Exploiting Mobility for Quality-Maximized Data Collection in Energy Harvesting Sensor Networks

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***Abstract*—With the advance of energy harvesting technology, more and more sensors now are powered by ambient energy. Energy harvesting sensor networks are a key step in paving the way for truly green systems that can operate 'perpetually' and do not adversely impact on the environment. In this paper we consider quality data collection in an energy harvesting sensor network by exploring sink mobility. That is, we consider a mobile sink traveling along a to-be-found trajectory for data collection, subject to a specified tolerant delay constraint. We first formulate this optimization problem as a data quality maximization problem. Since the problem is NP-hard, we then devise a scalable heuristic solution. Also, a distributed implementation of the proposed algorithm is developed too. We finally conduct extensive experiments by simulation to evaluate the performance of the proposed algorithms. Experimental results demonstrate that the proposed algorithms are promising and very efficient.**

I. Introduction

With the advance of energy harvesting technology, energy harvesting sensor networks are a key step in paving the way for truly green systems that can operate 'perpetually' and do not adversely impact on the environment. To mitigate uneven energy consumptions among sensors, the concept of mobile sinks has been exploited. Extensive studies have been conducted in traditional sensor networks, which have demonstrated that mobile sinks can significantly improve various aspects of network performance including network lifetime, data delivery reliability, throughput, etc [2], [9], [10], [11]. Most of these existing studies focused on the trade-off between maximizing data quantity and prolonging network lifetime. However, network lifetime maximization is no longer a main issue in energy harvesting sensor networks as sensors can get recharged by renewable energy. This creates a shift in research focus from network lifetime maximization to network utility (e.g. the quality of the collected data) maximization. It is noticed that sensors with sufficient energy replenishment will have more chances to transmit their data to the mobile sink, while sensors with low energy replenishment may not be able to transmit their data to the mobile sink at all. Consequently, the data collected by the entire network is biased. The monitoring quality of the network thus is seriously compromised. In this paper we consider data gathering with a mobile sink in energy harvesting sensor networks with the aim of maximizing the quality of the collected data.

A. Related work

By employing mobile sinks for data collection, it is unavoidable to have data delivery delays, where the data delivery delay usually represents the time duration of a sampling reading from its generation to its collection by the mobile sink. Xu *et al.* [11] addressed a delay-tolerant data collection problem for event-detection with a guaranteed collection rate. They formulated the problem as the sensor selection problem by incorporating spatial-temporal correlations of events so that the network lifetime can be significantly prolonged. Liang *et al.* [2] incorporated the travel distance of the mobile sink into the mobile data gathering problem formulation, and proposed several heuristics for finding feasible trajectories for the mobile sink so that the network lifetime can be maximized. Xu *et al.* [10] considered a delay-tolerant data collection problem to maximize the network lifetime by formulating a joint optimization problem of finding a trajectory for the mobile sink and designing an energy-efficient routing protocol to route sensing data to the sink. However, the network lifetime is no longer a main issue in energy harvesting sensor networks as the sensors can be continuously recharged by renewable energy. Furthermore, most existing studies of data collection in energy harvesting sensor networks assumed that sensing data is routed to a fixed base station through multi-hop relays [3], [4], and very few attention has been paid to data collection in energy harvesting sensor networks with mobile sinks until recent works by the authors [6], [7], [8], in which they provided solutions to the data volume maximization problem and time slot scheduling problem. Orthogonal to these existing works, in this paper we consider data gathering where a mobile sink traverses along a trajectory and stops at some locations for a certain amount of time to collect data from one-hop sensors with the aim of maximizing the quality of the collected data, subject to a given tolerant data delivery delay. With one-hop transmission, each sensor could send data directly to the mobile sink without any relay, and thus no energy are consumed on forwarding packets for others which is more energy efficient in comparison with multi-hop relays. Moreover, one-hop transmission particularly is very useful for a disconnected network (e.g. some sensors are physically isolated), while multi-hop transmission is not applicable.

