that hasn't been selected
      can_fusion =0; hop_count = (hop_count)×2;
      hop_jump = hop_count;
    }
  }
  else
   if can_fusion=0 then {
    hop_jump =(hop_jump) – 1
    if hop_jump == 0 then {
       diff = current gain – last gain;
       if diff ≥ threshold then {
         select this node as next source
         set last gain to the current gain
         can_fusion = 1; hop_count = 1;
         hop_jump = hop_count;
       }
       else {
         find the nearest neighbor that hasn't been selected
         can_fusion =0, hop_count = (hop_count)×2
         hop_jump = hop_count;
       }
    }
    else
      find the nearest neighbor that hasn't been selected
  }
```

Figure 2. The pseudocode of mobile agent migration process.

VII. Conclusion And Future Work

In this paper, we proposed a dynamic mobile agent routing algorithm in wireless sensor networks. Our proposed algorithm is an improvement of the dynamic model designed by Xu and Qi. The Xu-Qi's model is developed for target tracking application, but our scheme is not limited to special ones. In Xu-Qi's model, the node selection process is determined by the minimum value of cost function. The cost function is the trade-off between the information gain and the energy consumption. We improved the cost function so that, the highest information gain is achieved along the route by consuming the minimum energy. Therefore, our algorithm can increase the accuracy of the aggregated data. We verify the practicality of our algorithm using simulations and compare its performance to Xu-Qi's model. The simulation results show that our proposed algorithm outperforms the existing model in terms of energy and end-to-end delay. Future work includes extending this work to support multi-cooperative mobile agent to achieve more precision and less delay. Also, we would like to extend the proposed scheme for selecting a source node in the hostile environment by considering the reliability and security factors in the cost function.

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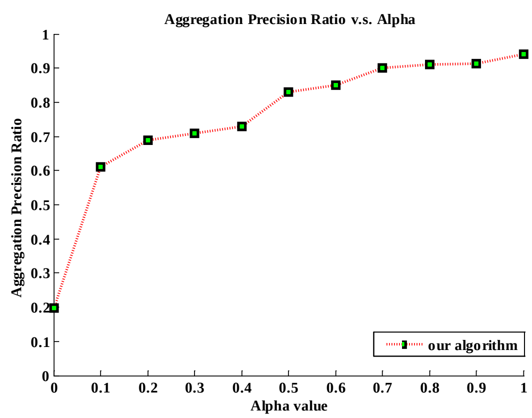

Figure 3. Aggregation precision ratio, when the factor-α varies from 0 to 1.

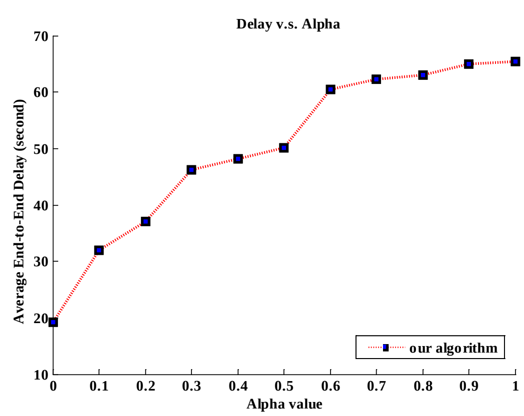

Figure 4. Average end-to-end delay, when the factor-α varies from 0 to 1.

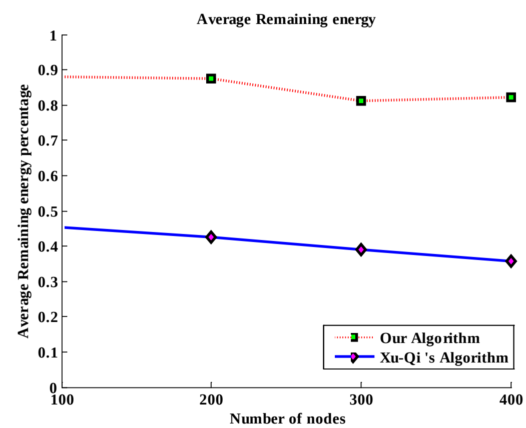

Figure 5. Comparison of average remaining energy percentage, when the number of nodes varies from 100 to 400.

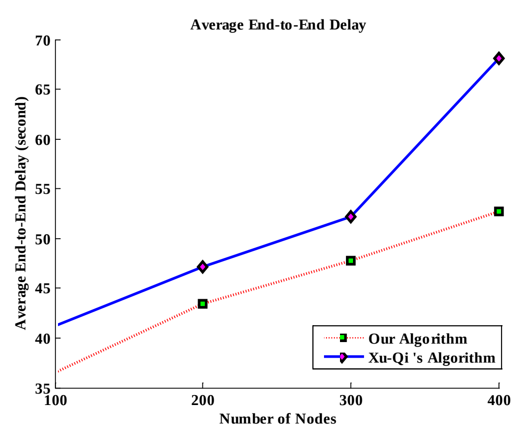

Figure 6. Comparison of average end-to-end delay, when the number of nodes varies from 100 to 400.