Mobile-Sink Path Selection Strategy with Energy-Efficient in WSN

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Abstract*:Several studies have demonstrated the benefits of using a mobile sink to reduce the energy consumption of nodes and to prevent the formation of energy holes in wireless sensor networks (WSNs). However, these benefits are dependent on the path taken by the mobile sink, particularly in delay-sensitive applications, as all sensed data must be collected within a given time constraint. An approach proposed to address this challenge is to form a hybrid moving pattern in which a mobile-sink node only visits rendezvous points (RPs), as opposed to all nodes. Sensor nodes that are not RPs forward their sensed data via multi-hopping to the nearest RP. The fundamental problem, then becomes computing a tour that visits all these RPs within a given delay bound. Identifying the optimal tour, however, is an NP-hard problem. To address this problem, a heuristic called weighted rendezvous planning (WRP) is proposed, whereby each sensor node is assigned a weight corresponding to its hop distance from the tour and the number of data packets that it forwards to the closest RP. WRP is validated via extensive computer simulation, and our results demonstrate that WRP enables a mobile sink to retrieve all sensed data within a given deadline while conserving the energy expenditure of sensor nodes. More specifically, WRP reduces energy consumption by 22% and increases network lifetime by 44%, as compared with existing algorithms.*

Keywords:*Data collection, mobile sink, scheduling.*

I. INTRODUCTION

Wireless sensor networks (WSNs) are composed of a large number of sensor nodes deployed in a field. They have wide-ranging applications, some of which include military, environment monitoring agriculture home automation, smart transportation and health. Each sensor node has the capability to collect and process data, and to forward any sensed data back to one or more sink nodes via their wireless transceiver in a multi-hop manner. In addition, it is equipped with a battery, which may be difficult or impractical to replace, given the number of sensor nodes and deployed environment. These constraints have led to intensive research efforts on designing energy-efficient protocols. In multi-hop communications, nodes that are near a sink tend to become congested as they are responsible for forwarding data from nodes that are farther away. Thus, the closer a sensor node is to a sink, the faster its battery runs out, whereas those

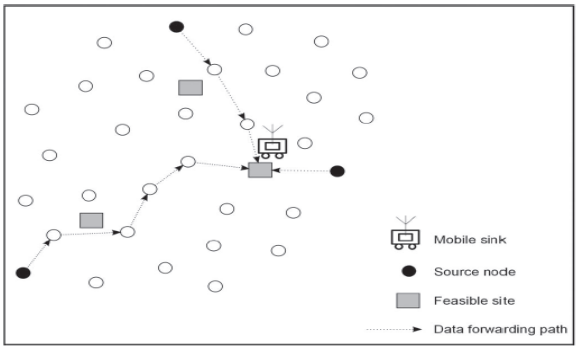


Fig.1. Example showing a mobile sinks performing data collection in a WSN.

A source node determines and sends all data to a suitable site.Farther away may maintain more than 90% of their initial energy. This leads to non-uniform depletion of energy, which results in network partition due to the formation of energy holes. As a result, the sink becomes disconnected from other nodes, thereby impairing the WSN. Hence, balancing the energy consumption of sensor nodes to prevent energy holes is a critical issue in WSNs.

To this end, previous works employ one or more mobile sinks. These mobile sinks survey and collect sensed data directly from sensor nodes and thereby help sensor nodes save energy that otherwise would be consumed by multi-hop communications. Fig. 1 shows the feasible sites of a mobile sink in an example WSN. Specifically, the squares denote the feasible sites that the mobile sink will visit and stop for data collection. The data forwarding path from sensor nodes to the sink is dependent on the sink's current position. This requires sensor nodes to dynamically plan one or more data forwarding paths to each feasible site whenever the sink node changes its position over time. As demonstrated, a mobile sink that moves at the periphery of a sensor field maximizes the lifetime of sensor nodes. Intuitively, by changing the position of the sink over time, the forwarding tree will involve a different set of sensor nodes and, hence, will help to balance energy consumption.

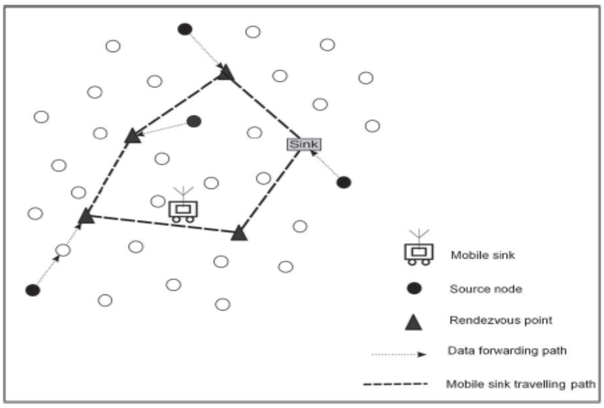


Fig.2. Hybrid movement pattern for a mobile sink node. Source nodes generate and send sensed data to the nearest RP.

Quickly Moreover, a mobile-sink node may change its position after a certain period of time and select another data collection/feasible site. The feasible sites and corresponding sojourn time are dependent on the residual energy of sensor nodes. In general, limitations such as the maximum number of feasible sites, maximum distance between feasible sites, and minimum sojourn time govern the movement of a mobile sink.