B. Contributions

The main contribution of this paper are as follows. We consider data collection in an energy harvesting sensor network, using a mobile sink. We first formulate this problem as a data quality maximization problem consisting of finding a trajectory and sojourn time scheduling. Since this is a NP-hard problem, we then devise a heuristic algorithm which

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exhibits low computational complexity and high scalability. A distributed implementation of the proposed algorithm is also developed. Finally, we conduct experimental simulations to evaluate the performance of the proposed algorithms. Experimental results demonstrate that the proposed algorithms are efficient in terms of the quality of data collected.

The rest of the paper is organized as follows. Section II introduces the network model and problem definition. Section III is devoted to devising algorithms for the data quality maximization problem, while Section IV evaluates the performance of the proposed algorithms through experimental simulations. Section V concludes the paper.

II. System Model and Problem Definition

A. Network model

We consider an energy harvesting sensor network $G = (V \cup S, E)$ deployed for monitoring purpose with a set V of stationary sensor nodes, a set E of links, a mobile sink, and a set S of potential sojourn locations which is known *a priori*. For the sake of simplicity, we assume that all sensors are homogeneous, where our solutions can be extended to heterogeneous scenario easily. Each sensor $v \in V$ is powered by a rechargeable battery whose energy is harvested from its surrounding environment, and senses its vicinity with a data generation rate g_v. Given a tolerant data delivery delay T, the sensing data is stored at the sensor temporarily and will be uploaded to the mobile sink with a data transmission rate r_v if possible. Assuming that the maximum transmission range of each sensor and the mobile sink is R, there is a link $l_{i,j} \in E$ between a sensor $v_i \in V$ and the mobile sink located at $s_j \in S$ if the sink is within the maximum transmission range of v_i, i.e., the Euclidean distance $|l_{i,j}|$ between v_i and s_j is no greater than R. Denote by $N(s_j)$ the neighboring set of sensors within the maximum transmission range of s_j.

We consider a communication model similar as the one used in [12]. Specially, the mobile sink is equipped with multiple antennas and has unlimited energy supply in comparison with energy-constrained sensor nodes. Being a receiver with multiple receiving antennas, the mobile sink makes it possible for multiple sensors to concurrently transmit their data to it.

B. Energy replenishment and consumption models

Following a widely adopted assumption, we assume that the energy replenishment rate of each sensor node is much slower than its energy consumption rate [1], the amount of energy harvested at a future time period is uncontrollable but predictable based on the source type and harvesting history [4]. Take solar energy prediction for instance, by effectively taking into account both the current and past-days weather conditions, Cammarano *et al.* [5] proposed a novel energy prediction model which is able to leverage past energy observations to provide accurate predictions. Nevertheless, the practical aspects about energy prediction (e.g. prediction approach, leakage) is out of the focus of this paper.

Denote by C_v the energy storage capacity and $B_v(t)$ the amount of residual energy at time t of each sensor $v \in V$. Then, $B_v(t)$ can be estimated as follows:

$$B_v(t) = \min\{B_v(t') + \int_{t'}^{t} H_v(t)dt, C_v\} \tag{1}$$

where t' is the latest time when sensor v finished a data uploading to the mobile sink, $0 \leq t' \leq t$, and $H_v(t)$ represents the pattern of energy acquisition of sensor v. For the sake of discussion, we use B_v to represent the residual energy of sensor v at the moment in the rest of the paper. We assume that each sensor node only consumes energy on wireless communication, while its other energy consumptions including sensing and computation are ignored. For each link $l_{i,j}$, let $e_{i,j}$ be the energy consumption of node v_i by transmitting a unit-length data to the mobile sink located at s_j. Then $e_{i,j}$ can be represented by the following equation.

$$e_{i,j} = \alpha + \beta \cdot |l_{i,j}|^{\gamma} \tag{2}$$

where α is a distance-independent constant that represents the energy consumption to run the transmitter circuitry which is negligibly small, and β is a constant that represents the transmitter amplifier. The exponent γ is the path loss factor, which is typically a constant between 2 and 4. In this paper unless otherwise specified we assume that $\gamma = 2$.

