Adaptive Mobility-Assisted Data Collection in Wireless Sensor Networks

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Abstract—Mobility-assisted data collection in wireless sensor networks offers us a new approach to reducing and balancing the energy consumption of sensor nodes, however, the resultant data collection latency may be large due to the limited travel speed. Much research effort has been made on reducing the data collection latency with the scenario of a single mobile device. A potential problem with this is its scalability, and a straightforward solution is to employ multiple mobile devices to collect data collaboratively. In this paper, the data collection with multiple heterogeneous mobile devices, in terms of the capability to conduct data collection, is investigated. Our previous work, which models the network where a mobile sink visits sensor nodes and collects data as an M/G/1 queue, is extended, and new analytical results on the response time distribution, or equivalently the distribution of the data collection latency in the network, are presented. In addition, an adaptive data collection scheme is proposed, which schedules the data collection based on the service demand to reduce the operation cost. The accuracy of our modeling and analysis, along with the performance evaluation of the proposed data collection scheme, is verified through extensive simulations.

Keywords—Wireless sensor networks, mobility-assisted data collection, data collection latency, M/G/1 queue

I. INTRODUCTION

Data collection is one of the most important tasks of wireless sensor networks [1]. Traditionally, data collection is carried out by the wireless communications between sensor nodes and the sink, which may suffer from the following problems. First, wireless communications may consume the limited energy supply of sensor nodes excessively due to super-linear path loss exponents [2]. Second, even if shorter-range, multi-hop wireless communications are adopted, due to the data aggregation towards the sink, nodes around the sink still have to consume much more energy than other nodes due to heavier volumes of traffic transmitted by them, leading to a lower overall network lifetime [3].

The mobility-assisted data collection is another approach to collecting data from sensor nodes, where certain kinds of mobile devices are employed to visit sensor nodes and collect data from them [4]. This mobility-assisted approach can not only conserve the energy and balance its consumption on sensor nodes, but also make the communications and networking become possible in very sparse networks with a “store-carry-and-forward” approach.

However, the main issue with this approach is the data collection latency may be large, due to the relatively slower travel speed of mobile devices, when compared with electromagnetic or acoustic waves [5]. Therefore, the optimal schedule of the limited mobility of mobile devices is the focus of many research efforts on this topic [6]–[8]. In our previous work [9], the network where a mobile sink travels around and collects data from sensor nodes is modeled as an M/G/1 queuing system, and system measures are derived to analytically evaluate the performance of data collection. Observing the fact that a single mobile sink, due to its limited mobility, may not be sufficient for certain applications with strict requirements on data collection latency, some work explored the case where multiple homogeneous mobile devices are available [8].

In practical networks, the mobile devices may not be homogeneous, e.g., they could be mobile sinks [4], data mules [10], and even mobile sensors [11]. Thus in this paper, we consider the network where not only a mobile sink is available for data collection, but also it can dispatch one or more lightweight mobile devices, referred to as mobile collector, to assist the data collection if needed. Note that the employment of mobile collectors also imposes extra costs in terms of manufacture, deployment, maintenance, and so on, so our objective is to utilize the mobile collectors as little as possible to reduce the operation cost, while still guaranteeing an acceptable data collection performance.

Our contributions in this paper are threefold. We extend the analysis on the M/G/1 queue modeling when only the mobile sink is available for data collection, and theoretically analyze the distributions of the queuing time and response time of data collection requests, which are critical metrics to evaluate the data collection performance. In addition, an adaptive data collection scheme is proposed based on the analysis, which schedules the work of the mobile sink and mobile collectors based on data collection demand. Finally, we verify our analysis and evaluate the performance of the proposed scheme through extensive simulations.

The rest of this paper is organized as follows. The work related to exploring mobility for data collection in wireless sensor networks is reviewed in Section II. In Section III, we present the network model and highlight our approach. In Section IV, we present the analytical results on the queuing time and response time distributions when only the mobile sink is available. Then in Section V we present the proposed adaptive data collection scheme based on the analysis. In
Section VI, we verify our analysis results and evaluate the performance of the proposed scheme. Finally, we conclude this paper with future work in Section VII.

