Evaluating Service Disciplines for Mobile Elements in Wireless Ad Hoc Sensor Networks

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***Abstract*—The introduction of mobile elements in wireless sensor networks creates a new dimension to reduce and balance the energy consumption for resource-constrained sensor nodes; however, it also introduces extra latency in the data collection process due to the limited mobility of mobile elements. Therefore, how to arrange and schedule the movement of mobile elements throughout the sensing field is of ultimate importance. In this paper, the online scenario where data collection requests arrive progressively is investigated, and the data collection process is modeled as an $M/G/1/c$–NJN queuing system, where NJN stands for *nearest-job-next*, a simple and intuitive service discipline. Based on this model, the performance of data collection is evaluated through both theoretical analysis and extensive simulation. The NJN discipline is further extended by considering the possibility of requests combination (NJNC). The simulation results validate our analytical models and give more insights when comparing with the *first-come-first-serve* (FCFS) discipline. In contrast to the conventional wisdom of the starvation problem, we reveal that NJN and NJNC have a better performance than FCFS, in both the average and more importantly the worst cases, which gives the much needed assurance to adopt NJN and NJNC in the design of more sophisticated data collection schemes for mobile elements in wireless ad hoc sensor networks, as well as many other similar scheduling application scenarios.**

***Keywords*-Wireless ad hoc sensor networks, queue-based modeling, mobile elements, service disciplines, nearest-job-next**

I. Introduction

Many applications in wireless sensor networks are data collection oriented [1], [2]. Data collection in sensor networks typically relies on the wireless communication between sensor nodes and the sink node, which may excessively consume the limited energy of sensor nodes due to super-linear path loss exponents. Sensor nodes near the sink also tend to deplete their energy much faster than other nodes due to the data aggregation towards the sink, which leads to a very unbalanced energy consumption in the entire network. In addition, these approaches are based on a fully connected network, which might require dense deployment and introduce extra costs.

Another approach to data collection utilizes the often-available, controlled mobility of certain devices, referred to as *mobile elements* in this paper [3], [4]. By utilizing mobile elements, not only more energy can be conserved and balanced on sensor nodes, but also the communications and networking become possible in very sparse networks with the “store-carry-forward” approach. For example, the seabed crawler deployed in NEPTUNE Canada can cruise through several experimentation sites, “talk” to experiment devices through very-short-range, high-data-rate underwater optical communication technologies, and bring the data back to the junction boxes [6]. Another example of mobile element is the Seaeye Sabertooth [7], a battery-powered autonomous underwater vehicle (AUV), which travels in deep water environments to collect data from deployed equipments through short-range, underwater radio communications, and uploads the data to the control center at the docking station. Other examples of the mobility-assisted data collection include the the smart buoy equipped with Seatext from WFS [8], the RQ-7 Shadow 200 unmanned aerial vehicle (UAV) used by the United States Army [9], and so on.

Although mobile elements create a new dimension for data collection, they also introduce some new challenges: first, the data collection latency may be large due to the relatively low travel speed of mobile elements [10], which must be considered for applications with certain requirements on the timely delivery of sensory data; second, with a large latency, sensory data might be lost if the buffers of certain sensor nodes are overflowed, which is not acceptable for data integrity sensitive applications; finally, mobile elements themselves are battery-powered as well in most cases (e.g., the traveling distance of Sabertooth is about 20–50 Km with a fully charged battery), so the data collection must be accomplished before mobile elements deplete their own energy.

A lot of efforts have attempted to address these challenges by finding the optimal data collection path for mobile elements, given the assumption that the locations of requesting sensor nodes are known in advance [11], [17]. However, in a more practical scenario, we need to determine how the mobile element should carry out the data collection task without such *a priori* information, i.e., sensor nodes initiate the requests for data collection only when they have enough data to report, and the mobile element obtains the knowledge about when and where to collect data only upon the reception of such requests. There are some existing efforts aiming to design data collection schemes in this *online* scenario [13], however, a critical issue with them is how to evaluate whether the proposed schemes are “efficient” or not, since no optimal solution is available as the benchmark in this case.

In this paper, we answer this question by theoretically analyzing the performance of data collection when some simple and intuitive disciplines are adopted through a queue-based modeling approach, which offers important guidelines in designing more sophisticated online data collection schemes for mobile elements. We first show that data collection requests in the online scenario can be represented by a Poisson arrival process, and with the travel distance (and time) distribution between any two sensor nodes in the sensing field, the system can be modeled as an $M/G/1/c$–NJN queue which accommodates at most c requests at the same time, and the mobile element (server) selects the next to-be-served request (client) according to the *nearest-job-next* (NJN) discipline. A challenge with the analysis of the NJN discipline is the state-dependent service time, which will be explained later. Furthermore, by considering the fact that multiple requests can be combined and served together by the mobile element if there exists a collection site within the communication ranges of their corresponding sensor nodes, we extend the NJN discipline to *NJN-with-combination* (NJNC) to explore how much performance gain can be achieved by considering the possible requests combination. We obtain the analytical results on the system measures of these models to evaluate the resultant data collection efficiency.

To the best of our knowledge, this is the first time that NJN and NJNC are explored analytically in wireless sensor networks with mobile elements, and the approach can be extended to other dynamically-prioritized scenarios as well. Our results show that even though NJN may be unfair for farther-away requests temporarily, its average performance outperforms FCFS greatly and more importantly, its worst-case performance is still better than FCFS, especially with NJNC. These results give the much needed assurance to adopt NJN and NJNC in the design of online data collection schemes.

The remainder of this paper is organized as follows. Section II briefly reviews the literature on the mobility-assisted data collection. In Section III, we outline the problem setting and list the assumptions and definitions used in this paper. We present the analytical models of NJN and NJNC in Section IV and Section V, respectively. The analytical and simulation results are given and compared in Section VI for model validation and further insights. In Section VII, we discuss the possible approaches to further extending and improving the work. Finally, we conclude this paper in Section VIII.