Given a sojourn location $s_j \in S$ of the mobile sink, if it is within the maximum transmission range of a sensor $v_i \in V$, *the survival time* $t_{i,j} = \min\{\frac{B_{v_i}}{e_{i,j} \cdot r_{v_i}}, \frac{D_{v_i}}{r_{v_i} - g_{v_i}}\}$ of a sensor v_i can be determined by its residual energy B_{v_i} and the amount of stored data D_{v_i}, where $\frac{B_{v_i}}{e_{i,j} \cdot r_{v_i}}$ represents the time allowed for data transmission prior to its energy depletion, and $\frac{D_{v_i}}{r_{v_i} - g_{v_i}}$ represents the time required to transfer all the stored data.

C. Data quality metric

To measure the contribution of each sensor node $v \in V$ to the data quality of the entire network in a time period of T, A monotonic increasing function $u(v)$ is used to represent such a contribution, When $u(v) = 1$, all sensed data by sensor v during the period of T has been collected by the mobile sink; otherwise, we assume that at any time point during the period, the data generated by node v is treated equally in terms of its contribution to the data quality of the entire network. In other words, we do not distinguish whether the sensing data is obtained at time point t_a or at time point t_b with $t_a \neq t_b$, and treat them equally. We then define the utility of sensor v in a tour of the mobile sink as $u(v) = f(x_v)$ where x_v is the ratio of the data collected to the data generated by sensor v, and the function $f(x)$ is a monotonic increasing function. If there is not any data sent from a sensor v to the mobile sink during the time period of T, then $u(v) = 0$. Clearly, $0 \leq u(v) \leq 1$. Thus, maximizing the *network data quality* is equivalent to maximizing the sum of utilities of all nodes, $\sum_{v \in V} u(v)$.

D. Problem definition

Given an energy harvesting sensor network $G(V \cup S, E)$ with sensor set V and potential sojourn location set S for a mobile sink, and a tolerant data delivery delay T, *the data quality maximization problem* in G is to find an optimal close trajectory for the mobile sink that consists of sojourn locations in S and time scheduling at each sojourn location such that the network data quality is maximized, subject to the tolerant delay T, assuming that the mobile sink only collects data from one-hop sensor nodes, where the tolerant delay T is the total amount of time spent by the mobile sink per tour. Notice that this one-hop data transmission can be easily extended to multi-hop data transmission. In this latter case, we can treat one-hop sensors as gateways that all other sensors' data will be relayed to them. In other words, let $S' = \langle s_0, s_1, s_2, \cdots, s_m \rangle$ be the sequence of sojourn locations in the trajectory of the mobile sink, where for all $s_j \in S'$ t'_j is the travel time from s_{j-1} to s_j, t_j is the sojourn time at location s_j, $1 \leq j \leq m$, and s_0 is the depot of the mobile sink. The utility of sensor $v \in V$ in a tour of the mobile sink is $u(v) = \sum_{j=1}^{m} \delta_j(v) \cdot u_j(v)$, where $\delta_j(v)$ is either 1 or 0, depending on whether v sends its data to the mobile sink when the mobile sink is located at s_j, and $u_j(v)$ is the utility gain of v if it does send its data to the mobile sink. Specifically, assume that sensor v sent its data to the mobile sink previously when the mobile sink was located at $s_{j_1}, s_{j_2}, \ldots$, and s_{j_l}, respectively. When the sink is located at s_j with sojourn duration of t_j, the utility gain $u_j(v)$ of v is calculated as follows.

$$u_j(v) = f\left(\frac{(\sum_{i=1}^{l} t_{j_i} + t_j) \cdot r_v}{T \cdot g_v}\right) - f\left(\frac{(\sum_{i=1}^{l} t_{j_i}) \cdot r_v}{T \cdot g_v}\right) \quad (3)$$

where t_{j_i} is the sojourn duration of the mobile sink at location s_{j_i} with $1 \leq i \leq l$. The data quality maximization problem in G therefore is to find a close trajectory for the mobile sink and the sojourn time for each chosen sojourn location in the trajectory such that the value of $\sum_{v \in V} u(v)$ is maximized, subject to the time constraint T. The data quality maximization problem is NP-hard, as the data quantity maximization problem is a special case of this general setting [6].