In WSNs with a mobile sink, one fundamental problem is to determine how the mobile sink goes about collecting sensed data. One approach is to visit each sensor node to receive sensed data directly. This is essentially the well-known traveling salesman problem (TSP), where the goal is to find the shortest tour that visits all sensor nodes. However, with an increasing number of nodes, this problem becomes intractable and impractical as the resulting tour length is likely to violate the delay bound of applications. To this end, researchers have proposed the use of rendezvous points (RPs) to bound the tour length. This means a subset of sensor nodes are designated as RPs, and non-RP nodes simply forward their data to RPs. A tour is then computed for the set of RPs, as shown in Fig. 2. As a result, the problem, which is called rendezvous design, becomes selecting the most suitable RPs that minimize energy consumption in multi-hop communications while meeting a given packet delivery bound. A secondary problem here is to select the set of RPs that result in uniform energy expenditure among sensor nodes to maximize network lifetime.

In this paper, we call this problem the delay-aware energyefficient path (DEETP). We show that the DEETP is an NPhard problem and propose a heuristic method, which is called weighted rendezvous planning (WRP), to determine the tour of a mobile-sink node. In WRP, the sensor nodes with more connections to other nodes and placed farther from the computed tour in terms of hop count are given a higher priority. Thus, this paper is summarized as follows.

- We define the problem of finding a set of RPs to be visited by a mobile sink. The objective is to minimize energy consumption by reducing multi-hop transmissions from sensor nodes to RPs. This also limits the number of RPs such that the resulting tour does not exceed the required deadline of data packets.
- We propose WRP, which is a heuristic method that finds a near-optimal traveling tour that minimizes the energy consumption of sensor nodes. WRP assigns a weight to sensor nodes based on the number of data packets that they forward and hop distance from the tour, and selects the sensor nodes with the highest weight.
- We mathematically prove that selecting the sensor node that forwards the highest number of data packets and have the longest hop distance from the tour reduces the network energy consumption, as compared with other nodes.Moreover, we show that, in contrast to cluster-based (CB), rendezvous design for variable tracks (RD-VT), and rendezvous planning utility-based greedy (RP-UG) algorithms, WRP is guaranteed to find a tour if the latter exists.
- We demonstrate via computer simulation the properties and effectiveness of WRP against the CB, RD-VT, and RP-UG algorithms. Our results show that WRP achieves 14% more energy savings and 22% better distribution of energy consumption between sensor nodes than the said algorithms.

The remainder of this paper is structured as follows. Section II presents DEETP. In Section III, we illustrate WRP and present a detailed analysis of WRP and key properties. Finally, in Section IV, we compare the performance of WRP with previous works before concluding in Section V.

II. PROBLEM FORMULATION

Let us consider a WSN in which sensor nodes generate data packets periodically. Each data packet must be delivered to the sink node within a given deadline. There is a mobile sink that roams around a WSN to collect data from a set of RPs. The objective is to determine the set of RPs and associated tour that visits these RPs within the maximum allowed packet delay.

A. Assumptions

Before describingDEETP,wefirst outline someassumptions.

1) The communication time between the sink and sensor nodes is negligible, as compared with the sink node’s traveling time. Similarly, the delay due to multi-hop communications including transmission, propagation, and queuing delays is negligible with respect to the traveling time of the mobile sink in a given round.

2) Each RP node has sufficient storage to buffer all sensed data.

3) The sojourn time of the mobile sink at each RP is sufficient to drain all stored data.

4) The mobile sink is aware of the location of each RP.

5) All nodes are connected, and there are no isolated sensor nodes.

6) Sensor nodes have a fixed data transmission range.

7) Each sensor node produces one data packet with the length of *b* bits in time interval *D*.

B. Notation

We model aWSN as $G(V,E)$, where V is the set of homogeneous sensor nodes, and E is the set of edges between nodes in V. If sensor node i sends$b$ bits to node j, its energy consumption is

$$ETX(i, j) = b(\alpha 1 + \alpha 2 \times d^{\gamma}_{i,j}) \qquad (1)$$

where$d_{i,j}$is the physical distance between sensor node i and j, and $\alpha 1$ is the energy consumption factor indicating the power per bit incurred by the transmitting circuit. The expression $\alpha 2 d^{\gamma}_{i,j}$indicates the energy consumption of the amplifier per bit, where $\alpha 2$ is the energy consumption factor of the amplifier circuit. Here, γ is the path-loss exponent, which usually ranges between 2 and 4, depending on the environment. Moreover, the power consumption incurred by node i to receive b bits from node j is

$$ERX(i, j) = b \times \beta \qquad (2)$$

The mobile-sink node moves with a constant speed v. Hence, the maximum length of the traveled path l is

$$l\text{max} = D \times v. \qquad (3)$$

A mobile-sink node starts its movement from a node $m0 \in V$ and before time D returns to its starting point. Each sensor node sends its generated data packets to the closest RP through multihop transmissions. We define a function called $H(i,M)$ that returns the closest RP in terms of hop count to the sensor node i, where M is the set of RPs. Specifically

$$H(i,M) = \{hi,mj \mid \forall mk \in M, hi,mj \leq hi,mk\} \qquad (4)$$

where$hi,j$is the hop distance between nodes i and j.

For each RP mi, our algorithm constructs a data forwarding tree Tmicomprising of the closest sensor nodes to said RP. The number of data packets NFD(i) that sensor node i

forwards to the closest RP mi in each time interval D is equal to its own generated data packet plus the number of its children in the data forwarding tree Tmi. Specifically

$$\mathbf{NFD}(i) = C(i, Tmj) + 1 \qquad (5)$$

where $C(i, Tmj)$ is a function that returns the number of children that node i has in the data forwarding tree rooted at its corresponding RP mj.