II. Related Work

Recently, a lot of efforts have been made on exploring the mobility-assisted data collection in wireless sensor networks [17], [18]. Many of them aimed to design the optimal data collection scheme when mobile elements (MEs) know all service requests in advance. E.g., in [11], Ryo et al. formulated the problem as a *label-covering problem* based on an TSP tour that visits all sensor nodes, which is proved to be NP-hard. A path selection algorithm for the ME was proposed in [12], which starts with a *connected dominating set* of the network, then gets a *minimum spanning tree* based on it, and finally generates a *Hamiltonian circuit* for the ME. The case where multiple MEs exist in the network was considered in [19]. Xing et al. jointly considered the ME travel tour and the data transmission routes in [24]. In contrast, the online case of the mobility-assisted data collection is much less explored, even though it is more practical in reality [13].

Comparatively speaking, the online case is more challenging, since the ME needs to determine which data collection request to serve next among the requests received, without knowing the requests to arrive in the near future. The most intuitive service discipline is *first-come-first-serve* FCFS, whose performance is analytically evaluated in [5]. With FCFS, due to the randomness of service requests, the ME may unnecessarily travel back-and-forth to serve requests, which is undesirable if a tight requirement on the data collection latency exists. Another intuitive service discipline is to serve the spatially-nearby requests first, or *nearest-job-next* (NJN), in order to reduce the distance that the ME has to travel and the time it has to spend on. In the literature and practical systems, NJN and its variants are much less explored, due to the concerns discussed below.

NJN is very similar to the traditional *shortest-job-next* (SJN) service discipline, which has been known to be optimal for minimizing the expected response time [14]. The efficiency of SJN and their similarity inspire us to explore the performance of data collection when NJN is adopted. However, two extra issues need to be considered. First, for SJN, the service time for each job has to be accurately estimated upon its arrival and remain fixed before its departure in the system, but as shown later, the service time with NJN for data collection in wireless sensor networks is jointly determined by the location of the requesting sensor node and that of the serving ME, which cannot be determined in advance until the job is *about* to be served. This makes not only the existing analytical results on SJN not applicable [15], but also the analysis of NJN much harder due to the dynamic priority of a particular request. Second, SJN is known to lead to the starvation problem for large jobs, which limits its practical implementation. Thus whether NJN suffers from the similar problem for mobility-assisted data collection is the another question we need to answer.

Another existing service discipline similar to NJN is the *shortest seek time first* (SSTF) in disk scheduling [16]. Although the service time with SSTF also changes with regard to the read/write head's position, the disk tracks are treated in a one dimensional space, while the sensing field of NJN is a two dimensional space. Clearly, this difference makes the analysis on NJN much harder.

To the best of our knowledge, this is the first work on the analysis of NJN and NJNC with dynamic priority and non-predetermined service time, and also the first work to demonstrate their practicality in the mobility-assisted data collection for wireless sensor networks.

III. Preliminaries

We consider the scenario where a single mobile element (ME) travels around in the sensing field to collect data from sensor nodes with short-range wireless communication technologies. Sensor nodes gather sensory data about the sensing field, and when they have enough data to report, they send the data collection requests to the ME by adopting some existing lightweight but efficient ME-tracking protocols [20]. Note that usually tracking protocols rely on the multi-hop forwarding among sensor nodes. Thus instead of using these protocols to carry the sensory data to the ME directly, which usually are of much larger size, e.g., in a camera sensor network [21], here only the requests for data collection is forwarded to reduce the communication overhead of sensor nodes. We assume that the time from a sensor node sending out its request to the ME receiving the request is negligible when compared with the data collection latency (our work can be easily extended to accommodate the cases where this assumption has to be relaxed, as being discussed in Section VII).

The ME maintains a service queue for the received requests, and serve them with its service discipline. Our approach is to model the network as a queuing system, and theoretically analyze the performance of data collection with different service disciplines, i.e., $M/G/1/c$–NJN and $M/G/1/c$–$NJNC$.

For a specific application, certain constraints on the maximal acceptable data collection latency exist, either because of the requirement on the timely delivery of sensory data or the possible buffer overflow problem of sensor nodes. Thus a finite capacity queuing model is a better choice to capture the system behavior when compared with the regular $M/G/1$ queue.

Definition 1: Requesting nodes are the sensor nodes that have initiated the data collection requests and whose requests are currently waiting in the ME's service queue.

The first service discipline we explore is the *nearest-job-next* (NJN) discipline, i.e., on finishing the service of the current data collection request, the ME selects the spatially nearest requesting sensor node in its service queue according to the current location, and travels to the node to collect data. Furthermore, it is possible for the ME to collect data from multiple sensor nodes at a single collection site, provided that the collection site is within the communication ranges of all these nodes. Based on this observation, we extend the NJN discipline to *NJN-with-combination* (NJNC), with which other requests in the queue can be combined with the nearest one and served together when possible. Analytical results for the system with NJNC are also derived to quantitatively evaluate how much performance gain can be achieved by considering the possible requests combination.

For clarity, we list and briefly explain here the assumptions and definitions used in this paper.

- We consider a unit square sensing field in which sensor nodes are uniformly deployed at random;
- v: the ME's travel speed (normalized w.r.t. the side length of the field);
- r: the wireless communication range (normalized w.r.t. the side length) between the ME and sensor nodes;
- c: the maximal number of requests that the ME can accommodate at the same time;
- $\mathcal{S}$: the service time of requests, or $\mathcal{S}_i$ for the to-be-served request selected when there are i data collection requests in the ME's service queue;
- $\mathcal{L}$: the size of the queuing system, i.e., the total number of requests that are waiting for or under the service;
- $\mathcal{I}$: the idle period of the queuing system;
- $\mathcal{B}$: the busy period of the queuing system;
- $\boldsymbol{\pi} = \{\pi_0, \pi_1, ..., \pi_{c-1}\}$: the system size probabilities at the departure time of requests;
- $\boldsymbol{w} = \{w_0, w_1, ..., w_c\}$: the system size probabilities at the arrival time of requests;
- $\boldsymbol{u} = \{u_0, u_1, ..., u_c\}$: the steady-state system size probabilities of the queuing system.

IV. Data Collection with NJN

We explore the case where the ME serves data collection requests with the NJN discipline in this section. More specifically, by considering the arrival and departure processes of data collection requests, we first model the system as a non-preemptive $M/G/1/c$–NJN queuing system, and then obtain the analytical results on the system measures, which offer important insights on evaluating the data collection performance.