III. Heuristic Algorithm

In this section we deal with the data quality maximization problem by devising a scalable heuristic. The proposed algorithm proceeds iteratively. Within each iteration a new sojourn location as well as the sojourn time is added to the constructed trajectory. This procedure continues until the specified tolerant delay of the trajectory does not hold any more.

A. Algorithm

Suppose that s_i is the current location of the mobile sink in the found trajectory so far, we consider the next sojourn location s_j of the mobile sink. Notice that a visited sojourn location can be revisited multiple times. A location $s_j \in S$ is a *feasible sojourn location* if the time spent on all previous sojourn locations and traveling plus the time t'_j from s_i to s_j, the sojourn time t_j at s_j, and the time $t'_{j,0}$ from s_j to the depot s_0 is no more than T, i.e., $\sum_{l=0}^{i}(t'_l + t_l) + t'_j + t_j + t'_{j,0} \leq T$.

Consider a potential next sojourn location s_j. The data collected by the mobile sink at s_j is determined jointly by its sojourn time t_j and its neighboring sensors. To maximize the quality of data collected at each sojourn location, ideally the mobile sink should move to a location a bit far away from its current location s_i, thus, all neighboring sensors of the new location will have enough energy to transmit their data to the mobile sink and the expected quality of data collected will be maximized because it is very likely that the sensing data from these sensors has not been collected yet. On the other hand, the travel distance between the current location and the next sojourn one should not be too far away from each other,otherwise no data will be collected during the traveling of the mobile sink. To mitigate the data loss due to mobile sink traveling, its travel distance should be shortened. Thus, there is a nontrivial trade-off between the travel distance and the amount of sojourn time at the next sojourn location when the mobile sink chooses its next sojourn location. In the following we show how to choose the next sojourn location $s_j \in S$.

Recall that $N(s_j)$ is the set of sensors that the mobile sink located at s_j is within their transmission ranges and $t_{i,j}$ is the survival time of sensor $v_i \in N(s_j)$ if it sends its data to the mobile sink. Let $v_{i_1}, v_{i_2}, \ldots, v_{i_{|N(s_j)|}}$ be the sensor sequence sorted by their survival time in decreasing order. Denote by $\Delta u(s_j, v_{i_{l'}}) = f(\frac{(T_i(v_{i_{l'}})+t_{i_l,j}) \cdot r_{v_{i_{l'}}}}{T \cdot g_{v_{i_{l'}}}}) - f(\frac{T_i(v_{i_{l'}}) \cdot r_{v_{i_{l'}}}}{T \cdot g_{v_{i_{l'}}}})$ the utility gain of sensor $v_{i_{l'}}$ by sending its data to the mobile sink at location s_j with the time duration of $t_{i_l,j}$ if $t_{i_l,j} \leq t_{i_{l'},j}$, where $T_i(v)$ is the accumulative sojourn time of sensor v prior to the sojourn location s_j. Otherwise, $\Delta u(s_j, v_{i_{l'}}) = f(\frac{(T_i(v_{i_{l'}})+t_{i_{l'},j}) \cdot r_{v_{i_{l'}}}}{T \cdot g_{v_{i_{l'}}}}) - f(\frac{T_i(v_{i_{l'}}) \cdot r_{v_{i_{l'}}}}{T \cdot g_{v_{i_{l'}}}})$ if $t_{i_l,j} > t_{i_{l'},j}$. Then, the utility gain $u(s_j, i_l)$ when the mobile sink at location s_j with a sojourn time $t_{i_l,j}$ is

$$u(s_j, i_l) = \frac{\sum_{v \in N(s_j)} \Delta u(s_j, v)}{\Delta t(s_j, i_l)}, \quad (4)$$

where $\Delta t(s_j, i_l) = t'_j + t_{i_l,j} + t'_{j,0} - t'_{i,0}$ is the time cost associated with this utility gain, assuming that the speed of the mobile sink r_m is fixed. Define the utility gain sequence at location s_j with different sojourn times as follows.

