Capacity and Delay Analysis for Data Gathering with Compressive Sensing in Wireless Sensor Networks

Haifeng Zheng, Shilin Xiao, *Member, IEEE,* Xinbing Wang, *Senior Member, IEEE,* Xiaohua Tian, *Member, IEEE,* and Mohsen Guizani, *Fellow, IEEE*

***Abstract*—Compressive sensing (CS) provides a new paradigm for efficient data gathering in wireless sensor networks (WSNs). In this paper, with the assumption that sensor data is sparse we apply the theory of CS to data gathering for a WSN where n nodes are randomly deployed. We investigate the fundamental limitation of data gathering with CS for both single-sink and multi-sink random networks under protocol interference model, in terms of capacity and delay. For the single-sink case, we present a simple scheme for data gathering with CS and derive the bounds of the data gathering capacity. We show that the proposed scheme can achieve the capacity $\Theta(\frac{nW}{M})$ and the delay $\Theta(M\sqrt{\frac{n}{\log n}})$, where W is the data rate on each link and M is the number of random projections required for reconstructing a snapshot. The results show that the proposed scheme can achieve a capacity gain of $\Theta(\frac{n}{M})$ over the baseline transmission scheme and the delay can also be reduced by a factor of $\Theta(\frac{\sqrt{n \log n}}{M})$. For the multi-sink case, we consider the scenario where n_d sinks are present in the network and each sink collects one random projection from n_s randomly selected source nodes. We construct a simple architecture for multi-session data gathering with CS. We show that the per-session capacity of data gathering with CS is $\Theta(\frac{n\sqrt{n}W}{Mn_d\sqrt{n_s \log n}})$ and the per-session delay is $\Theta(M\sqrt{\frac{n}{\log n}})$. Finally, we validate our theoretical results for the scaling laws of the capacity in both single-sink and multi-sink networks through simulations.**

I. Introduction

Wireless sensor networks (WSNs) consisting of a large number of nodes, are usually deployed in a large region for many applications, such as surveillance, security and habit monitoring. Data gathering is one of the most important functions provided by WSNs, where sensors are responsible for gathering information and delivering them to a destination node (sink). In many situations, it is inefficient for sensors to transmit all the raw data to the sink, especially when sensed data exhibits high correlation. To reduce transport load, conventional compression techniques are usually used to exploit the correlation among sensor data so that less data can be delivered to the sink without sacrificing the salient information. However, the efficiency of conventional compression techniques relies heavily on compression and routing algorithms, which result in large overhead cost of communication and computation for sensors. Moreover, distributed source coding techniques, such as Slepian-Wolf Coding [1], are also difficult to be applied in such scenarios in that the prior knowledge about the characteristics of data distribution should be known in advance. Fortunately, *compressive sensing* (CS) [2] provides a promising solution in a more efficient manner for the data gathering problem in WSNs, which attempts to reduce sensor data traffic over the network through collecting far fewer measurements than the number of original sensor data.

The applications of compressive sensing for data gathering in multi-hop WSNs have drawn much attention recently [3]–[7]. In [3], [4], Luo et al. applied CS theory for data gathering to efficiently reduce communication cost and prolong network lifetime for large scale multi-hop WSNs. In [5], Quer et al. studied the behavior of CS in conjunction network topology and routing to transmit random projections of the sensor data in a data gathering WSN. In [6], Lee et al. investigated CS for energy efficient data gathering in a multi-hop WSN. In [7], Xiang et al. proposed compressed data aggregation technique with CS to minimize the network energy consumption through joint routing and compressed aggregation scheme.

While various applications of compressive sensing for data gathering have been extensively studied, there have been few works on investigating the performance of data gathering with CS in terms of capacity and delay. In this paper, we will concentrate on the *capacity* and *delay* for data gathering with CS in random networks, where n sensor nodes are randomly deployed in a region. The typical traffic pattern for data gathering is many-to-one or many-to-many. The capacity of this traffic pattern has been extensively studied in a few papers [9]–[12]. Also, both capacity and delay scaling laws for this traffic pattern have been investigated in [13], [14]. However, the traffic model adopted in the above works is based on the baseline transmission scheme where the raw data is directly

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H. Zheng, and S. Xiao are with the State Key Laboratory of Advanced Optical Communication Systems and Networks, Shanghai Jiao Tong University, Shanghai, China (e-mails: zhenghf@sjtu.edu.cn, sxiao@sjtu.edu.cn). H. Zheng is also with the College of Physics and Information Engineering, Fuzhou University, Fuzhou, China.

X. Wang, and X. Tian are with the Department of Electronic Engineering, Shanghai Jiao Tong University, Shanghai, China (e-mails: xwang8@sjtu.edu.cn, xtian@sjtu.edu.cn).

M. Guizani is with the Qatar University, Qatar (e-mail: mguizani@ieee.org).

Correspondence author: Xinbing Wang.

transmitted to the sink(s) through multi-hop routing without any processing in intermediate nodes. It is assumed to be inefficient when the transmitted data exhibits high correlation. Therefore, it is necessary to characterize the improvement of the capacity and delay performance brought by the theory of CS for data gathering. The initial work on investigating the capacity of data gathering with CS in a single-sink network can be found in [3]. To derive the lower bound of the capacity, they assume that there exists an appropriate routing scheme such that each subtree contains roughly the same number of nodes and has relatively uniform characteristics of data sparsity distribution in each subtree. This assumption is quite strict since the characteristics of a sensed field may not be uniform. In this paper, we relax this constraint and extend the application of CS for data gathering to a more general case where the underlying data sparsity distribution can be *non-uniform* in each subtree.