II. RELATED WORK

Mobility-assisted data collection in sensor networks is currently one of the most active research topics [1]. Based on the application scenarios, the data collection problem can be classified into two categories, i.e., the offline and the online cases.

The objective of the offline scenario is to accomplish the data collection task from all sensor nodes within the shortest possible time, and the sensor locations are assumed to be available to the mobile device [6], [12], [13].

In [6], a Combine-Skip-Substitute (CSS) data collection scheme was proposed to obtain the optimal data collection tour for the mobile device, which consists of three steps: it starts with an TSP formulation based on the set of sensor nodes in the network, and uses an existing TSP solver to solve it; then based on the visiting order of sensor nodes in the optimal TSP tour, the combination of data collection jobs is conducted to reduce the number of locations that the mobile device has to visit; at last, the data collection tour is further shortened by the skip-and-substitute operations. The CSS scheme was shown to outperform the state-of-the-art Label-Covering Algorithm at that time [14]. Considering the limited scalability of data collection when only one mobile device is adopted, the CSS scheme was modified to fit the scenario where multiple mobile devices exist [12]. A multi-rate wireless communication model was proposed to take the data transfer rate between the mobile device and sensor nodes into account in [13], and the CSS scheme was extended accordingly.

In the online case, the data collection process is carried out in an on-demand way: sensor nodes send data collection requests when they have data to report, and on receiving these requests, the mobile device will move to the nodes and collect the data from them. No prior knowledge on when and where the requests will appear is available to the mobile device [8], [9], [15], [16].

The data collection process when a single mobile sink is available was modeled as an $M/G/1$ queuing system in [9], and several critical performance metrics, e.g., the average service time, and the average and the distribution of the queue length, were derived and verified. The single server queuing model was extended to the multiple servers in [8] to consider the scenario where multiple mobile devices are available, and noticing the analytical intractability of the $M/G/c$ model, approximation methods were adopted to evaluate the system metrics. Both [9] and [8] assume the first-come-first-serve (FCFS) service discipline for the mobile device(s), and the case when the mobile device adopts the nearest-job-next (NJN) discipline to carry out the data collection was analyzed in [15]. From the insights obtained through these queue-based analysis, a simple and efficient online data collection scheme was proposed in [7]. Another partition-based data collection algorithm with NJN as the fundamental service discipline was presented in [16].

In this paper, we extend the analysis in [9], and present new analytical results on the distributions of queuing time and response time, which offer important insights on the data collection latency. In addition, based on these analysis results and the idea of [3], we propose an adaptive data collection scheme for the network where heterogeneous mobile devices, i.e., mobile sink and mobile collectors, are available, which adaptively schedule the data collection task based on the service demand in the network. To the best of our knowledge, this is the first time in the literature where heterogeneous mobile devices are employed to carry out the data collection task in sensor networks.

III. PRELIMINARIES

We consider the scenario where a single mobile sink (MS) travels around in the sensing field to collect data from sensor nodes. Sensor nodes gather the sensory information about the environment, and when their buffers are about to be full, they initiate data collection requests to the MS, which can be sent to the MS by adopting certain existing simple and efficient MS-tracking protocols [4].

The MS maintains a service queue for the received data collection requests, and serve them with the first-come-first-serve (FCFS) discipline. By serving a request, we mean that the MS moves into the vicinity of the corresponding sensor node and collects data from it. For simplicity, we refer to the location of data collection request as the location of the sensor node that initiates the request. When there are too many requests in the queue, which means the service demand is too high for the MS, and may result in an unacceptable data collection latency and data loss eventually, the MS will send out one or more lightweight mobile collectors (MCs) to assist the data collection.

As a baseline, in the present work we assume the MC is only capable to serve one data collection request and must return to the MS afterwards for maintenance, i.e., battery recharging.

Two issues need to be addressed with this scenario: how could the MS determine whether MCs are needed under the current service demand? And in case MCs are needed, which requests should be assigned to them?

Our approach is to theoretically analyze the data collection latency when only the MS is available through an $M/G/1$ queue-based modeling, and adaptively decide whether the MS should send out MCs based on it. Furthermore, an adaptive data collection scheme is proposed to select the queued requests to assign to the MCs optimally.