C. Delay-Aware Energy-Efficient Traveling Path

The objective is to find a tour $M = m0, m1, m2, \dots, mn, m0$, where $mi \in V$, such that 1) the tour M is not longer than $l$max, and 2) the energy consumption for sending sensed data from sensor nodes to the tour M, as defined by $(ETX + ERX)\sum i \in V$ $H(i,M)$, is minimized within time interval D. DEETP is NP-hard by a reduction from TSP. Note that the minimum energy consumption occurs when all sensor nodes are designated as an RP. This is because they do not incur any energy expenditure related to the forwarding of packets from other nodes. In this case, the goal is then to determine whether there is a tour that is not longer than $l$max. Henceforth, in the following, we propose a novel heuristic method to approximate the optimal solution.

III. WEIGHTED RENDEZVOUS PLANNING

WRP preferentially designates sensor nodes with the highest weight as a RP. The weight of a sensor node is calculated by multiplying the number of packets that it forwards by its hop distance to the closest RP on the tour. Thus, the weight of sensor node i is calculated as

$$Wi = \mathbf{NFD}(i) \times H(i,M). \qquad (6)$$

Based on (6), sensor nodes that are one hop away from an RP and have one data packet buffered get the minimum weight. Hence, sensor nodes that are farther away from the selected RPs or have more than one packet in their buffer have a higher priority of being recruited as an RP.

From (1) and (2), the energy consumption is proportional to the hop count between source and destination nodes, and the number of forwarded data packets. Hence, visiting the highest weighted node will reduce the number of multi-hop transmissions and thereby minimizes the energy consumption. In addition, as dense areas give rise to congestion points due to the higher number of nodes, energy holes are more likely to occur in these areas. Hence, a mobile sink that preferentially visits these areas will prevent energy holes from forming in a WSN.

Algorithm 1 shows how WRP works. It takes as input $G(V,E)$, and it outputs a set of RPs. WRP first adds the fixed sink node as the first RP (see line 6). Then, in lines 9–17, it adds the highest weighted sensor node. After that, WRP calls TSP(·) to calculate the cost of the tour. If the tour length is less than the required length $l$max, the selected node from lines 9–17 remains as an RP. Otherwise, it is removed from the tour.

After a sensor node is added as an RP, WRP removes those RPs from the tour that no longer receives any data packets from sensor nodes. This is because adding a sensor node to the tour may reduce the number of data packets directed to these RPs. Consequently, this step affords WRP more opportunities to add other nodes into the tour. Note that the variable “removed” is used to guarantee that an RP will be deleted from the tour only once. If a removed RP is added to the tour for the second time, because its corresponding variable “removed” is true, it will not be removed from the tour again. In this way, all sensor nodes will be added to the tour when the required tour length for a mobile sink is bigger than the time to visit all sensor nodes.

Fig. 4 shows an example of how WRP finds a traveling tour for a mobile sink. The maximum tour length is $l$max = 90 m. WRP starts from the sink node and adds it to the tour, i.e.,M= [Sink]. Then, an SPT rooted at the sink node is constructed. In the first iteration, WRP adds node 10 to the tour because it has the highest weight, yielding$M$= [Sink, 10]. Fig. 4.Example of WRP operating in a WSN with ten nodes.

As Fig. 4(b) shows, the tour length of M is smaller than the required tour length (56 <90), meaning node 10 stays in the final tour (lines 22–32). In the second iteration, WRP recalculates the weight of sensor nodes because node 10 is now part of the tour. In this iteration, WRP selects node 6 as the next RP, which has the highest weight. As Fig. 4(c) shows, the tour length of M = [Sink, 10, 6] is larger than the required tour length (119 >90). Consequently, WRP removes node 6 from the tour$M$= [Sink, 10] (lines 33–37). In the third iteration, the weight of sensor nodes will not change because node 6 is not selected as an RP but it stays marked and will not be selected. WRP selects node 8 because it has the highest weight and is not marked [see Fig. 4(d)]. The TSP function returns 76 m for M = [Sink, 10, 8], which is less than 90 m. Therefore, node 8 is added to the tour. The process continues, yielding a final tour of M = [Sink, 8, 7, 10, 9] with a tour length of 81 m, which is less than the required tour length [see Fig. 4(e)].

As shown in Fig. 4, the final tour computed by WRP always includes sensor nodes that have more data packets to forward than other nodes as RPs. This ensures uniform energy consumption and mitigates the energy-hole problem. This is the key advantage of WRP over CB, RD-VT, and RP-UG. In Section V, we will show that this feature of WRP allows it to save 30% more energy than CB.

A. Analysis

The time complexity of our algorithm is dependent on how many times WRP calls the TSP solver to calculate a tour that visits all RPs. The worst case is when all sensor nodes are marked but not selected as an RP, which means WRP will iterate for $|V|$ times to check the possibility of adding nodes into a tour. After a node is selected as an RP, WRP again unmarks other sensor nodes and restarts the search process. This means our algorithm uses the TSP solver for a maximum of $n2$ times, where $n = |V|$. Therefore, the time complexity of WRP is $O(n2 \times O(\mathrm{TSP}))$. Hence, if we use Christofides’s heuristic [39], which has time complexity of $O(n3)$, the resulting time complexity is $O(n5)$. In our experiments, we used a local-search-based heuristic TSP solver. We like to point out that WRP always finds a tour when there is at least one possible tour in the network. This is because WRP checks the possibility of adding all sensor nodes to the tour. This is significant when compared with CB and RD-VT because the latter two algorithms fail in the following scenario. In CB, if the only possible tour consists of only the sink and a neighbor in the same cluster, CB will not be able to find this tour because two sensor nodes from the same cluster cannot be in the final tour. As for RD-VT, it will return no tour if the distance of the first sensor node in the SMT, as it starts its depth-first traversal, exceeds $l_{\max}$.

