Evaluating On-Demand Data Collection with Mobile Elements in Wireless Sensor Networks

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***Abstract*—Exploring mobility to accomplish the data collection in wireless sensor networks (WSNs) has become the focus of recent studies, which can improve the energy efficiency of sensor nodes by shifting the data forwarding task from them to *mobile elements* (MEs). However, the data collection latency in this case can be much higher. We consider an on-demand data collection scenario in this paper, in which sensor nodes broadcast service requests when their buffer is about to be full. On receiving such requests, the ME moves toward the sensor nodes to collect data, and uploads the data to the sink when possible. An $M/G/1$ queue-based analytical model is presented, and analytical results on several important system performance metrics are derived. Furthermore, we propose an improved service scheme, which combines requests whenever they are in proximity. The work is evaluated through extensive simulations, which validate the accuracy of our model. The efficacy of the proposed service scheme to improve the system performance is also verified.**

I. Introduction

Technology progresses have made the deployment of Wireless Sensor Networks (WSNs) a reality [1]. However, sensor nodes do not have access to unlimited power supplies in general, therefore they have to use the limited on-board battery in an efficient way. Energy consumption of sensor nodes is dominated by the over-the-air data transmission and reception. Many schemes have been proposed to deal with the energy efficiency problem, for example, energy-aware routing [2], sleep scheduling of sensor nodes [3] [4], and so on.

Recent research has shown that integrating mobility with WSNs, for example, by employing *mobile elements* (MEs), is a promising approach to reducing the communication-related energy consumption of sensor nodes [5]–[8]. The concept of ME was first proposed in [9], where it was referred to as *Data Mule*. The mules move around in the network to collect data from sensor nodes, and ultimately upload the data to the sink. With this approach, the amount of over-the-air data transmission is reduced—so is the energy consumption of sensor nodes. Further, the unbalanced energy consumption problem in traditional multi-hop sensor networks can be avoided, and the requirement on network connectivity is relaxed. However, this also brings new challenges. The performance bottleneck of mobile WSNs is the latency of data collection, which is largely determined by the speed of the ME and the length of its travel path. High latency is unacceptable for two reasons: applications may require data to be gathered and processed within a certain period of time; the ME may need to recharge itself after working for a certain amount of time.

In this paper, we consider an ME-based on-demand data collection scenario: sensor nodes send data collection requests through multi-hop forwarding when their buffer is about to be full; on receiving such requests, the ME will move toward the sensor node, and collect the data from it by single-hop communication; finally, the ME will upload the data to the sink when possible. We model this scenario by an $M/G/1$ queue to evaluate the system performance, in terms of queue length, response time, busy period, and busy cycle. Furthermore, an improved service scheme is proposed, which is able to combine data collection requests opportunistically.

The rest of this paper is organized as follows. The related work on exploring mobility to accomplish data collection in sensor networks is given in Section II. In Section III, we formulate the problem, together with the assumptions and definitions used in this paper. In Section IV, we present the $M/G/1$ queue-based analytical model, from which we derive the performance metrics of the queuing system, e.g., the first moment and the distribution of queue length. We propose the request-combining service scheme to improve the system performance in Section V. Evaluation results are presented in Section VI. Finally, we conclude this work in Section VII.

II. Related Work

Generally speaking, the data collection problem in sensor networks can be summarized with the following notation: $S/I/D$, where S, I, and D represent the mobility model of the source nodes, the intermediary nodes, and the destination nodes, respectively. Each of them can be S (stationary), R (random), P (predictable), or C (controlled).

By using this notation, our paper belongs to the $S/C/S$ category. There are several papers on this topic. In [5], the data collection problem was formulated as the *Min-Energy Rendezvous Planning Problem* (MERP), which was proved to be NP-hard. Two rendezvous planning algorithms, RP-CP and RP-UG, were proposed. RP-CP focused on the case where the MEs move along constrained paths (the data routing tree), while RP-UG considered the case with no motion constraints. The authors improved their work further in [6], which aimed to jointly optimize data routing paths and the base-station tour, and a Steiner-tree-based approach was adopted.

In [7], two cases of sink mobility were explored: predetermined path and localized movement decision. In the first case, the sinks move along the perimeter of a hexagonal tiling, and can stop at any one of the hexagon's vertexes, or multiple

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locations on the hexagon perimeter. For the latter, the sinks remain interconnected all the time, and the next destination of the moving sinks is determined by considering the residual energy of certain areas. Experimental results showed that the network lifetime is prolonged significantly in both cases. [8] extended this work with two distributed algorithms that take the coverage and timely delivery as further requirements.