A. $M/G/1/c$–NJN Queue Modeling

The client arrival and departure processes have a fundamental impact on any queuing models, so we characterize them respectively first in the following.

We assume a Poisson arrival process of the data collection requests to the ME, i.e., the inter-arrival time of the requests is exponentially distributed. This assumption holds since that first, the number of sensor nodes in the sensing field is relatively large, and second, the probability for a sensor node to initiate a data collection request is relatively small in a certain time slot. Theoretically, if the client population size of a queuing system is relatively large and the probability by which clients arrive at the queue is relatively small at any given time, the arrival process can be adequately modeled as a Poisson process [23]. This assumption is further verified in Section VI-A.

Because the data propagation speed in sensor networks is about several hundred meters per second [24], which is much faster than the ME's travel speed. We assume the data transmission latency is negligible (which will be further discussed in Section VII), and consider the service time for each request as the time from the service completion of the current request to the time when the ME moves to the sensor node that initiated the request chosen by the ME to serve next, or the to-be-served request.

Due to the fact that the last collection site is also the starting point of the travel when the ME serves the next request, the service time of each request seems not to be stochastically independent. However, denote the sequence of service times as $\{t_1, t_2, t_3, ...\}$, and if we examine only at every second variable of the original process, it is clear that $\{t_1, t_3, t_5, ...\}$ are independent of each other, and the distribution-ergodic property of this sub-process can be easily observed [25]. The same is true for sub-process $\{t_2, t_4, t_6, ...\}$. The distribution-ergodic property still holds if we combine these two sub-processes since their asymptotic behaviors do not change after the combination, which means that if we can find the time distribution when the ME travels between consecutive to-be-served sensor nodes, we can adopt it as the service time distribution for the queuing system over a period of time, i.e.,

$$F_{\mathcal{S}}(x) = \lim_{h \to \infty} \sum_{i=0}^{h} \frac{1}{h} \cdot \Pr\{t_i \leq x\}. \quad (1)$$

Following the results in [26], the distance density function of two random locations in a unit square is

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

with distribution function $F_D(d) = \int_0^d f_D(x)dx$.

Based on (2), and with the constant travel speed v of the ME, the travel time distribution between two uniformly and randomly distributed sensor nodes in the sensing field is thus $F_T(t) = \Pr\{D \le vt\}$, and $f_T(t) = \partial F_T(t)/\partial t$.

However, the actual service time in our scenario is more complicated due to the greedy nature of NJN: the service time of the to-be-served request tends to be shorter if more requests are waiting in the system. Furthermore, the service time of data collection requests is determined by both the location of the requesting sensor node and that of the ME just before its service. This state-dependent service time makes the existing results on the traditional *shortest-job-next* (SJN) discipline, which requires that the service times of clients are both known and fixed upon their arrival to the queue [15], not applicable in our scenario, and brings extra challenges for the analysis. In the next, we explore the service time distribution of requests with NJN by assuming a given system size first.

B. Service Time Distribution with a Given System Size

Assume $l > 0$ requests are available when the ME just accomplishes the service of the current request, and is about to select the next request to serve. Considering the randomness of both the current location of the ME and the requesting sensor nodes, the distances from these l requesting nodes to the ME can be viewed as l i.i.d. random variables with distribution $f_D(d)$, so the probability distribution of the distance between the ME and the nearest requesting node is

$$\begin{aligned} F_{D,l}(d) &= \sum_{i=0}^{l-1} \binom{l}{i} (1 - F_D(d))^i F_D(d)^{l-i} \\ &= 1 - (1 - F_D(d))^l, \end{aligned} \quad (3)$$

with probability density function $f_{D,l}(d) = \partial F_{D,l}(d)/\partial d$. The conditional service time distribution of the nearest request with a given system size is thus $f_{\mathcal{S}_l}(t) = v \cdot f_{D,l}(vt)$.

C. System Size Probabilities at the Departure Time

Assume the steady-state is achievable, we can observe a *discrete-time Markov chain* of the system size at the departure time of requests, which is similar to the case with the FCFS discipline [5] (Fig. 1). However, since the service time is now dependent on the current system size, the chain becomes heterogeneous in its transition probabilities, as shown in Fig. 2.

With the conditional service time distribution obtained above, we can define and obtain the probability of i new request arrivals during the time serving a request selected from l currently available ones as

$$k_i^l = \int_0^{\sqrt{2}/v} \frac{e^{-\lambda t}(\lambda t)^i}{i!} f_{\mathcal{S}_l}(t)dt, \quad (4)$$

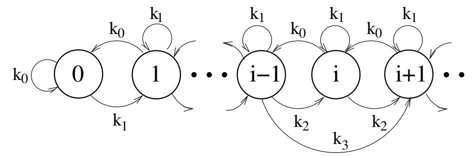

Fig. 1: State transition diagram at departure time with FCFS.

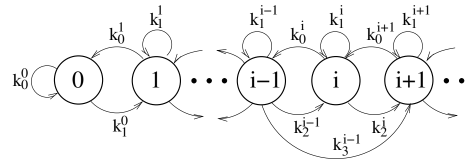

Fig. 2: State transition diagram at departure time with NJN.

where λ is the arrival rate of data collection requests. Note that for FCFS shown in Fig. 1,

$$k_i = \int_0^{\sqrt{2}/v} \frac{e^{-\lambda t}(\lambda t)^i}{i!} f_T(t)dt, \quad (5)$$

The state transition matrix of the finite capacity queue with NJN at the departure time of requests is then

$$\boldsymbol{P} = \begin{bmatrix} k_0^0 & k_1^0 & \cdots & k_{c-1}^0 & 1 - \sum_{i=0}^{c-1} k_i^0 \\ k_0^1 & k_1^1 & \cdots & k_{c-1}^1 & 1 - \sum_{i=0}^{c-1} k_i^1 \\ 0 & k_0^2 & \cdots & k_{c-2}^2 & 1 - \sum_{i=0}^{c-2} k_i^2 \\ 0 & 0 & \cdots & k_{c-3}^3 & 1 - \sum_{i=0}^{c-3} k_i^3 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & k_0^c & 1 - k_0^c \end{bmatrix}. \quad (6)$$

and

$$\boldsymbol{\pi} \boldsymbol{P} = \boldsymbol{\pi}. \quad (7)$$

Thus $\boldsymbol{\pi}$ can be calculated by considering another fact that $\sum_{i=0}^{c-1} \pi_i = 1$.