Furthermore, we also consider a scenario where multiple sinks are present in the network. In such a network, each sink is responsible for collecting data from some source nodes that are randomly selected from n nodes. We also assume that each sink can recover the entire sensed field from these source nodes. This assumption is built on the remarkable result of compressive sensing using *sparse random projections* [17], [18] which states that recovering an approximation of n sensor data can be obtained by querying any k randomly selected sensors, where k can be far smaller than n. Due to the fact that wireless network allows for spatial reuse [8], multiple sinks can collect data from their corresponding source nodes simultaneously without interfering with each other under an appropriate scheduling scheme. This also increases the network capacity for data gathering. The main contributions of our work are listed as follows.

- We apply the theory of CS to data gathering in both single-sink and multi-sink networks. In particular, we exploit the idea of sparse random projections for data gathering in multi-sink networks, which can reduce the communication cost and pre-processing of data. We analyze not only the capacity but also the delay under protocol interference model in single-sink and multi-sink networks, respectively. For each type of network, we derive matching asymptotic upper bound and lower bound on the data gathering capacity. We also present simulation results to verify the theoretical analysis on the scaling laws of the capacity in both single-sink and multi-sink networks.
- For the single-sink network, we consider the scenario where n source nodes are randomly deployed in the network. We present a simple scheme with CS for data gathering routing in random networks without the assumption on the relatively uniform characteristics of data sparsity distribution in each subtree, which is different from the work in [3]. We derive the upper bound of the data gathering capacity, and prove that the proposed scheme can achieve this upper bound in the order sense, i.e, the total capacity of $\Theta(\frac{nW}{M})$[1]. We also study the delay performance of the proposed scheme and show that the delay for collecting a snapshot with CS is $\Theta(M\sqrt{\frac{n}{\log n}})$[2]. The results show that the proposed scheme can achieve a capacity gain of $\Theta(\frac{n}{M})$ over the baseline transmission scheme and the delay can also be reduced by a factor of $\Theta(\frac{\sqrt{n\log n}}{M})$.
- For the multi-sink network, we consider multi-session data gathering with CS in random networks in which there are total n_d sinks in the network. For each session, each sink collects one random projection from n_s source nodes that are randomly selected from n nodes. Each sink can obtain n values of nodes from M random projections by means of CS. Under this model, we first derive the upper bound on the data gathering capacity. We then construct a simple architecture for data gathering routing and prove that the proposed scheme can achieve the upper bound in the order sense. We show that the per-session capacity of data gathering with CS is $\Theta(\frac{n\sqrt{n}W}{Mn_d\sqrt{n_s\log n}})$. Meanwhile, we find the average delay for each data gathering session in multi-sink networks is still $\Theta(M\sqrt{\frac{n}{\log n}})$. This is because delay is mainly determined by the number of hops required for sending a packet to the sink and the number of random measurements M.

The remainder of this paper is organized as follows. In Section II, we introduce the basic theory of compressive sensing and the network model used in the paper. In Section III, we consider the case with a single sink, and present a scheduling and routing scheme based on CS for data gathering in WSNs. We derive the bounds of data gathering capacity and delay for the proposed scheme. In Section IV, we extend the application of CS to data gathering in multi-sink networks. We construct an architecture for multi-session data gathering routing and derive the bounds of capacity and delay for the proposed scheme. In Section V, we validate our theoretical results through simulations. Finally, we conclude the paper in Section VI.

II. PRELIMINARIES

A. Compressive Sensing Basics

Compressive sensing has emerged as a new technique for signal acquisition and processing. CS provides a new sampling paradigm for sparse signals and enables to reconstruct a sparse signal from a small number of measurements. Consider a signal vector $\mathbf{x} = (x_1, \ldots, x_n)^T$. Suppose that $\mathbf{x}$ can be represented as $\mathbf{x} = \sum_{i=1}^{n}\theta_i\psi_i$ in domain $\Psi = (\psi_1, \ldots, \psi_n)$, where θ_i are the transform coefficients in domain Ψ. We say that the vector $\mathbf{x}$ is k-sparse if there are only k non-zero entries in vector $\boldsymbol{\theta} = (\theta_1, \ldots, \theta_n)$. Now considering in the

[1] We use the following asymptotic notation throughout this paper: Given non-negative functions $f(n)$ and $g(n)$: $f(n) = O(g(n))$ means $\limsup_{n\to\infty} f(n)/g(n) < \infty$; $f(n) = o(g(n))$ is equivalent to $\lim_{n\to\infty} f(n)/g(n) = 0$; $f(n) = \Omega(g(n))$ is equivalent to $g(n) = O(f(n))$; $f(n) = \omega(g(n))$ is equivalent to $g(n) = o(f(n))$; $f(n) = \Theta(g(n))$ means $f(n) = O(g(n))$ and $f(n) = \Omega(g(n))$.

[2] log denotes the logarithm to the base e throughout this paper.