We now prove that visiting the most weighted nodes by a mobile sink results in the least energy consumption, as compared with visiting any other nodes.

Theorem 1: Visiting sensor node P with weight wpreduces energy consumption more than visiting sensor node Q with weight wq, where $wp>wq$.

Proof: Recall that sensor node P forwards NFD(P) data packets to its closest RP. Therefore, the energy consumption of sensor nodes on the path from node P to the closest RP is

$$Ep = (ETX + ERX) \times (\mathrm{NFD}(P) \times H(P,M)) \,. \qquad (7)$$

However, if sensor node P becomes an RP, the energy consumption incurred by data packets at P is zero. Similarly, for sensor node Q that forwards NFD(Q) data packets to its closest RP, we have

$$Eq = (ETX + ERX) \times (\mathrm{NFD}(Q) \times H(Q,M)) \,. \qquad (8)$$

From (6), the weight of sensor node P is $wp= \mathrm{NFD}(P) \times H(P,M)$, and the weight of sensor node Q is $wq= \mathrm{NFD}(Q) \times H(Q,M)$. We know that $wp>wq$; therefore, it can be concluded that $Ep>Eq$, which means selecting sensor node P as an RP, which has a higher weight than Q, leads to less network energy consumption.

We now show the difference between WRP and the optimal solution. We first prove the following lemma.

Lemma 1: Let WRPop be a version of WRP that uses an optimal TSP solver. If there is an optimal tour named C with length $Lc\leq l\max$ comprising of all sensor nodes as RP, then WRPop is guaranteed to find tour C.

Proof: Assume there are n sensor nodes in a WSN and tour $C = m0,m1,m2, \ldots, mn,m0$, where$m0$ is the sink node.

Then

$$Lc=\sum^{n-1}{}_{0} dmi,mi+1 + dmn,m0. \qquad (9)$$

WRPop, after picking the sink, will select node mi=1 to include in the tour as it has the highest weight before running TSP(·) (see line 21 of Algorithm 1). The returned cost will be less than Lcas the tour connecting the set of nodes cannot be longer than the tour containing all nodes by the triangle inequality. Hence, WRPop will add mi=2 and so forth until $i = n$. WRPop then terminates as $Tn= |V|$.

Note that, in Lemma 1, the requirement on there being an optimal TSP solver can be relaxed if we assume that $\sum^{|E|}{}_{i=0} i \leq l_{\max}$. In other words, the sum of all distances between nodes is less than the required tour length.

Note that, intuitively, it would seem that the maximum difference in energy consumption occurs when the final tour returned by WRPop is not composed of any sensor nodes while the optimal tour visits all sensor nodes. However, as per Lemma 1, this will not happen.

Theorem 2: Assume a sensor node P that has the longest hop distance from the sink, and the average hop distance between sensor nodes and the sink is k; then, the maximum difference between the network energy consumption of WRPop and the optimal is within $((2 \times K \times (|V| - 1) + 1)/(|V| + 2))$.

Proof: The network energy consumption when the mobile sink visits only sensor node P is

$E\mathrm{Network}(p) = (ETX + ETX \times ((|V| - 1) \times k))+(ERX \times ((|V| - 1) \times k)) \,. \ (10)$

On the other hand, the minimum amount of energy consumed by visiting all sensor nodes except node P is

$$E\mathrm{Network}(|V|-1) = ETX \times (|V| + 1) + ERX. \ (11)$$

This means sensor node P has to send all its data packets to the closest RP, whereas other sensor nodes send their data packets directly to the mobile sink. From (10) and (11), the ratio of energy consumption in WRP in comparison to the optimal model is

$$\mathrm{Ratio}= \frac{ETX \times (1 + (|V| - 1) \times k) + ERX \times ((|V| - 1) \times k}{ETX \times (|V| + 1) + ERX} \qquad (12)$$

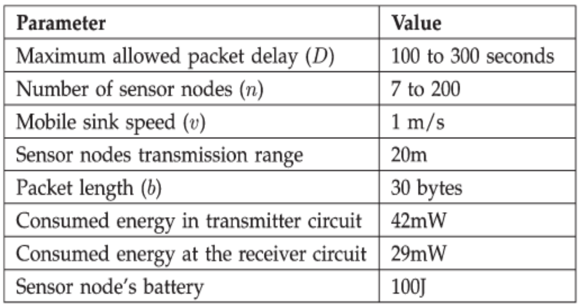
If we consider $ETX \sim= ERX$, (12) is equal to

$$\mathrm{Ratio} \sim= \frac{2 \times K \times (|V| - 1) + 1}{|V| + 2} \qquad (13)$$

V. EVALUATION

We compare WRP against three existing methods that have the same objective as ours, namely CB, RD-VT, and RP-UG, using a custom simulator written in C++.1 We consider a connected WSN where nodes are placed uniformly on a sensor field of size 200 × 200 $m2$. We note that interconnecting disconnected sensor nodes using a mobile node is a well-known and separate problem. Having said that, we remark that WRP can be also made to interconnect disconnected nodes if the required delivery time for data packets is greater than the 1Our simulator is available upon request.