D. General Service Time Distribution

We have derived the conditional service time distribution in Section IV-B, and just obtained the system size probabilities at departure times. Combining them together, we can obtain the general service time distribution of requests as

$$F_{\mathcal{S}}(t) = \pi_0 \cdot \int_0^t f_{\mathcal{S}_1}(x)dx + \sum_{l=1}^{c-1} \pi_l \cdot \int_0^t f_{\mathcal{S}_l}(x)dx, \quad (8)$$

and $f_{\mathcal{S}}(t) = \partial F_{\mathcal{S}}(t)/\partial t$. The expected service time of the system can be calculated by

$$E[\mathcal{S}] = \int_0^{\sqrt{2}/v} t \cdot f_{\mathcal{S}}(t)dt. \quad (9)$$

E. Steady-State System Size Probabilities

It is proved in [28] that with an infinite system capacity, the departure time system size probabilities of the standard $M/G/1$ queue are the same as those in the steady state. However, this conclusion does not hold in the finite capacity case, since we only have c states for the departure time system size $(0, 1, ..., c-1)$, while $c+1$ states $(0, 1, 2, ..., c)$ have to be considered for the steady state distribution. With the *level crossing methods* [29], we can observe the fact that the distribution of system sizes just prior to the arrival time is identical to the departure time probabilities as long as arrivals occur individually, which holds for the Poisson arrival, thus

$$\begin{aligned}\pi_i &= \Pr\{\text{new request finds } i \text{ in queue}|\text{request joins}\} \\ &= w_i/(1-w_c) \quad (0 \le i \le c-1), \end{aligned} \tag{10}$$

so

$$w_i = (1-w_c)\pi_i \quad (i = 0, 1, ..., c-1). \tag{11}$$

To obtain w_c, we can equate the arrival rate with the departure rate of the system,

$$\begin{aligned}\lambda(1-w_c) &= (1-w_0)/E[\mathcal{S}] \\ w_c &= 1-(1-w_0)/(\lambda \cdot E[\mathcal{S}]). \end{aligned} \tag{12}$$

Thus $\boldsymbol{w}$ can be calculated based on (11) and (12). Furthermore, with the PASTA property of the Poisson arrival process, $\boldsymbol{u} = \boldsymbol{w}$, therefore the steady state system size distribution is derived. The expectation of the steady state system size can be calculated as $E[\mathcal{L}] = \sum_{i=0}^{c} i \cdot u_i$, and a new request arrives to find a fully occupied system and thus get dropped with probability w_c. Note that certain existing hybrid data collection protocols (i.e., using multiple homogeneous or heterogeneous MEs) could be a good approach to addressing these dropped requests if they are indeed needed [12].

F. Expectation and Stochastic Bound of the Response Time

The ultimate metric to evaluate the data collection performance is the response time $\mathcal{R}$ of requests, i.e., from the time the request is received to the time it is served. With the expected system size and by *Little's Law*

$$E[\mathcal{R}] = \frac{E[\mathcal{L}]}{\lambda(1-w_c)}. \tag{13}$$

However, similar to the case with the traditional SJN discipline, people may concern about the possible starvation problem when NJN is adopted.

We argue that although NJN may suffer similar problem, its severity would be much less significant, for the reason that, first, the service time of requests with NJN cannot be arbitrarily large, and is bounded by the maximum travel time of the ME, i.e., $\sqrt{2}/v$ to cross the sensing field; second, the service time of a given request changes as the ME travels in the network, and the probability that it keeps at a large value during a long time period is small.

However, the expected response time alone is not enough to verify the above reasoning, and direct analysis on the response time distribution with NJN is non-trivial (convolution theorem could be a choice, but cannot guarantee the existence of a closed-form solution). Thus, we tackle the distribution of the system's busy period in the following, which is a stochastic upper bound of the response time. Our approach is to approximate the distribution of the busy period based on the analytical results of its statistical moments.

Note that the idle period distribution of the system is $F_{\mathcal{I}}(t) = 1 - e^{-\lambda t}$, and denote $\mathcal{T}_{i,j}$ as the time takes the system from entering state i till it entering state j, so $\mathcal{T}_{0,0}$ is the busy cycle of the system. By definition and with some simple arrangement, we have

$$E[\mathcal{T}_{i,0}] = \begin{cases} E[\mathcal{I}] + E[\mathcal{S}_1] + \sum_{j=1}^{c} E[\mathcal{T}_{j,0}]k_j^1 & i = 0 \\ E[\mathcal{S}_i] + \sum_{j=1}^{c} E[\mathcal{T}_{j,0}]k_{j-i+1}^i & i \ge 1. \end{cases} \tag{14}$$

Thus $E[\mathcal{T}_{0,0}]$ can be calculated, and the second-order moment of $\mathcal{T}_{0,0}$ can be obtained with a similar approach

$$E[\mathcal{T}_{i,0}^2] = \begin{cases} \sum_{j=1}^{c} E[(I+S_1+T_{j,0})^2]k_j^1 & \\ +E[(I+S_1)^2]k_0^1 & i = 0 \\ \sum_{j=1}^{c} E[(S_1+T_{j,0})^2]k_j^1 & \\ +E[S_1^2]k_0^1 & i = 1 \\ \sum_{j=1}^{c} E[(S_i+T_{j,0})^2]k_{j-i+1}^i & i \ge 2 \end{cases}$$

Therefore, the first and second-order moments of the ME's busy period $\mathcal{B}$ can be calculated as

$$E[\mathcal{B}] = E[\mathcal{T}_{0,0}] - E[\mathcal{I}] \tag{15}$$

$$E[\mathcal{B}^2] = E[\mathcal{T}_{0,0}^2] - E[\mathcal{I}^2] - 2E[\mathcal{B}]E[\mathcal{I}]. \tag{16}$$

Observing the fact that the busy period of the system is actually the sum of the service times of several continuously served requests, we can adopt the Gamma distribution to approximate that of the busy period as

$$f_{\mathcal{B}}(t) = t^{\eta-1}\frac{e^{-t/\theta}}{\theta^{\eta}\Gamma(\eta)} \ (t > 0), \tag{17}$$

where $\eta = 1/(E[\mathcal{B}^2]/E[\mathcal{B}]^2 - 1)$ and $\theta = E[\mathcal{B}]/\eta$. The accuracy of this approximation is verified in Section VI-B.