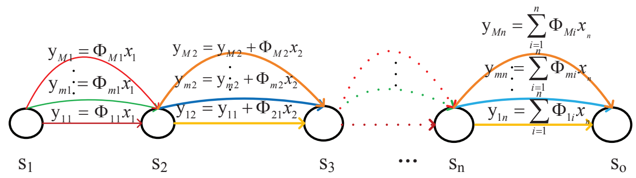

Fig. 1. Illustration of data gathering with CS in a line network with n source nodes and one sink. Each node generates M random measurements, aggregates and transmits them to the sink along the line path.

framework of CS, instead of directly sampling $\mathbf{x}$, we obtain the compression version $\mathbf{y}$ through a measurement matrix Φ, i.e., $\mathbf{y} = \Phi\mathbf{x}$, where Φ is $M \times n$ measurement matrix with $M \ll n$. The theory of CS states that the k-sparse signal $\mathbf{x}$ can be recovered from M measurements with high probability if $M \geq ck \log n$, where c is a constant [15]. This indicates that the number of required measurements M scales linearly with signal sparsity k, and is only logarithmic in signal length n. Recovering the signal $\mathbf{x}$ from $\mathbf{y}$ can be conducted through solving an ℓ_1-minimization problem:

$$\min_{\boldsymbol{\theta} \in \Re^N} \| \boldsymbol{\theta} \|_{\ell_1} \text{ s.t. } \mathbf{y} = \Phi\Psi\boldsymbol{\theta}, \ \mathbf{x} = \Psi\boldsymbol{\theta}. \tag{1}$$

Let us take an example for the application of CS in a data gathering scenario. Considering the line network with n source nodes in Fig. 1, each node s_i has a value x_i to transmit to the sink s_o. In the baseline transmission scheme, the value x_i at each node s_i is directly transported via multi-hop transmissions to the sink without any computation performed at the intermediate nodes. In a CS manner, each node s_i calculates a new value y_{mi} by multiplying its value x_i with a random coefficient Φ_{mi} $(1 \leq m \leq M)$, i.e., $y_{mi} = \Phi_{mi}x_i$. Then, the new value y_{mi} is aggregated and transmitted along the line path to the sink. Finally, the sink receives the value $y_{mn} = \sum_{i=1}^{n} \Phi_{mi}x_i$. The process is repeated for M times so that the sink will receive M measurements. Hence, one round of data gathering is completed. An illustration for data gathering with CS is shown in Fig. 1. The sink can reconstruct all the values of n nodes from the M measurements using recovering algorithms, such as linear programming (LP) techniques [2]. In the following sections, we will illustrate in detail how to combine CS with scheduling and routing algorithms for data gathering in both single-sink and multi-sink WSNs.

B. Sensor Data and Network Model

In this paper, we consider a wireless sensor network, where n nodes are randomly and independently deployed in a unit square area. At a sampling instant, each node i measures a real value x_i. Let $\mathbf{x} = (x_1, \dots, x_n)^T$ denote the vector of sampling values. We assume that there are only spatial correlations among sampling values and $\mathbf{x}$ is k-sparse under a transform basis Ψ. We can use the eigenvectors of the graph Laplacian as an orthonormal basis to sparsify the sensor data as done in [25]. However, how to use such a transform basis Ψ to sparsify the sensor data is beyond the scope of this paper. Meanwhile, we assume the number of measurements M is chosen so as to guarantee that the k-sparse signal $\mathbf{x}$ can be completely recovered, i.e., $M \geq ck \log n$, as stated above. We also assume all nodes share a common wireless channel and the communication distance of each node is $r(n)$. We further assume the constant capacity of each link is W which means that each node can transmit at W bits/second through the wireless channel. A time-division multiplexing access (TDMA) scheme is adopted in our data gathering scheme for cell scheduling. We adopt a *protocol interference model*, which is defined as follows [8]:

Definition 1: Let X_i denote the location of sensor node i and $|X_i - X_j|$ denote the Euclidean distance between node i and node j. When node i transmits to node j, the transmission is successful if the following two conditions are satisfied: (1) $|X_i - X_j| \leq r(n)$. (2) For other node k which transmits simultaneously, $|X_k - X_j| \geq (1 + \Delta)r(n)$, where Δ is a positive constant that determines the size of the guard zone to prevent interference.

C. Cell Partition and Scheduling

Now we introduce the cell partition method adopted in our work. We divide the unit square area into cells with side length $c_n = \sqrt{3 \log n/n}$ so that the number of nodes in each cell is $\Theta(\log n)$ with high probability [19, Lemma 3.1]. Hence, the unit square area is tessellated into $\sqrt{n/3 \log n}$ rows and $\sqrt{n/3 \log n}$ columns of cells. The transmission is restricted between adjacent cells (horizontal and vertical). To guarantee the network connectivity with high probability, we set the transmission range of a node to be $r(n) = \sqrt{5}c_n = \sqrt{15 \log n/n}$ which is the maximum distance between two arbitrary nodes in adjacent cells so that any two nodes from two adjacent cells can communicate with each other.

In this work, a K^2-TDMA cell scheduling scheme is adopted where K^2 colors are used to schedule cells transmissions. Each time slot corresponding to one color is assigned to one of K^2 cells in a super cell, which is composed of $K \times K$ cells. Thus, cells with the same color in the adjacent super cells are Kc_n distance apart from each other. According to the protocol model, the minimum distance between a receiver and other simultaneous transmitter is $(K-2)c_n \geq (1+\Delta)\sqrt{5}c_n$ to guarantee that concurrent transmissions can be successful. Hence, if $K \geq 2 + (1 + \Delta)\sqrt{5}$, there exists a TDMA scheme such that one node per cell with the same color can simultaneously transmit a packet to the nodes in adjacent cells successfully. Here, K is a constant. Fig. 2 describes an example of TDMA cell scheduling scheme with $K = 3$.

D. Capacity and Delay

In this paper, we investigate the capacity and delay of data gathering with CS in WSNs. When a sink collects M random measurements for a snapshot, it forms a reconstruction of the snapshot. Therefore, we are particularly interested in how frequently a snapshot can be collected by a sink. Let b denote the number of bits that each sensor node generates a reading. Time is divided into time slots with a fixed length $t = b/W$ seconds. Each node takes one time slot to transport a reading to its one-hop neighbor. Then, the capacity and delay are defined as follows:

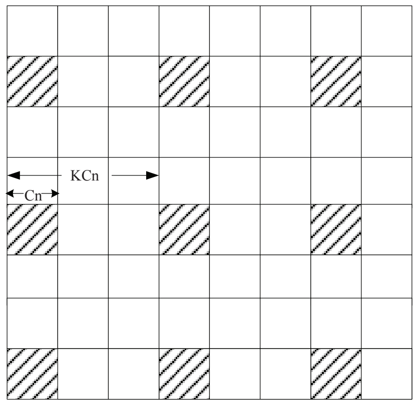

Fig. 2. An example of K^2-TDMA cell scheduling scheme with K=3.