$$u(s_j, i_1), u(s_j, i_2), \ldots, u(s_j, i_{|N(s_j)|}). \quad (5)$$

Since we aim to maximize the aggregate utility of all sensors, we can choose a sojourn time $t_{i_k,j}$ for the mobile sink at each sojourn location s_j such that the utility gain $u(s_j, i_k)$ is maximized, i.e., we identify an index i_k of a maximum term in sequence (5) as the utility gain of the mobile sink at location s_j, $1 \leq k \leq |N(s_j)|$ and $1 \leq j \leq |S|$. If we choose location s_j as the next sojourn location of the mobile sink, the sojourn time of the mobile sink at s_j is $t_j = t_{i_k,j}$, and the utility gain is $U(s_j) = u(s_j, i_k)$. Thus, given all feasible sojourn locations, to maximize the network data quality, a location s_j with the maximum value of $U(s_j)$ will be chosen as the next sojourn location of the mobile sink. With more and more sojourn locations added to the trajectory, we then reach a point where no any location in S will be a feasible sojourn location for the trajectory. Consider a location s_j which has $T_i + t_j + t'_j + t'_{j,0} > T$ while $T_i + t'_j + t'_{j,0} < T$, where T_i is the amount of time spent by the mobile sink prior to location s_j and $t_j = t_{i_k,j}$ defined as the above. For this case, if s_j is chosen as a sojourn location of the mobile sink, it must be the last sojourn location in the trajectory, and at which the sojourn time of the mobile sink should be no more than $\Delta t_j = T - (T_i + t'_j + t'_{j,0})$. To find an appropriate sojourn time at location s_j, we re-examine sequence (5) by identifying these terms whose survival times are no greater than Δt_j and choosing a term among them with the maximum value (the maximum utility gain) and put its relevant time as the sojourn time of the mobile sink at s_j. If there are multiple such locations, we choose the one that results in the maximum utility gain.

The detailed algorithm for the data quality maximization problem, `Max_Utility`, is described in **Algorithm** 1.

Algorithm 1: `Max_Utility`

Input: The set of potential sojourn locations $S \cup \{s_0\}$, the tolerant delay T, and the sink speed r_m
Output: The sink trajectory and the relevant sojourn time
begin
  $S' \leftarrow \langle s_0 \rangle$; $max\_gain \leftarrow 0$;
  while *there is a feasible sojourn location* **do**
    for *each feasible sojourn location* $s_j \in S$ **do**
      for *each sensor* $v_i \in N(s_j)$ **do**
        Compute the survival time $t_{i,j}$;
      Find the maximum term in sequence (5). Let i_k be the index of the maximum term;
      $t_j \leftarrow t_{i_k,j}$; $U(s_j) \leftarrow u(s_j, i_k)$;
      if $max\_gain < U(s_j)$ **then**
        $next\_soj\_location \leftarrow s_j$;
        $next\_soj\_time \leftarrow t_j$;
        $max\_gain \leftarrow U(s_j)$;
    $S' \leftarrow S' \cup \{next\_soj\_location\}$;
    Update the residual energy B_v for every sensor v;
  Add the last sojourn location;
  return S' and the sojourn time t_j for each $s_j \in S'$

B. Distributed implementation

So far the proposed algorithm is a centralized algorithm. As the network we are dealing with is a distributive sensor network, we now provide a distributed implementation of the proposed algorithm, where each node has only the knowledge of its neighbors not the entire network and harvesting energy prediction at each sensor is not required, assuming that the mobile sink knows the network topology and the location information of potential sojourn locations.