TABLE I SIMULATION PARAMETERS



Parameter	Value
Maximum allowed packet delay (D)	100 to 300 seconds
Number of sensor nodes (n)	7 to 200
Mobile sink speed (v)	1 m/s
Sensor nodes transmission range	20m
Packet length (b)	30 bytes
Consumed energy in transmitter circuit	42mW
Consumed energy at the receiver circuit	29mW
Sensor node's battery	100J

shortest traveling tour to visit all sensor nodes. The reason that we have assumed uniform sensor-node distribution is because energy holes are more likely to form when nodes are distributed uniforml. Experimental results is demonstrated that, if sensor nodes are distributed uniformly, up to 90% of residual energy is unused when the first sensor node dies. In addition, we adopt uniform distribution to ensure fair comparison with RD-VT, CB, and RP-UG.

Similar to, we have set the radio parameters as per the CC1000 radio, which is used byMica2 Motes. Each sensor node generates one data packet every T time, which is then forwarded to an RP via an SPT. We assume nodes are aware of the mobile sink's movement and, hence, arrival time.We record and compare the network energy consumption every T time.

Moreover, there are a maximum of 200 sensor nodes, which is reasonable for most applications.

To measure network lifetime, we assume that all sensor nodes have a fully charged battery with 100 J of energy. Other parameters are summarized in Table II.We set the mobile sink's speed to 1 m/s. We further assume that it visits each

RP. Given a transmission range of 20 m, which is feasible for Mica2 or TelosB nodes, the mobile sink will be in a sensor node's transmission range for 20 s. Assuming a data transmission rate of 40 Kb/s, each sensor node will be able to send 3413 data packets with a length of 30 b to the mobile sink in 20 s. This means that the mobile sink has sufficient time to drain the buffer of all sensor nodes even when there are 200 sensor nodes. To reduce the run time of RP-UG, we set *L*0 to 20 m, which corresponds to the transmission range of sensor nodes.

We use standard deviation (SD) to measure the imbalance between the energy consumption of sensor nodes, i.e., a wide variation means some parts of a WSN is likely to exhaust its energy sooner. The metric SD is calculated as follows:

$$\mathbf{SD} = \sqrt{\frac{\sum_{i \in V}(\mathrm{EN}[i] - \mu)^2}{|V|}} \qquad \mathbf{(14)}$$

where EN[*i*] is the energy consumption of node *i*, *V* is the set of sensor nodes, and *μ* is the average energy consumption of sensor nodes.

In our evaluation, we consider two scenarios involving an SPT and an SMT for the RD-VT model: RP-UG and WRP. In WRP, we find the Steiner points and treat them as real nodes. This means that Steiner points have a weight and are not replaced with real sensor nodes in the final tour.

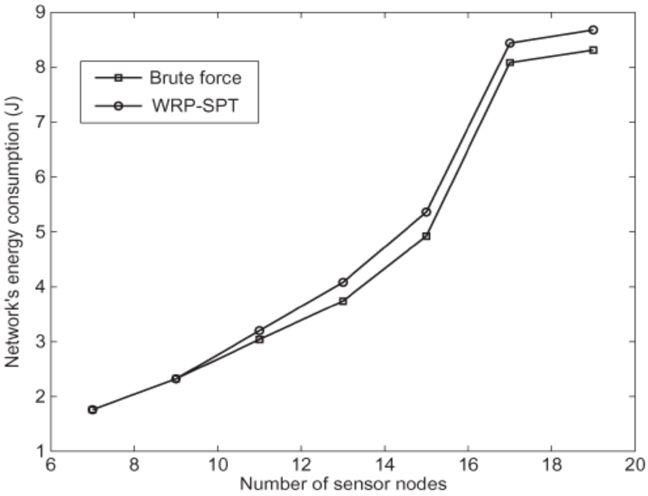


Fig. 5.Network energy consumption between brute force and WRP.

Two sets of experiments are carried out. Initially, the number of nodes is limited to 20, and WRP is compared against a bruteforce approach that yields the optimal tour with 2.5 min as the required tour length. In the second experiment, the number of nodes is increased to 200, and WRP is compared against RD-VT and CB with 5 min as the required tour length. In all experiments, we designate the node with the highest ID as the sink node, and the results are an average of ten simulation runs over different topologies.

A. Performance Under SPT

Fig. 5 shows the energy consumption of sensor nodes for WRP versus brute force. Both algorithms yield higher energy consumption when the number of sensor nodes increases as the length of data forwarding paths from sensor nodes to RPs increases. The energy consumption of WRP is very close to the brute-force approach. In particular, brute force only outperforms WRP by 5%.

Fig. 6 shows the difference, as per SD, between sensor nodes energy consumption. A small SD value means uniform energy consumption and longer network lifetime. The performance of WRP is only 16% less than the optimal or brute-force approach. This is because, in WRP, sensor nodes that forward more data packets and cause more multihop transmissions than other sensor nodes are likely to be designated as an RP.

Fig. 7 shows the energy consumption for WRP, CB, RDVT, and RP-UG with a large number of sensor nodes. RDVT leads to the highest energy consumption because of its preorder traversal of the SPT and long data forwarding paths from sensor nodes to the RPs. WRP recorded 47% reduction in energy consumption, as compared with RD-VT. CB has better performance than RD-VT because, in its finalization process, if the required delivery time is not violated, it replaces the selected RP in each cluster with a node closer to the cluster head to reduce the number of multihop transmissions. CB's performance is 28% better than RD-VT in terms of energy consumption.