Definition 2: The *capacity* of data gathering C is the maximum rate at which the sink can receive a snapshot, i.e., the maximum rate at which the sink can receive all the nb bits of data generated by sensor nodes during a time duration T (i.e., $\frac{nb}{T}$). When multi-sinks are present in the network, the capacity of data gathering is the maximum total data rate of all the data gathering sessions.

Definition 3: The *delay* of data gathering D is the time transpired between the time when a snapshot is sampled by the sensor nodes and the time when the last random measurement reaches the sink.

Notice that all the readings in a snapshot are generated by sensor nodes at the same time. Meanwhile, the sampling and data transport can be pipelined in the sense that further snapshots may be taken and transported to the sink before the sink receives prior snapshots. Furthermore, we consider the sum delay of a snapshot rather than the maximum delay of independent sensor readings since the sink should collect all M measurements for a snapshot so that it can reconstruct n sensor readings.

III. Data Gathering with Compressive Sensing in Single-Sink Networks

In this section, we consider the case for data gathering in a single-sink wireless sensor network. We first propose a routing scheme combined with a pipelining scheduling algorithm for data gathering. With the pipeline scheduling algorithm, a new snapshot can be taken and transported to the sink before the sink receives a prior snapshot. Then, we analyze the performance of our data gathering scheme in terms of capacity and delay.

A. Constructive Lower Bound on the Capacity of Data Gathering with Compressive Sensing

We assume that the sink s is located in cell (u, v), where u and v are Euclidean coordinates. We only consider the region which has the largest number of sensor nodes since the total capacity of the network will be the same in the order sense as that we derive in this paper. For example, the region at

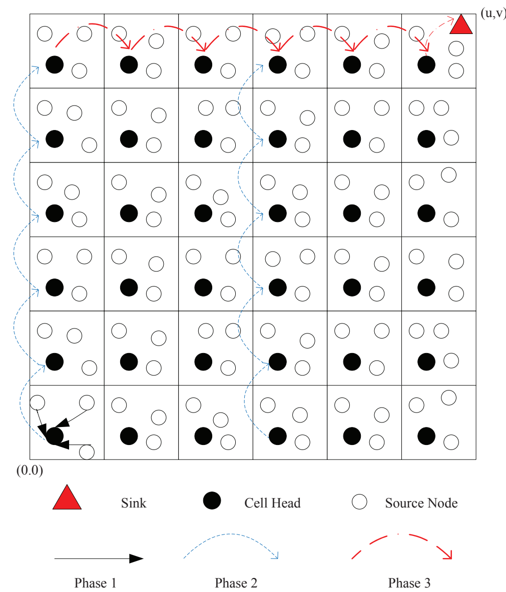

Fig. 3. The proposed data gathering with CS scheme which contains three phases.

the lower left corner is considered in this paper. The proposed routing scheme for data gathering has three phases. In the first phase, a cell head is designated to collect the data from the neighboring nodes in the same cell. In the second phase, the packets sent by cell heads are relayed along the columns to the vth row cells in a compressive sensing fashion. In the third phase, the packets in the vth row cells are relayed along the row to the sink. Fig. 3 shows an example of our data gathering scheme. Fig. 4 gives the illustration for each phase. The detailed explanation for each phase is given in the following.

$$C = \frac{nb}{O(Mt)} = \Omega(\frac{nW}{M}) \tag{2}$$

Phase 1: For each cell (i, j), we randomly choose one node as a cell head H_{ij}. Then, for each time slot, each node in cell (i, j) takes turns to transmit data to the cell head H_{ij}. Let d_{ij}^k with $k = 1, \ldots, l$ be the data collected by the cell head including its own packet in the cell (i, j), where k is the index of nodes and l is the number of nodes in cell (i, j). Thus, the cell head H_{ij} has l packets including its own packet at the end of Phase 1.

Phase 2: In this phase, each cell head processes the coming packets from the lower cell. Let m denote the transmission index for each cell head. After the cell head receives the packet from the cell head in the lower cell $(i, j-1)$, the cell head generates l random coefficients Φ_{ij}^{mk} from a Gaussian or Bernoulli matrix, computes the value $\sum_{k=1}^{l} \Phi_{ij}^{mk} d_{ij}^k$ and updates the received data by computing

$$y_{ij}^m = y_{i(j-1)}^m + \sum_{k=1}^{l} \Phi_{ij}^{mk} d_{ij}^k \tag{3}$$

and sends out y_{ij}^m to the next cell $(i, j+1)$. The process is repeated for M times for each cell. In this way, packets from the nodes in the ith column cells are forwarded to the top cell