The distributed algorithm constructs the trajectory iteratively too. Within each iteration, one sojourn location is added to the trajectory. Assume that the mobile sink is currently located at s_i and tries to find its next sojourn location and the sojourn time at that location. To choose its next sojourn location s_j, the following metrics must be considered. (i) Prior to arriving its next location s_j, the mobile sink does not know the residual energy of sensors in $N(s_j)$. We here use a 'time-stamp' to approximately represent such information associated with each potential location of the mobile sink, which is the most recent visited time by the mobile sink. Intuitively, when a location has a larger time stamp value, it implies that the location should be avoided to be revisited soon because its neighboring sensors just sent their data recently and they have not been yet fully recharged. (ii) The ideal distance of the next sojourn location from the current one should be twice the maximum transmission range of the mobile sink. Otherwise, if the next sojourn location is within the transmission range of the current one, it is very likely that the data generated by most of its neighboring sensors has been collected in the previously visited sojourn locations. On the other hand, if the next sojourn location is chosen far from the current one, although a large volume of data can be collected from that location, the time overhead on traveling is relatively large, as the total amount of time per tour is bounded by T. Thus, each potential sojourn location $s_j \in S$ will be ranked based on its *priority weight* consists of its time stamp, the distance to the current sojourn location, and the amount of traveling time $t'_j + t'_{j,0}$ of s_j. The mobile sink then chooses a location with the highest priority.

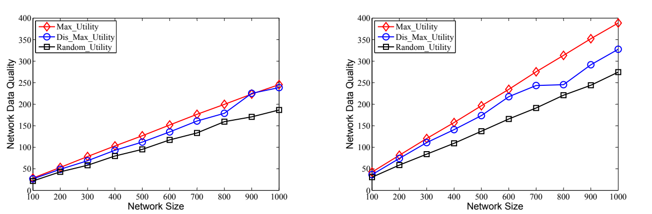
The distributed algorithm for the data quality maximization problem, `Dis_Max_Utility`, is described as follows. For the mobile sink located at the current sojourn location s_i (initially located at s_0), it repeats the following procedure. It finds its next sojourn location s_j and the sojourn time based on the priority weight metric. If no such a location exists, this implies that adding any new location will violate the specified tolerant delay constraint, the algorithm terminates. Otherwise, a location s_j with the highest priority will be chosen as its next sojourn location, and the mobile sink travels from s_i to s_j. It then broadcasts a 'Hello' message at location s_j. Upon receiving 'ACK' messages from all responded sensors $v_{i'} \in N(s_j)$, the mobile sink computes the survival time $t_{i',j}$ of each sensor $v_{i'}$. The mobile sink then finds the maximum term from sequence (5) and let i_k be the index of the maximum term. The mobile sink then updates the time-stamp of location s_j by a new value $T_i + t'_j + t_j$ and broadcasts the sojourn time t_j to all sensors in $N(s_j)$, where $t_j = t_{i_k,j}$. It finally receives the sensed data from the responded sensors. For each sensor $v_{i'} \in N(s_j)$, upon receiving the 'Hello' message, it responds by sending an 'ACK' message. The 'ACK' message contains its current residual energy and its distance to location s_j. Upon receiving the sojourn time t_j from the mobile sink located at s_j, sensor $v_{i'}$ sends its data to the mobile sink for a time duration of t_j if $t_{i',j} \geq t_j$. Otherwise, it sends its data to the mobile sink for a time duration of $t_{i',j}$ if $t_{i',j} \leq t_j$.