V. Data Collection with NJNC

We have theoretically analyzed the system measures when NJN is adopted in the previous section. In this section, we extend the NJN discipline by taking the wireless communication properties into account: with wireless communications, the ME can collect data from several requesting nodes at the same collection site, provided that the site is within the communication ranges of these nodes. We consider this NJNC discipline in the following, with which the ME still selects the nearest requesting node to serve, except that if there are other requesting nodes within distance r from the nearest one, the ME will combine these requests and serve them together.

The combination, if happens, can effectively reduce the system size, and thus shorten the response time of requests. It can also alleviate the possible starvation problem, since intuitively, starvation is less likely to happen with a smaller system size. We mainly deal with two questions in this section: how likely the combination can happen, and if it happens, how many requests can be combined; to what degree the combination can improve the data collection performance.

A. Combination Probability

For the requests combination to happen, the collection site must be covered by the communication ranges of at least another requesting node, besides the nearest one. Same as before, assume l requests are currently available when the ME selects the next request, the probability that X_l requesting nodes, including the nearest one, can be combined together and served from one collection site is

$$\Pr\{X_l = x\} = \binom{l-1}{x-1} F_D(r)^{x-1}(1-F_D(r))^{l-x}. \tag{18}$$

Thus the expected number of combined requests is

$$E[X_l] = \sum_{i=1}^{l} i \cdot \Pr\{X_l = x\}, \tag{19}$$

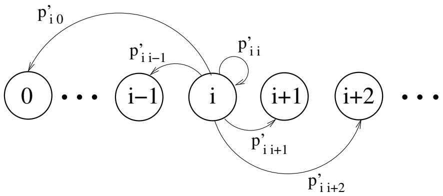

Fig. 3: State transition diagram at departure time with NJNC (only those for state i are shown for clarity).

and the probability for the combination to happen is

$$\Pr\{X_l > 0\} \quad = \quad 1 - (1 - F_D(r))^{l-1}. \tag{20}$$

Intuitively, requests combination improves the system performance by effectively reducing the system size. Based on a similar queuing model as that for NJN, i.e., $M/G/1/c$–$NJNC$ for NJNC, we present quantitative analytical results of its impact on the system performance in the following.

B. System Size Probabilities at the Departure Time

The ME still selects the nearest request in its queue to serve with NJNC, so given the system size, the service time distribution is identical to that of NJN. Following a similar idea of the embedded Markov chain, we can derive its departure time system size probabilities.

The difference between the heterogeneous Markov chains of NJNC and NJN is that, it is now possible to have multiple departures after one service period, as shown in Fig. 3. With the current system size l, denote $a_{n,l}$ as the probability of n arrivals during the service of the nearest requests selected from l requests with possible requests combination. Since the combination does not affect the arrival process, we have

$$a_{n,l} \quad = \quad k_n^l. \tag{21}$$

Denote $d_{m,l}$ as the probability of m departures after serving the nearest requests selected from l requests with possible requests combination, which means $m-1$ requests have been served together with the nearest one, so

$$d_{m,l} = \Pr\{X_l = m\} = \binom{l-1}{m-1} F_D(r)^{m-1}(1-F_D(r))^{l-m}. \tag{22}$$

Thus the state transition probabilities of the embedded Markov chain for NJNC are

$$\boldsymbol{P}' = [p'_{ij}] = [\sum_{m=1}^{i} d_{m,i} \cdot a_{j-i+m,i}], \tag{23}$$

and $\boldsymbol{\pi}'\boldsymbol{P}' = \boldsymbol{\pi}'$, where $\boldsymbol{\pi}'$ is the departure time system size distribution with NJNC. Hence, the general service time distribution, steady state system size probabilities, and the expected response time can be calculated with similar approaches as those for the NJN discipline, except that with possible requests combination, the effective arrival rate of requests is

$$\lambda_e = (w'_0 + \sum_{i=1}^{c-1} w'_i(1 - F_D(r)))\lambda, \tag{24}$$

where $\boldsymbol{w}$ is the arrival time system size distribution with NJNC, and $1 - F_D(r)$ is the probability that the newly arrived request cannot be combined with the next to-be-served request at its arrival time.

The analysis on the system's busy period is much more complicated with NJNC, due to the possibility of multiple departures after one service. However, the idea of deriving its moments for the stochastic upper bound as that in the NJN case still holds, and corresponding results can be obtained, which are not shown here due to the space limit.

VI. Performance Evaluation

We evaluate our modeling and analytical results on the performance of data collection with NJN and NJNC disciplines in this section, and we also show the corresponding results with FCFS in certain cases for comparison. Note that we have already explored the case of *FCFS-with-combination* (FCFSC) in [5], whose results are not shown here due to the space limit. We consider a 100×100 m^2 square sensing field with 100 uniformly and randomly distributed sensor nodes, and based on the parameters from real systems [24], the travel speed of ME is 1 m/s. The communication range r is 20 m by default unless otherwise specified.

To deal with the inconvenience of the piecewise distance density function in (2), we approximate it by a high-order polynomial function using *least squares fitting*

$$\begin{aligned} \widetilde{f}_D(d) \quad = \quad & 0.2802d^{10} - 2.0964d^9 + 2.2349d^8 \\ & +24.3629d^7 - 106.8231d^6 + 194.4928d^5 \\ & -182.8093d^4 + 91.8223d^3 - 29.3663d^2 \\ & +8.2843d - 0.0402. \end{aligned} \tag{25}$$

The norm of the residuals for the poly-fitting is 0.0749, which shows the approximation is quite accurate, and thus we adopt the approximated polynomial function for easy calculation.