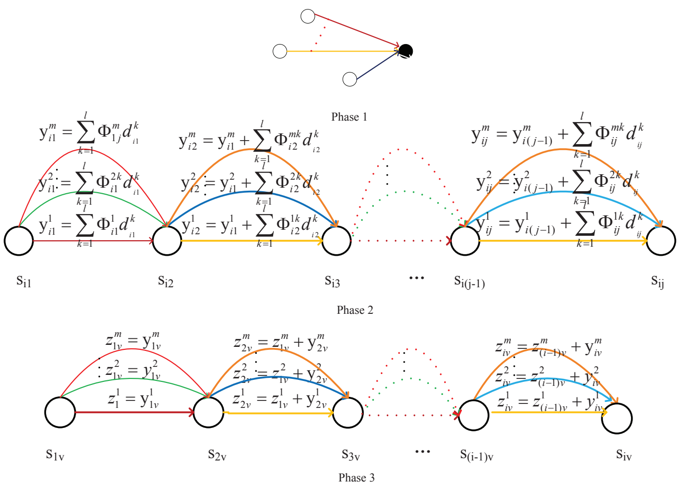

Fig. 4. Three phases for our data gathering scheme: In Phase 1, each node transmits its original readings to the cell head; In Phase 2, cell heads generate M random measurements and vertically aggregate and transmit them towards the cell heads in the vth row. In Phase 3, cell heads in the vth row horizontally aggregate random measurements towards the sink.

(i, v). Finally, each cell head in the top cell (i, v) will receive M random measurements from the ith column cells. *Phase 3*: In this phase, the packets in the vth row cells are relayed along the row to the sink. After the second phase, each cell head in the vth row cells has already received M packets y_{iv}^m with $m = 1, \ldots, M$. In this phase, the cell head in the cell (i, v) receives the packet $z_{(i-1)v}^m$ from the neighboring cell head, computes $z_{iv}^m = z_{(i-1)v}^m + y_{iv}^m$ and transmits z_{iv}^m to the next cell head. In this way, the packets generated in the second phase are forwarded to the sink. Finally, the sink receives M packets containing the sum of all packets from all nodes in the network, which completes one round of data gathering. In this phase, since each cell head in the vth row cells has M random measurements when Phase 2 is completed, the cell heads in the vth row cells do not need to regenerate random measurements with new random coefficients and just aggregate these random measurements and transmit them to the sink.

The above scheme only considers how the sink collects data for one snapshot. To enable the sink to collect snapshots continually, we propose a pipelining scheduling scheme. With the pipelining scheduling scheme, it allows a node to send data for the next snapshot before the sink collects all the data in the previous snapshot. Therefore, the above procedures in three phases can be performed in pipelining. This can be achieved by allowing the next snapshot to begin the first phase when the M measurements of the previous snapshot have been transmitted to the cell, which is Kc_n distance away from the current cell, as illustrated in Fig. 5. Thus, transmissions for the next snapshot will not be interfered by the current snapshot. Recall that it takes $O(K^2 \log nt)$ time for cell heads to collect data in the first phase. Therefore, the time difference for the sink to collect two continuous snapshots is $O(K^2 \log nt + K^2 Mt)$. Since $M \geq \Theta(\log n)$ and K is a constant, $O(K^2 \log nt + K^2 Mt) = O(Mt)$. Thus, the lower bound on the capacity of our data gathering scheme is

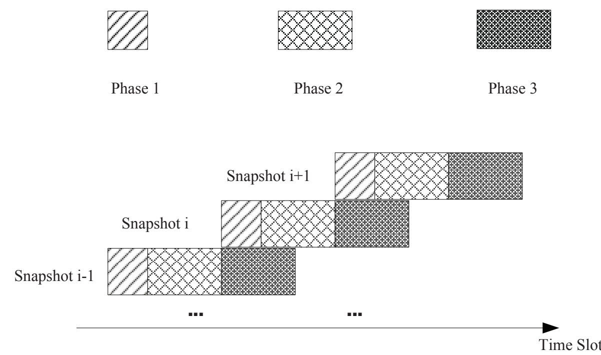

Fig. 5. Transmission for different snapshots with pipelining.

B. Upper Bound on the Capacity of Data Gathering with Compressive Sensing

We now consider the upper bound on the capacity of our data gathering scheme with CS. Assume that the sink can be 100% busy receiving data from neighboring nodes at any time slot. In order to reconstruct a snapshot, the sink should continually receive M measurements. Hence, it takes at least M time slots for the sink to collect M measurements. Thus, the upper bound on the capacity of our data gathering scheme with CS is

$$C = \frac{nb}{\Omega(Mt)} = O(\frac{nW}{M}) \tag{4}$$

Based on the above analysis, we can conclude the following theorem:

Theorem 1: The proposed data gathering scheme with CS achieves the capacity $\Theta(\frac{nW}{M})$ in random networks with a single sink, which implies that the per-node capacity is $\Theta(\frac{W}{M})$.

From Theorem 1, we can see that our data gathering scheme can achieve order optimal capacity, which indicates that our scheduling and routing schemes are optimal. Note that although the specific scheduling and routing schemes are used in our construction, the other deterministic schemes can also be used in our case. However, these schemes can only improve a constant factor of the capacity performance.

C. Delay Analysis

In this subsection, we analyze the delay of the proposed data gathering scheme. The analysis can be done in a way similar to [14]. We analyze the time taken for the above three phases in our scheme, respectively. Recall that nodes with the same color can be transmitting simultaneously and each cell has at most $O(\log n)$ nodes. Thus, the time for collecting all the packets for a snapshot in the first phase is $T_1 = K^2 O(\log n)t$. In the second phase, in order to transmit packets to the top cells, each cell head would send out M packets to the next cell head. Therefore, the total time for cell heads to complete one round of transmission is Mvt. According to K^2-TDMA scheduling scheme, the cell head with the same color in each super cell can transmit simultaneously for each time slot. Hence, the total time for completing transmitting the packets of all the nodes to the top cells in the second phase is