IV. Performance Evaluation

In this section we study the performance of the proposed algorithms through experimental simulation, using a simulator built by Java. We consider an energy harvesting sensor network consisting of 100 to $1,000$ sensors randomly deployed in a $100m \times 100m$ square region. The depot of the mobile sink is located at one corner of the square. For the sake of convenience, we assume that the maximum transmission range of both the mobile sink and the sensor nodes is 20 meters. The potential sojourn locations in S are also randomly generated with the default value $|S| = 50$. Each sensor v has a data generation rate $g_v = 1Kbps$ and a data transmission rate $r_v = 5Kbps$. Each sensor is powered by a solar panel with a dimension $(10mm \times 10mm)$ and its battery capacity is $10,000Jules$. The solar power harvesting profile is built upon the real solar radiation measurements [4], in which the total amount of energy collected from a $37mm \times 33mm$ solar cell over a 48-hour period is $655.15mWh$ in a sunny day and $313.70mWh$ in a partly cloudy day. Furthermore, we set $\beta = 150nJ/bit/m^2$ for the energy consumption model and $r_m = 2m/s$ for the speed of the mobile sink. We here adopt $f(x) = \sqrt{x}$ as the utility function, which can be easily extended to other utility functions. Each value in figures is the mean of the results by applying each mentioned algorithm to 30 different network topologies of the same network size.

A. *Performance evaluation*

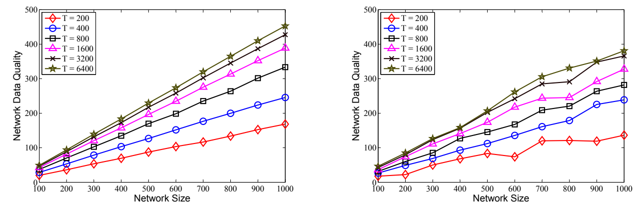
We first investigate the performance of algorithms `Max_Utility` and `Dis_Max_Utility` against that of another heuristic `Random_Utility` - a variant of algorithm `Max_Utility` by randomly selecting a feasible sojourn location in S within each iteration. We vary network size n from 100 to $1,000$ and set tolerant delay T as $400s$ and $1,600s$, respectively. Fig. 1 clearly shows that both algorithms `Max_Utility` and `Dis_Max_Utility` outperform algorithm `Random_Utility` significantly. For instance, when $T = 400s$ or $T = 1,600s$, the network data quality of algorithms `Max_Utility` and `Dis_Max_Utility` is around 32% and 21%, or 40% and 25% higher in comparison with that of algorithm `Random_Utility`.



(a) $T = 400s$ (b) $T = 1,600s$

Fig. 1. The network data quality performance of different algorithms by varying network size n and setting tolerant delay $T = 400s$ and $1,600s$.

We then study the impact of tolerant delay T and network size n on the performance of algorithms by varying n from 100 to $1,000$ while keeping tolerant delay T at $200s$, $400s$, $800s$, $1,600s$, $3,200s$, and $6,400s$, respectively. Fig. 2 shows that with the growth of T, the performance of algorithms `Max_Utility` and `Dis_Max_Utility` significantly improves. However, the performance gap among the mentioned algorithms becomes marginal when $T \geq 3,200s$, this is because all potential sojourn locations in S have almost been visited during this long time period. With the increase of network size, we observe that the network data quality of all proposed algorithms increases, too. For example, when T is fixed at 800s and n varies from 100 to $1,000$, the network data quality of algorithm `Max_Utility` is 37.1, 70.2, 102.7, 134.7, 169.7, 198.4, 235.1, 263.7, 301.5, and 333.5, respectively. The network data quality of algorithm `Dis_Max_Utility` is 31.5, 59.9, 85.1, 127.1, 145.5, 167.5, 208.8, 220.6, 263.8, and 281.8, respectively. Notice that algorithm `Max_Utility` outperforms algorithm `Dis_Max_Utility`, as `Dis_Max_Utility` only has the local knowledge of the network and does not need harvesting energy predictions of sensors.



(a) Algorithm `Max_Utility` (b) Algorithm `Dis_Max_Utility`

Fig. 2. Impact of parameters tolerant delay T and network size n on the network data quality performance of different algorithms.

V. Conclusion

In this paper we have studied mobile data collection in an energy harvesting sensor network with a mobile sink, subject to the tolerant delay constraint. We first formulated a data quality maximization problem. We then devised a heuristic algorithm, and provided an efficient distributed implementation of the proposed algorithm. Finally, we evaluated the performance of the proposed algorithms through experimental simulation, and experimental results demonstrate that the proposed algorithms are very promising.

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