It is clear that if all the MCs are kept working all the time, the data collection performance could be further improved, however, this also increases the network operation cost. Our objective here is to utilize the MCs as little as possible, while guaranteeing an acceptable data collection latency.

We list below the definitions and assumptions used in this paper and give a short description for each of them.

- we assume a square sensing field of the unit size;
• $v$: the travel speed of the MS and the MCs, normalized w.r.t the size of sensing field;
• $T_d$: the maximal tolerable data collection latency for the considered network application, after which the sensory data will be considered as outdated and erased from the buffers of sensor nodes;
• $\alpha$: the maximal tolerable data loss rate for the particular application;
• the arrival process of the data collection requests to the MS is a Poisson process, which is verified in [15];
• the time since the data collection request is initiated at sensor nodes till its reception at the MS is negligible [8];
• sensor nodes are uniformly deployed in the sensing field at random.

IV. DATA COLLECTION LATENCY WITH THE MS ALONE

In our previous work [9], we have shown that in the case of only a single MS is available to collect data from sensor nodes, the data collection process can be modeled as an $M/G/1$ queuing system. In this section, we further present the analytical results on the distribution of the system’s response time, or equivalently, the distribution of the data collection latency in the network. This result assists us to shed light on the time since the data collection request is initiated at the current condition.

A. $M/G/1$ Queue Modeling

It is shown in [5] that the data relay speed in sensor networks is about several hundred meters per second, which is much faster than the speed of a mobile device, and the travel time for the MS to move to a sensor node is much longer than the time needed for transmitting the data. Thus the service time of the request can be modeled as the time that the MS takes to move to a sensor node is much longer than the travel speed of the MS, and the travel distance tends to decrease with the increasing of the sensing field size, and eventually becomes negligible when the field side goes large enough.

Define the probability that there are $i$ new arrivals when serving the current request as

\[
\begin{align*}
    k_i &= \Pr\{i \text{ new arrivals during service} \} \\
    &= \int_0^\infty \frac{e^{-\lambda t} (\lambda t)^i}{i!} s(t) dt. \quad (2)
\end{align*}
\]

where $\lambda$ is the arrival rate of the requests to the MS, and the state transition of this Markov chain can be shown as in Fig. 1.

Fig. 1: State transition diagram of the embedded discrete-time Markov Chain.

With $k_i$, we can construct the following state transition matrix

\[
    P = \begin{bmatrix}
    k_0 & k_1 & k_2 & k_3 & \ldots \\
    k_0 & k_1 & k_2 & k_3 & \ldots \\
    0 & k_0 & k_1 & k_2 & \ldots \\
    0 & 0 & k_0 & k_1 & \ldots \\
    \vdots & \vdots & \vdots & \vdots & \ddots
    \end{bmatrix}. \quad (3)
\]

Denote $\pi = \{\pi_i\} (i = 0, 1, 2, \ldots)$ as the queue length probabilities at the departure times, then

\[
    \pi P = \pi. \quad (4)
\]

Define

\[
    \Pi(z) = \sum_{i=0}^{\infty} \pi_i z^i \quad (|z| \leq 1) \quad (5)
\]

\[
    K(z) = \sum_{i=0}^{\infty} k_i z^i \quad (|z| \leq 1) \quad (6)
\]
and consider another fact that \( \pi_0 = 1 - \rho \), we know
\[
\Pi(z) = \frac{(1-\rho)(1-z)K(z)}{K(z) - z},
\]
and \( \pi \) can be calculated. Although \( \pi \) is generally different from the steady state probabilities, the following theorem is proved for \( M/G/1 \) queue [21].

**Theorem 1:** Denote \( \mathbf{p} = \{ p_i \} (i = 1, 2, \ldots) \) as the steady state queue length distribution of an \( M/G/1 \) queue, then \( \pi = \mathbf{p} \).

Thus the steady state queue length probabilities are obtained.