Ryo et al. formulated the data collection problem with a single ME as the *Label Covering Tour Problem* in [10], which is also shown to be NP-hard. An approximation algorithm is proposed, which first finds a TSP tour by using any (exact or approximate) algorithm, and then the shortest label covering tour can be obtained by pruning the TSP tour.

These research efforts followed a scheme-based approach, i.e., they tried to design optimal schemes for the ME to improve the system performance. What we are trying to do in this paper is to build an accurate model of the system, which can be used to guide the scheme design. As far as we know, the most related work is [13], which modeled the system as a *closed queuing network*. The transition probability from one queue to another is assumed to be known, and the service time is assumed to be exponentially distributed. In this paper, we relax the first assumption, and derive the accurate service time distribution based on our previous work.

III. Problem Formulation

A. Network Model

We consider the scenario where a single ME moves around in the network to collect data from sensor nodes. Sensor nodes generate data at different rates, and store them in their buffers, which are limited in size. When the buffer is about to be full, sensor nodes will send a data collection request to the ME through multi-hop forwarding. The ME maintains a service queue for data collection requests. On receiving a new request, the ME will insert the request into its queue, and serve the request according to its service discipline. By serving the request, we mean that the ME will move toward the sensor node that sends the request, and collect the data from the sensor node through short-range communications.

A potential problem is that the data collection latency may be very high because of the relatively low traveling speed of the ME, compared with multi-hop communications. Our objective is to make the optimal use of the ME's mobility to minimize the data collection latency in the network.

Because the speed that the data is relayed in WSNs is about several hundred meters per second [11], which is much faster than the speed of a mobile device, we can consider the service time for each request as the time from the service completion of the previous request, to the time when the ME moves to the sensor node that sends the next request to be served. With this approximation, we can formulate the on-demand data collection problem as: *given its limited speed, how should the ME schedule its movement to minimize the waiting time of sensor nodes, and thus, the data collection latency?*

The followings are the assumptions and definitions that we will use throughout the paper.

B. Assumptions

- Data transmission time is negligible when compared with the ME traveling time, due to the short-range, high-speed wireless communication technology used;
- Buffer size and energy supplies of the ME are unlimited;
- ME can either move at a constant speed, or stop at a certain location for a while;
- As a baseline, the ME serves the requests according to their arrival order, that is, it works according to the *First Come First Serve* (FCFS) service discipline;
- The inter-arrival time of the requests at the ME is exponentially distributed [12] [13];
- We do not consider the communication between ME and the sink here, which is assumed to be always successful.

C. Definitions

- L: the size of the square sensor network, i.e., the total network area is $(L \times L)\ m^2$;
- S: the total number of sensor nodes;
- v: the traveling speed of the ME;
- R: the single-hop communication range between the sensor node and the ME;
- B: the buffer size of the sensor node;
- f_i: the data generation rate of the i-th sensor node, where $f_i \in [f_{\min}, f_{\max}]$;
- λ: the arrival rate of the service requests at the ME.

IV. Analytical Model

A. M/G/1 Modeling

From our previous work [14], we know that the distance distribution between two arbitrary points in a unit square is

$$f_D(d) = \begin{cases} 2d(\pi - 4d + d^2) & 0 \le d \le 1 \\ 2d[2\sin^{-1}(\frac{1}{d}) & \\ -2\sin^{-1}\sqrt{1-\frac{1}{d^2}} & \\ +4\sqrt{d^2-1} - d^2 - 2] & 1 \le d \le \sqrt{2} \\ 0 & \text{otherwise.} \end{cases} \quad (1)$$

If we examine the network only at the departure time of a request, the service time of the request can be modeled as the time that the ME moves from the previous request location to the current request location, with distribution

$$\begin{aligned} P_T(t) &= P_D\{d \le vt\} \\ &= \begin{cases} \int_0^{vt} 2x(\pi - 4x + x^2)dx & t \le \frac{1}{v} \\ \int_0^1 2x(\pi - 4x + x^2)dx + & \\ \int_1^{vt} 2x[2\sin^{-1}(\frac{1}{x}) - & \\ 2\sin^{-1}\sqrt{1-\frac{1}{x^2}} & \\ -x^2 - 2]dx & \frac{1}{v} < t \le \frac{\sqrt{2}}{v} \\ 1 & t > \frac{\sqrt{2}}{v}. \end{cases} \end{aligned} \quad (2)$$

Also, its expectation, variance and coefficient of variation are

$$E[T] = E[\frac{D}{v}] = \frac{1}{v}E[D] \quad (3)$$

$$V[T] = V[\frac{D}{v}] = \frac{1}{v^2}V[D] \quad (4)$$

$$Cov[T] = \frac{\sqrt{V[T]}}{E[T]} = \frac{\sqrt{V[D]}}{E[D]} = Cov[D]. \quad (5)$$

With the exponential inter-arrival time of data collection requests and the service time distribution obtained above, we can model the system as an $M/G/1$ queue.