$T_2 = KvMt \leq KMO(\sqrt{\frac{n}{\log n}})t$. We now consider the time needed for transmitting packets in the top cells to the sink in the third phase. Analysis is similar to the second phase. Each cell head in the top cells has M packets before transmission. Therefore, each cell head only needs M time slots to transmit its packets received in the second phase. Hence, the total time needed for this phase is $T_3 = Mut \leq MO(\sqrt{\frac{n}{\log n}})t$. Recall that $M \geq \Theta(\log n)$. Therefore, the total time needed for transmitting all the packets to the sink is

$$T_u = T_1 + T_2 + T_3 \leq O(M\sqrt{\frac{n}{\log n}}t) \tag{5}$$

We are now ready to prove that a lower bound on the delay for our data gathering scheme achieves $\Omega(M\sqrt{\frac{n}{\log n}}t)$. Considering the farthest cell head which is located in the cell $(0, 0)$, the minimum distance away from the sink is $L = c_n\sqrt{u^2 + v^2}$. Recall that we assume that the region at the lower left corner has the largest number of sensor nodes and the maximum transmission range between two adjacent nodes is $r = \sqrt{5}c_n$. The minimum length of L is $\frac{\sqrt{2}}{2} \cdot \sqrt{\frac{n}{3\log n}} \cdot c_n$, i.e., the sink is located in the center of the network. Hence, the minimum time taken by the farthest cell head to transmit a packet to the sink is $\frac{Lt}{r} = \Omega(\sqrt{\frac{n}{\log n}}t)$. Therefore, to transmit M packets to the sink the minimum time $\frac{ML}{r}t$ is needed. Thus, the minimum time required for the sink to collect M packets is

$$T_l = \frac{ML}{r}t = \Omega(M\sqrt{\frac{n}{\log n}})t \tag{6}$$

Summarizing the above analysis, we can conclude the following theorem:

Theorem 2: The proposed data gathering with CS scheme achieves delay $\Theta(M\sqrt{\frac{n}{\log n}})$ in random networks with a single sink.

D. Discussion

Combining theorems 1 and 2, we can conclude that the proposed data gathering scheme with CS can achieve the capacity $\Theta(\frac{nW}{M})$ and the delay $\Theta(M\sqrt{\frac{n}{\log n}})$. Specially, with the assumption that the sensor data from the entire network is k-sparse, the number of random projections needed for data recovery is $M = \Omega(k \log n)$. It is interesting to compare our results with those of the baseline transmission scheme for data gathering [14]. In the baseline transmission scheme, each node just receives and forwards data to the next nodes. As shown in [14], the authors show that the proposed data gathering scheme can achieve the order optimal capacity and delay, which are $\Theta(W)$ and $\Theta(n)$, respectively. In such a scheme, it is obvious that the data rate at which the sink receives data cannot be faster than W and for each time the sink can receive at most one packet. Therefore, the capacity of the baseline transmission scheme is at most $O(W)$ and the delay for receiving a complete snapshot is at most $O(n)$. *This indicates that our data gathering scheme can achieve a capacity gain of* $\Theta(\frac{n}{M})$ *over the baseline transmission scheme and the delay can also be reduced by a factor of* $\Theta(\frac{\sqrt{n\log n}}{M})$.

Furthermore, we also compare the performance of data gathering capacity with the finding of [3], which also applies compressive sensing to data gathering in WSNs. In [3], the authors show that the proposed compressive data gathering scheme can achieve a capacity gain of $\Theta(\frac{n}{M})$ over the baseline transmission scheme given that sensor readings are k-sparse. In their work, they assume that there exists an appropriate routing scheme such that each subtree contains roughly the same number of nodes and has relatively uniform characteristics of data sparsity distribution in each subtree. Whereas in our work, we propose a simple routing scheme with a pipelining scheduling algorithm, which can relax this constraint and achieve the same performance in the order sense. This is because data gathering and data reconstruction in our work are performed on the sink rather than on the subtree basis in [3].

IV. Data Gathering with Compressive Sensing in Multi-Sink Networks

In this section, we consider the case where multiple sinks are present in the network. We assume that there are n nodes in the network, among which n_d nodes are randomly selected as destination nodes (sinks) and $n - n_d$ nodes are randomly selected as source nodes. We further assume that in each data gathering session each sink generates a random projection by collecting random measurements from n_s randomly chosen source nodes. Note that the choice of source nodes for each random projection in one session may be different. We assume that $n - n_d$ can be exactly divisible by n_s, i.e., $n = (n_s + 1) \cdot n_d$. For simplicity, we assume that $n = n_s \cdot n_d$ when n_s is far larger than 1. Thus, the number of sessions is n_d. We assume that each sink can recover the entire sensor data in the network through collecting M random measurements for each session. This assumption is built on the work of Wang et al. [17], [18], where they show that the result of compressive sensing can be obtained with sparse random projections with the assumption that sensor data is compressible or sparse. Different from the approach in the previous section which is built on dense random projections, the proposed approach in this section allows to support multiple simultaneous sessions and reconstruct the whole sensed field by each session. This paradigm can be employed in many application scenarios. For example, in many cases, users distributed in different locations are interested in gathering data to obtain a view over the entire field. The scheme can also be extended to the case in a multiresolution manner, where each user collects different number of random projections to reconstruct a multiresolution signal.