### C. Response Time Distribution

In the following we derive the distribution of the response time based on \( \mathbf{p} \). The response time of a request consists of two parts: the queuing time since its arrival to the starting point of being served, and its service time. With the FCFS discipline, for a new request arriving at the queue with \( n \) existing requests, its queuing time is the sum of the service times of those \( n \) requests. By convolution theorem [18], we have
\[
q(t, n) = \begin{cases} 
0 & n = 0 \\
\sigma(t) & n = 1 \\
q(t, n - 1) * \sigma(t) & n > 1
\end{cases}
\]

from which the CDF of the general queuing time in the system can be derived as
\[
Q(t) = \sum_{i=0}^{\infty} \Pr\{ i \text{ existing requests} \}
\cdot \Pr\{ \text{queuing time } \leq t \mid i \text{ existing requests} \}
= \sum_{i=0}^{\infty} p_i \int_{0}^{t} q(x, i)dx
\]
and its density function \( q(t) = \frac{\partial Q(t)}{\partial t} \).

Similarly, the distribution of the response time for a request arriving at the queue and finds \( n \) existing requests is
\[
r(t, n) = \begin{cases} 
\sigma(t) & n = 0 \\
q(t, n) * \sigma(t) & n > 1
\end{cases}
\]

and its CDF can be calculated as
\[
R(t) = \sum_{i=0}^{\infty} \Pr\{ i \text{ existing requests} \}
\cdot \Pr\{ \text{response time } \leq t \mid i \text{ existing requests} \}
= \sum_{i=0}^{\infty} p_i \int_{0}^{t} r(x, i)dx
\]
and \( r(t) = \frac{\partial R(t)}{\partial t} \).

Note that by applying the convolution theorem again, \( r(t) \) can also be obtained by
\[
r(t) = q(t) * \sigma(t)
\]

### V. Adaptive Data Collection Scheme

We derived the response time distribution of the queuing system in the previous section. In this section, we present the adaptive data collection scheme based on it. As mentioned in Section III, two questions need to be answered in the adaptive scheme design: when the MS should send out the MC, and which requests should be assigned to the MC.

Given the maximal tolerable latency \( T_d \) and the maximal tolerable data loss ratio \( \alpha \), i.e., at least \( 1 - \alpha \) of the gathered sensory data have to be collected by the MS, or MCs, within time \( T_d \), based on (10) or (12), the MS can decide whether to send out MCs by solving the following optimization problem with regard to \( \sigma \) (\( \sigma = 0, 1, 2, \ldots \))
\[
\arg \min_{\sigma} \int_{0}^{T_d} r(x, \sigma)dx < 1 - \alpha.
\]

When the MS accomplishes the service of the current data collection request, and is about to select the next one to serve, it will check if the current queue length is smaller than \( \sigma \). If not, an MC will be sent out and one request from the queue is assigned to it. This sent-out and assignment process is repeated until the queue length becomes smaller than \( \sigma \).

Note that \( \sigma \) is only dependent on the deployment condition of the network, e.g., the size of the field and the travel speed of the MS, and it can be pre-calculated with different \( \lambda \) and stored in a lookup table at the MS.

The next question is which request should be assigned to the MC. Given the assumption that the MC is only capable to serve one request during each dispatch, it is obvious that we should assign the queuing request which can maximize the reduction in the total latency of all requests in the queue to the MC. Assume \( n \) queuing requests are available when the MS needs to decide which request should be assigned to the MC, and \( B = \{ b_1, b_2, \ldots, b_n \} \) is the set of the corresponding requesting sensor nodes according to their arrival order. Denote the current location of the MS as \( l \). The MS will select the \( b_i \) (\( i = 1, 2, \ldots, n \)) that maximize
\[
G = \begin{cases} 
(b_{i-1}b_i + b_ib_{i+1} - b_{i-1}b_{i+1})(n - i) & i > 1 \\
+ (\sum_{j=1}^{i-1} b_jb_{j+1} + b_{i+1}) - b_i & i = 1
\end{cases}
\]
and assign it to the MC.

The proposed adaptive data collection scheme is shown in Algorithm 1.