B. Expected Number of Requests in the Queue

By *Pollaczek-Khinchine Mean Value Formula* [17], the expected number of requests in the ME's queue is

$$\overline{N} = \rho + \frac{\rho^2(1 + Cov[t]^2)}{2(1-\rho)}, \quad (6)$$

where ρ is the utilization factor. Note that for the queue to be stable, ρ should be smaller than 1, thus

$$\rho = \lambda E[t] = \frac{\sum_{i=1}^{S} f_i}{B \times S} \times \frac{1}{v} E[d] < 1, \quad (7)$$

which implies

$$v > \frac{E[d] \sum_{i=1}^{S} f_i}{B \times S}. \quad (8)$$

C. Expected Response Time for the Requests

With the expected number of requests in the queue, by *Little's Law*, the expected response time of requests, $\overline{T}$, is

$$\overline{T} = \frac{\overline{N}}{\lambda} = \frac{\rho E[t](1 + Cov[t]^2)}{2(1-\rho)} + E[t]. \quad (9)$$

D. Busy Period and Busy Cycle of the ME

With this modeling, the expected length of the busy period and busy cycle of the ME are given by

$$E[T_{bp}] = \frac{1}{\frac{1}{E[t]} - \lambda} \quad (10)$$

$$E[T_{bc}] = \frac{1}{\lambda} + \frac{1}{\frac{1}{E[t]} - \lambda}. \quad (11)$$

E. Distribution of the Queue Length

Let X_n be the number of requests in the queue immediately after the departure of the request at time t_n, then

$$X_{n+1} = \begin{cases} X_n - 1 + A_{n+1} & (X_n \geq 1) \\ A_{n+1} & (X_n = 0), \end{cases} \quad (12)$$

where A_{n+1} is the number of requests that arrive during the service time of the $(n+1)$-th request.

We can see that A_{n+1} only depends on the length of the service time of the $(n+1)$-th request, rather than any events that occurred earlier (i.e., the queue length at earlier departure points, $X_{n-1}, X_{n-2}, ...$). Thus, the embedded discrete-time process $X_1, X_2, ...$, observed at departure times is a *Discrete-Time Markov Chain*, whose transition probabilities are

$$p_{ij} = P\{X_{n+1} = j | X_n = i\}. \quad (13)$$

The state transition of this Markov Chain is shown in Fig. 1.

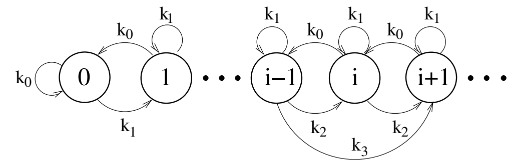

Fig. 1. State transition diagram of the embedded discrete-time Markov Chain

Define the probability that there are i arrivals of data collection requests when serving a request as

$$\begin{aligned} k_i &= P\{A = i\} \\ &= \int_0^{\infty} P\{A = i | S = t\} \times f_T(t) dt \\ &= \int_0^{\infty} \frac{e^{-\lambda t}(\lambda t)^i}{i!} f_T(t) dt. \end{aligned} \quad (14)$$

With k_i, we have the following state transition matrix

$$\boldsymbol{P} = \{p_{ij}\} = \begin{bmatrix} k_0 & k_1 & k_2 & k_3 & ... \\ k_0 & k_1 & k_2 & k_3 & ... \\ 0 & k_0 & k_1 & k_2 & ... \\ 0 & 0 & k_0 & k_1 & ... \\ 0 & 0 & 0 & k_0 & ... \\ \vdots & \vdots & \vdots & \vdots & \end{bmatrix}. \quad (15)$$

Denote π_n as the steady-state queue length probabilities at the departure times, then

$$\boldsymbol{\pi P} = \boldsymbol{\pi}, \quad (16)$$

from which we know that

$$\pi_i = \pi_0 k_i + \sum_{j=1}^{i+1} \pi_j k_{i-j+1}, \text{ for } i = 0, 1, 2, ... \quad (17)$$