Recall that in Section II-B2, CB does not consider node density or hop counts when selecting RPs. As a result, WRP achieves

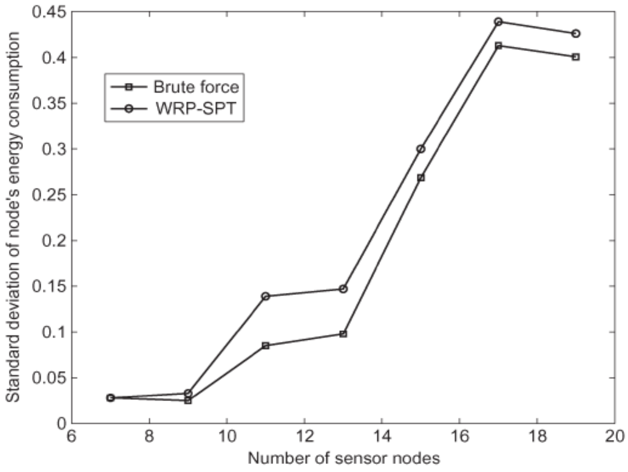


Fig. 6.Standard deviation of sensor nodes' energy consumption.

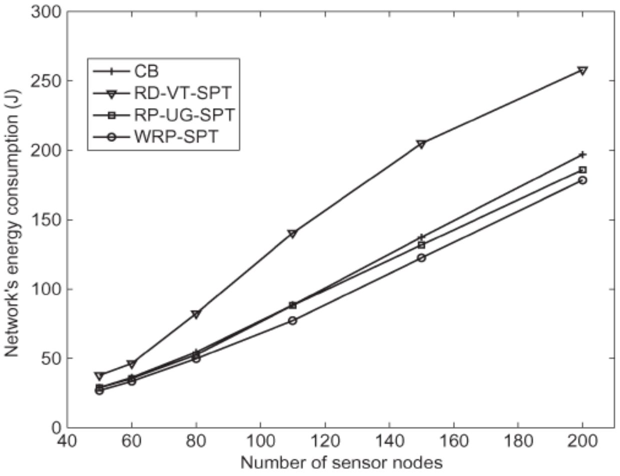


Fig. 7.Network energy consumption for WRP, CB, RD-VT, and RP-UG.

a 10% reduction in energy consumption, as compared with CB. RP-UG and WRP have nearly the same performance; WRP reduces energy consumption by an additional 6%, as compared with RP-UG.

The ability of the four algorithms to uniformly distribute energy consumption is shown in Figs. 8 and 9. WRP distributes energy more uniformly than the other approaches, specifically, 12% more than RP-UG, 28% more than CB, and 53% better than RD-VT. Similarly, RP-UG does not aim to balance the energy consumption rate of sensor nodes. RP-UG adds sensor nodes that are close to the sink as RPs, which may not necessarily have the highest energy consumption rate. Moreover, although RP-UG considers nodes that are on many routing paths, WRP preferentially selects nodes with high energy consumption rate and hop count from the sink. As shown in Fig. 9, WRP improves network lifetime by 13%, as compared with RPUG. With regard to CB, as shown in Fig. 3, the random cluster-head selection process causes nonuniform energy consumption. Moreover, two sensor nodes from the same cluster cannot be in the final tour. Hence, when there are a large number of sensor nodes, energy holes are likely to occur around the RP for a given cluster. In contrast, WRP avoids this scenario by having the mobile sink visits dense parts of a WSN, which helps to reduce the number of multi-hop transmissions. In RD-VT, long forwarding paths are observed from sensor nodes to RPs, which results in nonuniform energy consumption and 25% reduction in network lifetime, as compared with CB.

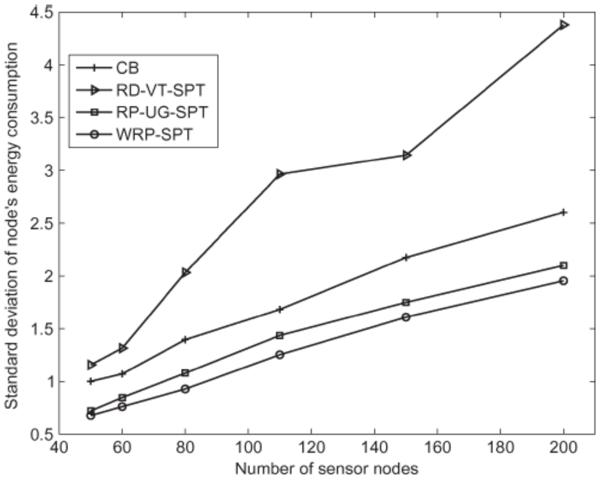


Fig. 8.Standard deviation of sensor nodes' energy consumption for WRP, CB, RD-VT, and RP-UG models.

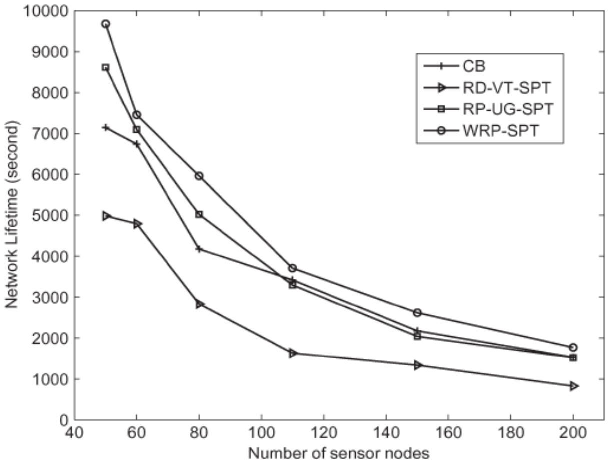


Fig. 9.Network lifetime for WRP, CB, RD-VT, and RP-UG.