The main objective is to investigate how many simultaneous sessions can be supported by the network and how much time it takes for one sink to collect measurements in one session. We observe the dataflow structure of our data gathering scheme is similar as that of multicast. One of the differences between these two cases lies on the transmission direction. An example is illustrated in Fig. 6. As shown in Fig. 6(a), in the multicast scenario, node c just relays data to child nodes a and b. In our data gathering scheme, node c receives random

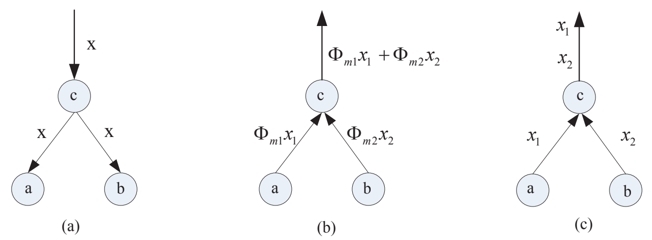

Fig. 6. Structures for three different dataflows. (a) Dataflow for Multicast. (b) Dataflow for data gathering with CS. (c) Dataflow for conventional data gathering.

measurements from nodes a and b, sums them and transmits a new random measurement to the next node, as shown in Fig. 6(b). Therefore, the traffic on each link in these two cases will not change. Unlike the conventional data gathering scheme, as shown in Fig. 6(c), node c has to forward two packets to the next node. Hence, we can use some similar techniques for multicast to analyze the capacity for our data gathering scheme in multi-sink networks. In the following subsections, we first derive an upper bound on the data gathering capacity and then present a simple architecture for data gathering routing to achieve the upper bound in the order sense. Finally, we analyze the delay performance of data gathering with CS in multi-sink networks.

A. Upper Bound on the Capacity of Data Gathering with Compressive Sensing

In this subsection, we derive the upper bound on the capacity of data gathering with CS. To derive the upper bound, we still exploit the idea that each transmission consumes valuable area as in [8]. Suppose the transmission radius be $r(n)$. Under the protocol model, when node X_i transmits successfully to node X_j, no other node X_k within a distance $\Delta r(n)$ of X_j can be simultaneously receiving another transmission due to interference. Since each successful transmission occupies at least a disk with radius $\frac{\Delta r(n)}{2}$ and the area of such a disk is $\frac{\pi\Delta^2 r^2(n)}{4}$, the number of simultaneous transmissions in a unit square area that can be supported by the network is no more than $\frac{4}{\pi\Delta^2 r^2(n)}$. Assume that there are n_d sinks in the network and each sink i requires at least $H_i(r)$ transmissions to collect a projection from n_s source nodes. Recall that each sink needs to collect M projections to form a snapshot. Define λ as the largest achievable rate (snapshots/slot) at which per sink collects a snapshot. Hence, λ satisfies the following condition

$$\lambda \leq \frac{4}{\pi\Delta^2 r^2(n) M \sum_i H_i(r)}. \tag{7}$$

Consider a minimum spanning tree for each data gathering flow which contains n_s source nodes and one sink. Source nodes and sink nodes are independently and uniformly distributed in the unit square area. Such a minimum spanning tree has the same structure as that of multicast tree, which has the average length $L(n_s) = \Omega(\sqrt{n_s})$ with high probability, and the minimum number of transmissions $\sum_i H_i(r)$ satisfies the following condition [16, Lemma 2]

$$\mathbb{P}\{\sum_{i=1}^{n_d} \frac{r(n)H_i(r)}{n_d} > C_1\sqrt{n_s}\} \to 1 \tag{8}$$

where C_1 is a constant. Thus, combining (7) and (8), λ satisfies the following condition with high probability

$$\lambda \leq \frac{4}{\pi C_1 \Delta^2 r(n) M n_d \sqrt{n_s}}. \tag{9}$$

Recall that t denotes the time duration for one time slot and per sink collects a snapshot at a rate of λ snapshots/slot. Therefore, it takes $T = t/\lambda$ for per sink to collect a snapshot. Also, it has been shown that $r(n) > \sqrt{\log n/n}$ is necessary to guarantee the network connectivity with high probability in random networks [8]. By Definition 2, hence, the capacity of data gathering with CS for each session is upper-bounded by

$$C = \frac{nb}{T} = \frac{nb\lambda}{t} = O(\frac{n\sqrt{n}W}{Mn_d\sqrt{n_s \log n}}) \tag{10}$$

B. Constructive Lower Bound on the Capacity of Data Gathering with Compressive Sensing

In this section, we first present a simple architecture for data gathering routing with CS in multi-sink networks and then derive the lower bound of our data gathering scheme. The cell partition method and the cell scheduling scheme adopted in this section are the same as those described in Section II.

First, we construct a spanning tree for each data gathering session, which is similar as the multicast structure in [16], [21]. The structures of the constructed spanning trees for two data gathering sessions are shown in Fig. 7. For each session, the sink is located in the root of the spanning tree. A vertical branch across the sink is formed, which has the same x coordinate as the cell where the sink is located. There are $\sqrt{c_0 n_s}$ horizontal branches separated by a distance of $\frac{1}{\sqrt{c_0 n_s}}$ in the spanning tree, among which there is only one branch passing through the sink, where c_0 is a constant. Since n_s nodes are randomly selected as active source nodes, n_s small vertical paths which originate from source nodes to the nearest vertical branches are formed. We now describe the proposed routing scheme for our multi-session data gathering with CS. Different from multicast which distributes packets from a single source node to all the destinations along the multicast tree, the aim of our data gathering scheme is to collect all the measurements from randomly selected source nodes to their corresponding sink. The process of data gathering with CS contains three stages. In the first stage, each source node j generates M independent random coefficients $\{\Phi_{1j}, \ldots, \Phi_{Mj}\}$ which take the values of $\pm\sqrt{n_s}$ with probability 1/2. Then each source node computes M random measurements $\Phi_{ij}x_j$ with its reading value x_j where $i = 1, \ldots, M$. According to the theory of compressive sensing using sparse random projections, for each sparse random projection, each sink will collect random measurements from n_s randomly selected source nodes. Thus, each source node needs to randomly pick up one out of n_d sinks as its destination, and send each random measurement to the corresponding sink. These measurements will be transmitted to the routers along their