A. Validation of the Queue Modeling

To validate the queuing model, we need to examine the assumptions of both the Poisson arrival of data collection requests and the distribution-ergodic property of their service time. We adopt a hot-spot model to capture the data generation in the sensing field in our event-driven simulator [27]. Specifically, several hot spots (10 in our simulation) exist in the sensing field, and the probability for an event to occur at a certain location is inverse proportional to its distance to the closest hot spot. When an event occurs, sensor nodes whose sensing range covers it can detect the event and generate sensory data of size $\alpha e^{-\alpha d}$ bits to record it, where d is the distance between the node and the event, and α is set to 0.5 in our simulation. Sensor node sends out a data collection request when a total volume of 1 KB data are accumulated in its buffer. A total number of 100 data collection requests are generated and served during each simulation, which is repeated for 100 times. For each simulation run, we record the inter-arrival time of the requests, with the service discipline of FCFS and NJN respectively, and use an exponential distribution with the same mean value to approximate it. We adopt the *Kolmogorov-Smirnov* (K-S) test to verify the goodness-of-fit of the approximation, and record the percentage of runs that pass it. The whole process is repeated for 40 times. We also

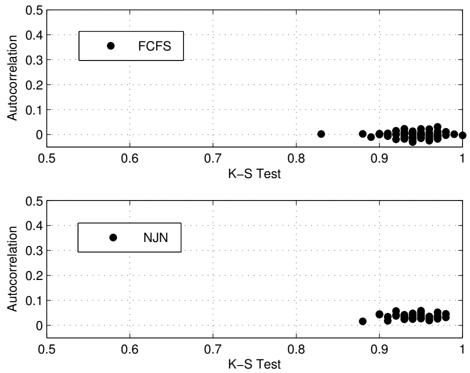

Fig. 4: Validation of Poisson arrival and the distribution-ergodic property of the service of data collection requests.

record the service time of each request, and calculate their one-lag autocorrelation to validate the distribution-ergodic property of the service time, for both the FCFS and NJN disciplines.

Figure 4 gives the results of the K-S test and the autocorrelation on the queuing model, where each point corresponds to one of the 100×100 simulation runs. The x-value of the point is the percentage of simulation runs that pass the K-S test, and the y-value is the one-lag autocorrelation. Thus we expect that, if these points are clustered around the right bottom corner, as being observed from the validation results in Fig. 4, the queuing model used in this paper is confirmed sound and acceptable.

B. System Measures

We focus on the evaluation of the analytical results on the system measures of the queuing model in the following. Our analysis for both NJN and NJNC starts with the state-dependent service time distribution, so we first examine the results on the service time distribution with a given system size for both NJN and NJNC. Two cases with a small and a large system size of 5 and 9 are explored respectively, and the results are shown in Fig. 5. We can see that the analysis and simulation agree with each other nicely, and the conditional service time becomes shorter with a larger system size, which is consistent with the nearest-job-next nature: more queued requests in the system brings more opportunities to have nearer ones.

However, the ultimate performance metric of data collection is the response time of requests, which is determined by both the service time and system size, and a shorter service time does not necessarily lead to a shorter response time. Next, we move on to evaluate the results on system size. The average system sizes with different request arrival rates λ for FCFS, NJN, and NJNC are shown in Fig. 6. The system sizes under all the three disciplines are small and comparable to each other with a light traffic, since the potential for both NJN and NJNC to take effect is quite limited in this case. The system size for FCFS increases very quickly when λ increases, and cannot keep stable anymore when λ exceeds a certain threshold (0.018 in Fig. 6). In fact, the case of $\lambda = 0.018$ in our simulation roughly corresponds to the case

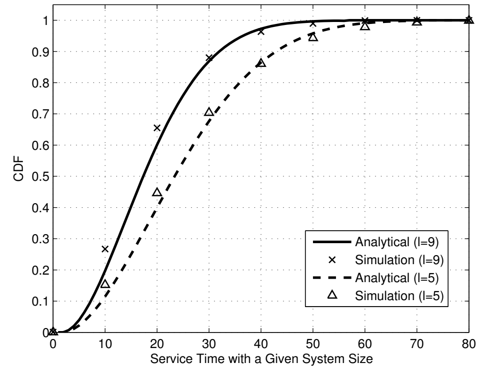

Fig. 5: Service time with a given system size.

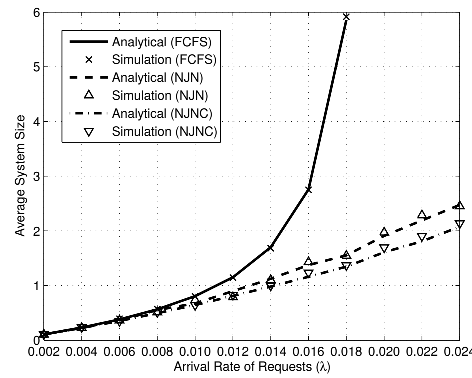

Fig. 6: Average system size.

that $\rho = \lambda \cdot E[\mathcal{S}] = 1$ for FCFS, where ρ is the system utilization factor, and increasing λ further will result in an unstable system where the steady state does not exist. When compared with FCFS, NJN can reduce the system size greatly because it tries to serve and finish nearby requests in a shorter time, and NJNC can further decrease the system size as a result of possible requests combination. Note that the capability of NJNC to further reduce the system size becomes more obvious when λ increases, since a larger system size leads to a larger potential to combine already queued requests. (One thing to mention is that, not surprisingly, the resultant system size with FCFSC falls between those with FCFS and NJN, e.g., 1.9 with a λ of 0.018 [5].)

We then examined the general service time distribution for both NJN and NJNC, as shown in Fig. 7, where the service time distribution for FCFS is also shown for comparison. NJN and NJNC can shorten the service time noticeably because of their nature to serve nearby requests with less time, and the service time of NJNC is slightly longer than that of NJN, as a result of possible requests combination, which reduces the system size more aggressively and also the possibility of finding a nearby requesting sensor node in the future.