In this experiment, we simulated the algorithms in a network with 110 sensor nodes and data packets with a packet delivery time ranging from 100 to 300 s. Figs. 10 and 11 show network energy consumption and network lifetime for WRP, CB, RDVT, and RP-UG. Consistent with the result shown in Fig. 7, WRP yields the best performance among all algorithms. The energy consumption for RD-VT reduces by 21% when the required packet delivery time is changed from 100 to 300 s, whereas WRP, RP-UG, and CB observed a reduction of 41%, 33%, and 37%, respectively. WRP observed a superior performance, as compared with other algorithms, even with small packet delivery times. This is because WRP always checks the possibility of adding the node with the highest weight first.

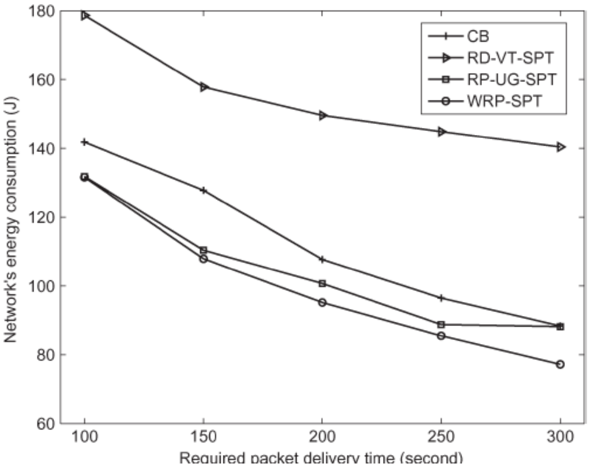


Fig. 10. Network energy consumption for WRP, CB, RD-VT, and RP-UG under different required delivery times for data packets.

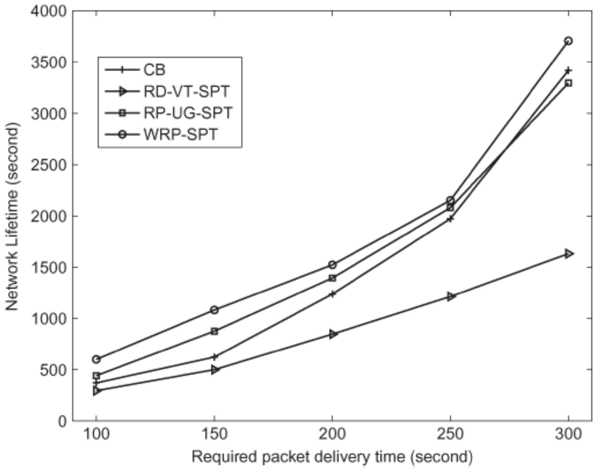


Fig. 11. Network lifetime for WRP, CB, RD-VT, and RP-UG under different required delivery times for data packets.

Finally, we recorded the simulation time of each algorithm. For RP-UG, we set $L0 = 20$ m, i.e., the transmission range of sensor nodes. The value of 20 m is the maximum possible for $L0$ because otherwise, edges bigger than $L0$ are split into edges with length $L0$. Virtual nodes are then added as necessary to connect these new edges.

Consequently, this process, depending on the value of $L0$, increases run time significantly. In fact, even with $L0$ set to 20 m, the running time of RP-UG is six times bigger than WRP, 36 times more than CB, and 72 times longer than RD-VT. This is because, in each iteration, RP-UG calculates the utility of each sensor node by calling a TSP solver. RD-VT has the lowest running time because it only calls the TSP solver once in each iteration.

B. Performance Under SMT

We have also considered using the SMT for RP-UG, RDVT, and WRP; this tree is constructed using the function in

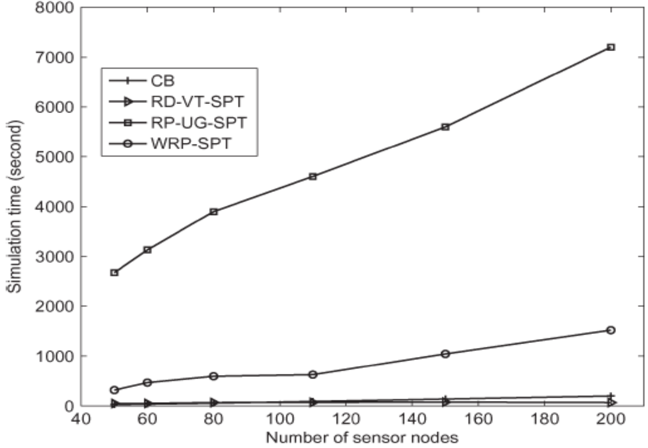


Fig. 12.Simulation time for WRP, CB, RD-VT, and RP-UG.

Specifically, the Steiner tree function uses the principal of an equilateral triangle, a circle, and a line to construct a Steiner point for a set containing three points on the minimum spanning tree (MST). When an SMT is formed, there are two types of Steiner points. The first type corresponds to real sensor nodes, which are called real Steiner points, and the other type is simply a physical position with no sensor nodes, which are called virtual Steiner points. In RD-VT and RP-UG, virtual RPs are replaced with the closest physical sensor nodes. In WRP, when a sensor node notices that the succeeding hop destination for its data packets is a virtual RP, the sensor node stores its data until the mobile sink arrives at the virtual RP's position. Upon arrival, the sensor node forwards its data to the mobile sink.