Define the following generating functions

$$\Pi(z) = \sum_{i=0}^{\infty} \pi_i z^i, \quad |z| \leq 1 \quad (18)$$

$$K(z) = \sum_{i=0}^{\infty} k_i z^i, \quad |z| \leq 1. \quad (19)$$

Since $\pi_0 = 1 - \rho$, we have

$$\Pi(z) = \frac{(1-\rho)(1-z)K(z)}{K(z) - z}, \quad (20)$$

from which $\{\pi_n\}$ can be derived. Notice that $\{\pi_n\}$ are not the same as the steady-state queue length probabilities $\{p_n\}$ in general. However, for the $M/G/1$ queue, it can be proved that these two quantities are asymptotically identical [18].

V. Request-Combining Service Scheme

The $M/G/1$ queue-based analysis in the previous section provides us a lower bound of the system performance, since the ME only serves requests according to the order of their arrival, instead of also using their location information. In this section, we propose an improved service scheme for the ME by

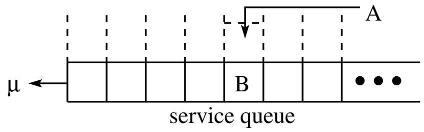

Fig. 2. Request-combining when possible

following a request-combining approach, in order to improve the system performance.

The basic idea of this improvement is to use the wireless communication capability of the ME and sensor nodes to combine several nearby requests into one. On receiving a new request, e.g., request A in Fig. 2, the ME checks its service queue to see whether the sensor node that sends request A is within the transmission range R of some sensor nodes that are currently waiting to be served in the queue. If this is the case, the first such request found in the queue, e.g., request B, is selected and combined with request A. Then ME will serve these two requests simultaneously at the location of the sensor node that sends request B. In case the new request cannot be combined with any existing requests in queue, the ME will append the request at the end of its service queue, and serve the request with the normal FCFS scheme.

Notice that request B should not have been combined with other requests before (C, for example). Otherwise, by this request-combining scheme, the ME will try to serve the three requests at the location of the sensor node that sends request C, which may not be in the range of A. Actually, the request-combining service scheme can be further improved by taking this case into account, which is our ongoing work.

VI. Performance Evaluation

We verify the accuracy of our analytical model and the efficacy of the improved service scheme in this section. Based on the parameters from the real systems in [15], we consider a square network with size $(100 \times 100)\ m^2$, where a total number of 100 sensor nodes are uniformly deployed, and set the moving speed of the ME to $1\ m/s$. The communication range R between the ME and sensor nodes is $20\ m$. Simulation results shown in the following figures are the average of 10 runs, and error bars are also plotted when possible to show the maximum variability of the results.

We first examine the assumption of exponential inter-arrival time for data collection requests by an event-driven case study, in which stochastic events happen randomly in the network. Sensor nodes within a certain distance of the event can detect it, and generate sensing data to record the event. Events happen independently in space and time (e.g., uniform distribution or following Poisson arrival). Sensor nodes will send a request when their buffers become full. The simulation ends when a total number of $10,000$ requests are generated. We record the inter-arrival time of requests, and compare them with an exponential distribution with the same mean value. The results show that they agree with each other very well, and thus support our assumption of exponential service requests.

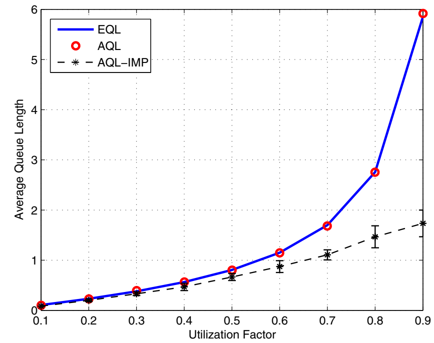

Fig. 3. Mean queue length

To deal with the inconvenience of the piecewise distance probability density function in (1), we approximate it by a high order polynomial, using Least Squares Fitting [16]:

$$\begin{aligned}\widetilde{f}(d) \quad = \quad & 0.2802d^{10} - 2.0964d^9 + 2.2349d^8 \\ & +24.3629d^7 - 106.8231d^6 + 194.4928d^5 \\ & -182.8093d^4 + 91.8223d^3 - 29.3663d^2 \\ & +8.2843d - 0.0402. \qquad (21)\end{aligned}$$

We adopt this approximation function to derive the service time distribution in our performance evaluation.