### VI. Performance Evaluation

We verify our analysis results and evaluate the performance of the proposed adaptive data collection scheme in this section. Based on the parameters from a real system in [19], we consider a square sensing field with size \((100 \times 100) \text{ m}^2\), where a total number of 100 sensor nodes are uniformly deployed at random, and the travel speed of both the MS and MCs are 1 \text{ m/s}. A total number of 20,000 requests are initiated and served during each run of the simulation, which is repeated for 50 times.
Algorithm 1 Adaptive Data Collection Scheme

Input: the pre-calculated $\sigma$, the current location of the MS $I$, and the set of requesting sensor nodes waiting in the queue $B = \{b_1, b_2, ..., b_n\}$, according to their arrival order;

Output: the requests set $\Gamma$ that should be assigned to the MCs. $\Gamma = \emptyset$ means no MC is needed.

1: $\Gamma = \emptyset$;
2: while $n \geq \sigma$ do
3: \quad $G = 0$, $b = -1$;
4: \quad for all $b_i \in B$ ($i = 1, 2, ..., n$) do
5: \quad \quad if $G_i > G$ then
6: \quad \quad \quad $G = G_i$, $b = b_i$;
7: \quad end if
8: \quad end for
9: \quad delete $b$ from $B$;
10: $\Gamma \leftarrow \{b\}$, $n = n - 1$;
11: end while
12: return $\Gamma$;

To deal with the inconvenience of the piecewise distance probability density function in (1), we use the least squares fitting [20] to approximate it with an order-10 polynomial

$$\tilde{f}_D(d) = 0.2802d^{10} - 2.0964d^9 + 2.2349d^8 + 24.3629d^7 - 106.8231d^6 + 194.4928d^5 - 182.8093d^4 + 91.8223d^3 - 29.3663d^2 + 8.2843d - 0.0402,$$

and adopt the approximation polynomial to calculate the service time in our performance evaluation.

We first examine the accuracy of the analysis results on the conditional queuing time distribution, i.e., the queuing time a newly arrived request has to wait before being served, given the number of already queued requests at its arrival. We explore the cases where the arrival time queue length is $5$ and $10$, respectively, as shown in Fig. 2(a). We can see that the analysis and simulation match each other very well, and not surprisingly, with a longer queue at the arrival time, the request needs to wait a longer time before being served.

Next we verify the result on the response time distribution of the requests when no MC is utilized, which is the foundation of the proposed adaptive data collection scheme. Figure 2(b) shows the verification results, in which two cases with the request arrival rate $\lambda$ of $0.012$ and $0.018$ are explored. We can see when only the MS is available for data collection, the average response time increases very fast when $\lambda$ increases, which agrees with the observation from Fig. 2(b). Furthermore, the average data collection latency is greatly reduced by employing the MCs, and this gain becomes more apparent when the arrival rate is higher: in the case when $\lambda$ is $0.018$, the average data collection latency is almost halved with MCs.

Next we examine the resultant data loss rate, as shown in Fig. 3(b). Compared with the case where the MS works alone, the adaptive data collection scheme can greatly reduce the data loss rate, and control it well within the tolerable range, i.e., less than $\alpha = 0.05$, even when the traffic load is very heavy.

At last we examine the issue that how many MCs are needed to guarantee an acceptable latency. Each time the MS accomplishes a data collection job, we record the number of busy MCs at that time. Again, we explore the three cases with different $\lambda$. The simulation results are shown in Fig. 3(c). We can see that even with a large $\lambda$ of $0.018$, more than $94\%$ of the cases only require one MC; when two MCs are available, the data collection latency for about $97.7\%$ of the recorded data collection requests can be satisfied. These observations assure us that the proposed scheme can effectively keep a low network operation cost, while at the same time guaranteeing a reasonable data collection performance.
In this paper, we explored the problem where the mobile sink (MS) and several mobile collectors (MCs) collect data collaboratively in wireless sensor networks. By using an \( M/G/1 \) queuing model when only the MS is available for data collection, we theoretically obtained the distributions of the queuing time and response time of the data collection requests. In addition, an adaptive data collection scheme for the MS and MCs was proposed, which schedules the work of the MS and MCs based on both the application requirement and network condition. Through an extensive simulation verification, we showed that our analytical results on the response time distribution are very accurate, and the proposed scheme can effectively reduce the data collection latency and data loss rate eventually. As a baseline, we assume the MCs are only capable of serving one request in this paper. Exploring the cases where more powerful MCs can be employed will be one of our future work.

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