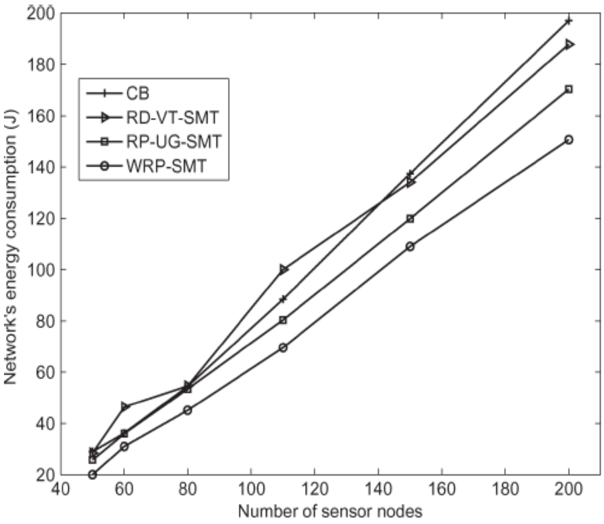


Fig. 13.Network energy consumption for WRP, CB, RD-VT, and RP-UG in SMT scenarios.

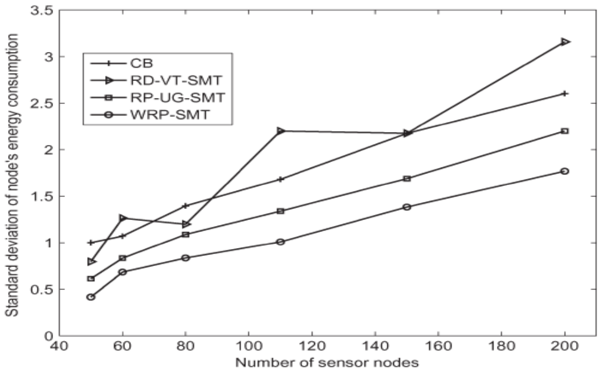


Fig. 14.Standard deviation of sensor nodes' energy consumption in SMTscenarios.

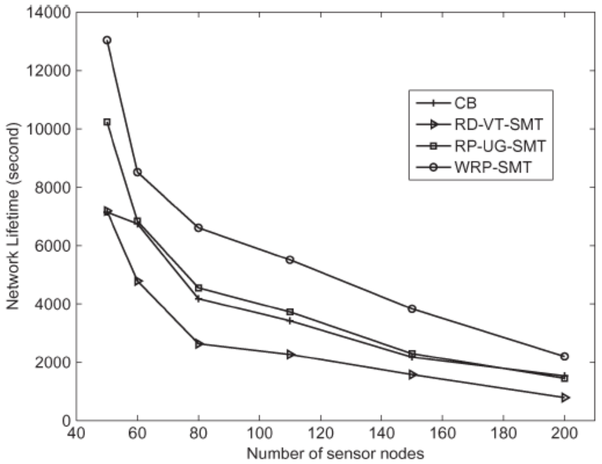


Fig. 15.Network lifetime for WRP, CB, RD-VT, and RP-UG in SMT scenarios.

when using the SPT. This is because virtual Steiner points, which are in the final tour, do not receive data from other sensor nodes. Instead, these points are visited by the mobile sink. In comparison, when we use the SPT, RPs have a higher energy consumption, as compared with other sensor nodes. However, for the SMT case, when virtual points are in the final tour, we observe fewer RPs; thus, actual nodes that act as RPs reduces and thereby reduces consumed energy. Moreover, the energy consumption between sensor nodes is distributed uniformly. For these reasons, the SD for WRP-SMT is 16% less than WRP-SPT and 39% less than CB (see Fig. 14). The SD for RDVT- SMT is 28% less than RD-VT-SPT, and for RP-UG-SMT, it is 5% less than RP-UG-SPT. This is because visiting more RPs leads to shorter data forwarding paths and, thereby, better network lifetime. The difference between the SD ofWRP-SMT and RD-VT-SMT is 44%, and between WRP-SMT and RP-UGSMT, it is 22%, which is less than the results recorded in SPT experiments. This thus confirms that the better performance gained by WRP in the SMT scenario is due to the use of virtual RPs.

VI. CONCLUSION

In this paper, we have presented WRP, which is a novel algorithm for controlling the movement of a mobile sink in a WSN. WRP selects the set of RPs such that the energy expenditure of sensor nodes is minimized and uniform to prevent the formation of energy holes while ensuring sensed data are collected on time. In addition, we have also extended

WRP to use an SPT and an SMT. Apart from that, we have also considered visiting virtual nodes to take advantage of wireless coverage. Our results, which are obtained via computer simulation, indicate that WRP-SMT reduces the energy consumption of testedWSNs by 22% in comparison to CB. We also benchmarked WRP against existing schemes in terms of the difference between sensornode energy consumption. Our simulation results show that WRP uniformly distributes energy consumption by 39% and 44% better than CB and RD-VT, respectively. As a future work, we plan to enhance our approach to include data with different delay requirements. This means a mobile sink is required to visit some sensor nodes or parts of a WSN more frequently than others while ensuring that energy usage is minimized, and all data are collected within a given deadline. Moreover, we plan to extend WRP to the multiple mobile sinks/rovers case. This case, however, is nontrivial as it involves subproblems such as interference and coordination between rovers. Having said that, we note that WRP remains applicable if a large WSN is partitioned into smaller areas where each area is assigned a mobile sink. WRP can be thus run in each area. We defer the evaluation of such an approach to a future paper.

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