We first evaluate the results in terms of the expected queue length and response time. In Fig. 3, EQL is the analytical result for the *E*xpected *Q*ueue *L*ength, AQL is the *A*verage *Q*ueue *L*ength in FCFS simulation, and AQL-IMP is the result obtained with the *IMP*roved scheme by request-combining.

For Fig. 4, ERT, ART, and ART-IMP are for the *E*xpected *R*esponse *T*ime, *A*verage *R*esponse *T*ime simulation, and its improvement, respectively. The results obtained by the FCFS discipline match our analytical results very well. Furthermore, the improved service scheme can reduce the queue length and the response time considerably and the improvement on the system performance becomes significant when ρ increases. This is because when more requests are buffered in the queue, it is more likely to combine those nearby requests and optimize the service sequence.

We also verify our analysis on the busy period and busy cycle of the ME. This information can help us arrange the ME's maintenance schedule and operations appropriately, e.g., recharging it or recalling it back to the sink. We use EBP and EBC to represent our analytical results for *E*xpected *B*usy *P*eriod and *B*usy *C*ycle, respectively, ABP and ABC to represent the *A*verage values of these two metrics in FCFS simulation, and ABP-IMP and ABC-IMP to represent those for the improved request-combining service scheme. The FCFS simulation results agree with our analytical results very well (Fig. 5), and again, the improvement of the request-combining service scheme becomes significant when ρ increases. With a larger ρ, the busy period becomes a major part in ME's busy cycle, which means a much heavier workload for the ME.

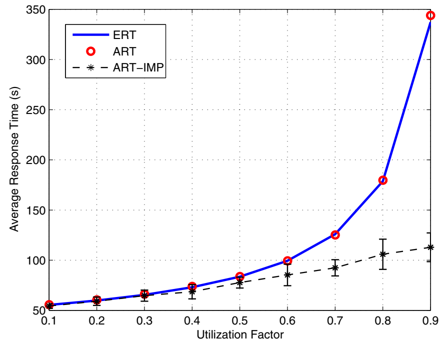

Fig. 4. Mean response time

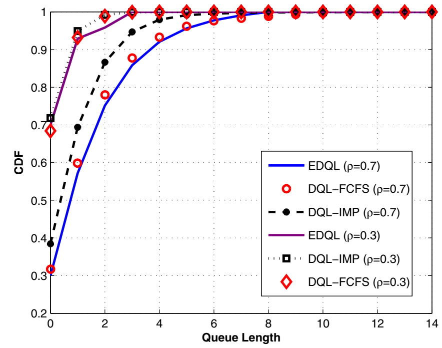

Fig. 6. Distribution of queue length

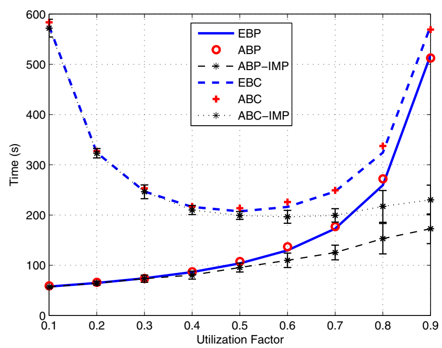

Fig. 5. Busy period and busy cycle

Finally, we verify our $M/G/1$ queue-based model of the queue length distribution. We set ρ to be 0.3 and 0.7 to represent light and heavy workload, and compare the results obtained by our analytical model, with FCFS simulation and the request-combining service scheme in Fig. 6. EDQL, DQL-FCFS, and DQL-IMP represent the results obtained by our analytical model for the distribution of queue length, the FCFS simulation and the request-combining service scheme. We can see that the analytical model and the FCFS simulation results match each other closely, and the request-combining service scheme can reduce the queue length significantly.

VII. Conclusions

In this paper, we model the problem of using ME to accomplish data collection in mobile sensor networks as an $M/G/1$ queue. The mean value and distribution of queue length, and the mean value of response time, busy period and busy cycle are derived, respectively. The $M/G/1$ queuing model helps us to understand the impact of different parameters on the system performance, and the corresponding analytical results can serve as a lower bound for more advanced schemes. Furthermore, we propose a request-combining service scheme, which takes the communication capability of the ME and sensor nodes into account to improve the system performance and is verified by simulation results. Our future work includes extending a single ME to multiple MEs, the design of more advanced service schemes in terms of combining service requests, and exploring optimal non-FCFS disciplines to further improve the system performance.

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