As mentioned above, both service time and system size affect the response time. Since NJN has a shorter service time and NJNC has a smaller system size, next we need to examine their response time. The average response time for FCFS, NJN

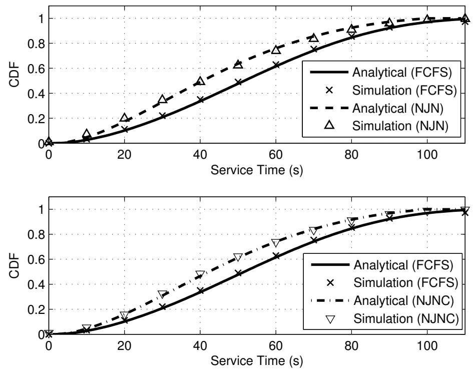

Fig. 7: General service time distribution.

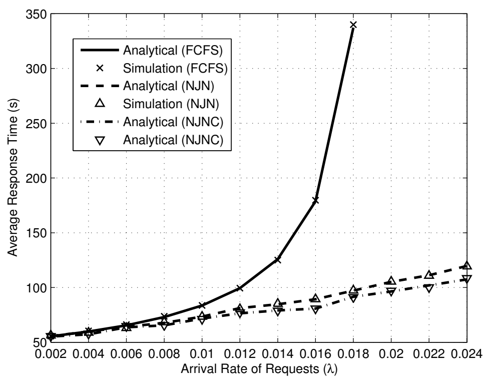

Fig. 8: Average response time with service disciplines of FCFS, NJN, and NJNC, respectively.

and NJNC is shown in Fig. 8, from which we can see that when compared with FCFS, NJN and NJNC can greatly shorten the response time of requests, especially when λ is large. NJNC can further reduce the response time as a result of possible requests combination, which also becomes more obvious as λ increases. It shows that between a shorter service time for NJN and a smaller system size for NJNC, the system size reduction is more dominating for the resultant response time. A smaller system size also indicates a lower overflow probability for a given system capacity limit.

People may have concerns about the possible starvation problem when NJN discipline is adopted, and to gain insights on this problem, we have obtained a Gamma approximation of the busy period distribution for NJN, which serves as the stochastic upper bound of the response time of requests. The evaluation results of this approximation, along with the response time distribution with the FCFS discipline (obtained according to [28]), are shown in Fig. 9, where BP and RT stand for the busy period and response time, respectively, and λ is 0.018. We can see that for NJN, its busy period is even stochastically smaller than the response time obtained by FCFS, which alleviates the concerns about the starvation problem.

As a summary of these observations on the system measures, NJN and NJNC achieve a much better data collection

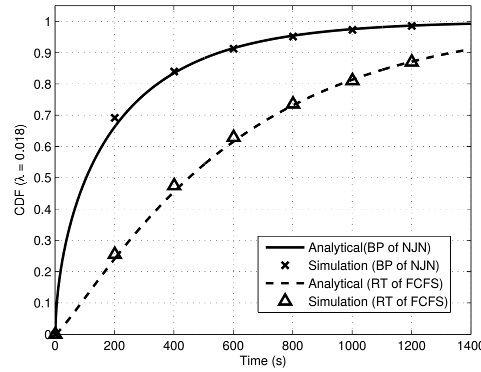

Fig. 9: Gamma approximation of the busy period distribution with NJN, compared with the response time distribution with FCFS discipline.

performance than FCFS. Even facing the possible starvation problem, the worst-case performance of NJN is still stochastically better than that obtained by FCFS. Another advantage of NJN and NJNC is that they can keep the system in a stable state even when the arrival rate of requests is very high, while that for FCFS is quite limited. As a result of possible requests combination, NJNC can further improve the system performance, especially with a heavy traffic. These observations can assure us that NJNC is an attractive discipline to adopt when designing more sophisticated online data collection schemes for MEs in wireless sensor networks, especially with a tight bound on the data collection latency.

VII. Discussion and Ongoing Work

Our modeling and analysis are shown accurate but some issues need to be further explored. Here we discuss some of these issues and the directions of ongoing work.

Clearly, the assumption of a square sensing field may not hold in practice. However, our queue-based modeling and analysis approaches are still feasible even for any general sensing fields, provided that the distance distribution between arbitrary locations in the field can be obtained, e.g., we have also analytically derived the random distance distributions associated with rhombuses and hexagons [31], [32]. Furthermore, if the sensing field is of irregular shape, which may be true in certain cases, we can adopt the polygon-approximation approach to approximate the field by the combination of several regular shapes, and derive the random distance distributions within and between them.

Another assumption we made is the time for transmitting the data from sensors to the ME is negligible, which may not hold if the data volume is very large. However, note that given any sensor network deployment, the knowledge on the data transmission rate and communication range is available, or at least can be estimated. Based on such knowledge, we can estimate the data volumes that can be collected if the ME travels without any stops, and then the time that the ME has to pause or slow down to collect the remaining data can be calculated as well. The statistics of this additional time can be easily considered when formulating the service time distribution.

The request response time in this work does not include the time since the request is sent by the sensor node to its reception at the ME, which we assumed to be negligible. Observing the fact that these two times are independent to each other, thus by the convolution theorem, we can easily take the latter into account provided that its distribution $g(t)$ can be obtained, i.e.,

$$f'_{\mathcal{R}}(t) = g(t) * f_{\mathcal{R}}(t). \quad (26)$$

We have also taken the delivery of the requests from sensor nodes to the ME into account in [30], in which the ME collects data from sensor nodes with NJN discipline in a partitioned network.

When multiple MEs are available, a straightforward approach is to extend the $M/G/1/c$ model to $M/G/c/c$. However, in addition to the queue length and response time, we also need to consider the load balance among the MEs as another metric to evaluate the system performance.

This paper can serve as a starting point to further explore mobile elements in wireless ad hoc sensor networks and similar application scenarios with dynamic-priority scheduling, e.g., adaptive channel assignment in cognitive radio networks.

VIII. Conclusions

In this paper, we have analytically evaluated an intuitive service discipline, NJN, for data collection with mobile elements in wireless sensor networks, and also explored the case where the ME follows NJN and combines requests whenever possible, i.e., NJNC. We have modeled the system as an $M/G/1/c$ queue, and then with different service disciplines (NJN and NJNC), critical system metrics have been derived. We have verified our analytical results through extensive simulation, and gained more insights on the starvation problem that NJN and NJNC may suffer from. Our results have showed that not only the average performance of NJN is much better than that of FCFS, but also the worst-case performance of NJN is still better than that of FCFS, even though according to the conventional wisdom, NJN may suffer from the starvation problem. A possible reason is that the service time is not arbitrary for data collection applications in wireless sensor networks. Moreover, NJNC can further improve the performance as a result of possible requests combination. We have also discussed several possible extensions as ongoing and future work.

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References

[1] C. Wang, C. Jiang, Y. Liu, S. Tang, X. Li, and H. Ma, "Aggregation capacity of wireless sensor networks: extended network case", in *Proc. IEEE INFOCOM'11*, 2011.

[2] Z. Li, M. Li, J. Wang, and Z. Cao, "Ubiquitous data collection for mobile users in wireless sensor networks," in *Proc. IEEE INFOCOM'11*, 2011.

[3] W. Wang, V. Srinivasan, and K. Chua, "Extending the lifetime of wireless sensor networks through mobile relays," *IEEE/ACM Transaction on Networking*, vol. 16, no. 5, pp. 1108–1120, 2008.

[4] J. Luo and J. Huabux, "Joint sink mobility and routing to maximize the lifetime of wireless sensor networks: the case of constrained mobility," *IEEE/ACM Transaction on Networking*, vol. 18, no. 3, pp. 871–884, 2010.

[5] L. He, Y. Zhuang, J. Pan, and J. Xu,, "Evaluating on-demand data collection with mobile elements in wireless sensor networks," in *Proc. IEEE VTC'10-Fall*, 2010.

[6] NEPTUNE Canada, 2011. http://www.neptunecanada.ca/

[7] Sabertooth, 2011. http://www.rov-online.com/?p=290

[8] WFS, 2011. http://www.wirelessfibre.co.uk/

[9] Shadow 200, 2011. http://en.wikipedia.org/wiki/AAI_RQ-7_Shadow

[10] R. Sugihara and R. Gupta, "Optimal speed control of mobile node for data collection in sensor networks," *IEEE Transaction on Mobile Computing*, vol. 9, no. 1, pp. 127–139, 2010.

[11] R. Sugihara and R. Gupta, "Optimizing energy-latency trade-off in sensor networks with controlled mobility," in *Proc. IEEE INFOCOM'09*, 2009.

[12] A. Srinivasan and J. Wu, "Track: a novel connected dominating set based sink mobility model for WSNs," in *Proc. IEEE ICCCN'08*, 2008.

[13] X. Xu, J. Luo, and Q. Zhang, "Delay tolerant event collection in sensor networks with mobile sink," in *Proc. IEEE INFOCOM'10*, 2010.

[14] A. Tanenbaum, *Modern Operating Systems* (3rd ed.), Pearson Education, Inc.. pp. 156.

[15] N. Bansal and M. Balter, "Analysis of SRPT scheduling: investigating unfairness," in *Proc. ACM SIGMETRICS'01*, 2001.

[16] Silberschatz and Galvin, *Operating System Principles*, (7th ed.), Jone Wiley.

[17] M. Ma and Y. Yang, "SenCar: an energy-efficient data gathering mechanism for large-scale multihop sensor networks," *IEEE Transaction on Parallel and Distributed Systems*, vol. 18, no. 10, pp. 1476–1488, 2007.

[18] A. Somasundara, A. Ramamoorthy, and M. Srivastava, "Mobile element scheduling for efficient data collection in wireless sensor networks with dynamic deadlines," in *Proc. IEEE RTSS'04*, 2004.

[19] O. Tekdas, V. Isler, J. Lim, and A. Terzis, "Using mobile robots to harvest data from sensor fields," *IEEE Wireless Communications*, vol. 16, no. 1, pp. 22–28, 2009.

[20] X. Liu, H. Zhao, X. Yang, X. Li, and N. Wang, "Trailing mobile sinks: a proactive data reporting protocol for wireless sensor networks," in *Proc. IEEE MASS'10*, 2010.

[21] M. Rahimi, et al., "Cyclops: in situ image sensing and interpretation in wireless sensor networks," in *Proc. ACM SenSys'05*, 2005.

[22] D. Jea, A. Somasundara, and M. Srivastava, "Multiple controlled mobile elements (data mules) for data collection in sensor network," in *Proc. IEEE DCOSS'05*, 2005.

[23] G. Grimmett and D. Stirzaker, *Probability and Random Processes*, (3rd ed.), Oxford University Press, July 2010.

[24] G. Xing, T. Wang, W. Jia, and M. Li, "Rendezvous design algorithms for wireless sensor networks with a mobile base station," in *Proc. ACM MobiHoc'08*, 2008.

[25] C. Bettstetter, H. Hartenstein, and X. Perez-Costa, "Stochastic properties of the random waypoint mobility model," *Wireless Networks*, vol. 10, no. 5, pp. 555–567, 2004.

[26] Y. Zhuang, J. Pan, and L. Cai, "Minimizing energy consumption with probabilistic distance models in wireless sensor networks," in *Proc. IEEE INFOCOM'10*, 2010.

[27] J. Zhao, R. Govindan, and D. Estrin, "Residual energy scans for monitoring wireless sensor networks," in *Proc. IEEE WCNC'02*, 2002.

[28] D. Gross, *Fundamentals of Queueing Theory*, (4th ed.), pp. 232, New Jersey: John Wiley & Sons, 2008.

[29] P. Brill, *Level Crossing Methods in Stochastic Models*, Springer, 2008.

[30] M. Ahmadi, L. He, J. Pan, et al., "A Partition-based Data Collection Scheme for Wireless Sensor Networks with a Mobile Sink," accepted by *IEEE ICC'12*, 2012.

[31] Y. Zhuang and J. Pan, *Random Distances Associated with Rhombuses*, arXiv:1106.1257, 2011.

[32] Y. Zhuang and J. Pan, *Random Distances Associated with Hexagons*, arXiv:1106.2200, 2011.