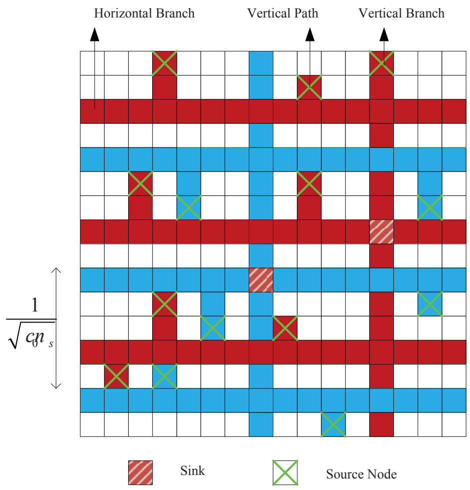

Fig. 7. Structure of the constructed spanning trees for the proposed data gathering scheme in a multi-sink network. Two data gathering sessions are shown here.

corresponding vertical paths. The routers belonging to the same session will combine the received measurements with their own random measurements while the routers belonging to different sessions just relay the received measurements. The choice of source nodes in each session and the generation of random coefficients can be achieved by the following strategy, similarly to [3]. Before transmission, one of sinks broadcasts a globe random seed to the entire network. Then each source node generates its own seed using the globe seed and its address. Using its own seed, each source node can generate a series of random coefficients $\{\Phi_{1j}, \ldots, \Phi_{Mj}\}$ through a pseudo-random number generator. Similarly, each source node generates M random seeds using the globe seed and then uses these seeds to generate a series of random variables to determine its destination for each random projection. By the similar method, each sink can reproduce these variables using the globe seed and the addresses of the source nodes. Thus, each sink is able to know which source nodes in its session for each random projection and the corresponding random coefficients for data recovery. In the second stage, these measurements are transmitted and aggregated along the routers in the horizontal branches. In the third stage, the process of data gathering is carried out along the routers in the vertical branches. Then these measurements will be aggregated in the corresponding sinks. Finally, each sink can reconstruct sensor data from its respective received M measurements through recovering algorithm of compressive sensing. Since the K^2-TDMA scheduling scheme is used, the transmission of a node can be well scheduled without interfering with each other in any time slot.

Next, we study the upper bound on the load of each cell. The load of a cell is defined as the total number of data gathering sessions that a cell will be used as a router by nodes inside this cell. We have the following lemmas about the average and maximum number of routing flows passing through a given cell. The proofs of these two lemmas are included in Appendix A and B, respectively.

Lemma 1: Given n_d data gathering sessions, the average number of routing flows passing through a given cell is at most $\rho = c_1 n_d \sqrt{\frac{n_s \log n}{n}}$, where c_1 is a constant.

Lemma 2: The number of data gathering flows passing through a given cell is at most $2\rho = 2c_1 n_d \sqrt{\frac{n_s \log n}{n}}$ with high probability when $n_d \sqrt{n_s} = \Omega(\sqrt{n \log n})$.

By using K^2-TDMA scheduling scheme, each cell is scheduled with a periodicity of K^2 slots. From Lemma 2, we know that the number of routing flows passing through a cell is at most 2ρ with high probability. Therefore, each sink can collect a projection at a rate of $\lambda_1 = \frac{1}{2K^2\rho} = \frac{\sqrt{n}}{2K^2 c_1 n_d \sqrt{n_s \log n}}$ projections/slot with high probability from its n_s randomly chosen source nodes. Recalling that each sink shall collect M projections to recover a snapshot for each session. Therefore, it takes per sink $T = Mt/\lambda_1$ to collect M projections. Thus, the per-session capacity of our data gathering scheme with CS is

$$C = \frac{nb}{T} = \frac{nb\lambda_1}{Mt} = \Omega(\frac{n\sqrt{n}W}{Mn_d\sqrt{n_s}\log n}). \tag{11}$$

Combining (10) and (11), we have

Theorem 3: The per-session capacity of data gathering with CS in multi-sink random networks is $\Theta(\frac{n\sqrt{n}W}{Mn_d\sqrt{n_s}\log n})$. With n_d sinks, the total capacity of data gathering with CS in multi-sink random networks is $\Theta(\frac{n\sqrt{n}W}{M\sqrt{n_s}\log n})$.

C. Delay Analysis

In this subsection, we analyze the delay performance of data gathering with CS in a multi-sink network. We have the following theorem

Theorem 4: The proposed data gathering with CS scheme achieves per-session delay $\Theta(M\sqrt{\frac{n}{\log n}})$ in multi-sink random networks.

Proof: See Appendix C. ■

D. Discussion

We have proved that our data gathering scheme can obtain order optimal capacity with high probability through a simple architecture, which can minimize the number of transmissions needed for the measurements transmitting from randomly chosen source nodes to their respective sinks. Ideally, we would like to construct a spanning tree for multi-session data gathering which has a length as small as possible for the measurements to be routed along. For example, a Steiner tree [16] can also be used in our case. On the other hand, our scheme for multi-session data gathering is based on the assumption that each sink can recover k-sparse data by collecting a sufficient number of random projections from randomly chosen source nodes [17]. For instance, when the number of nodes for each sink selected as source nodes is $n_s = \log n$, the number of random projections needed for data recovery is $M = \Omega(k^2 \log^2 n)$. When the number of source nodes for each session is $n_s = \log^2 n$, then the number of random projections needed for data recovery is $M = \Omega(k^2 \log n)$.

We would like to point out that compressive sensing can be used to perform distributed source coding with linear network

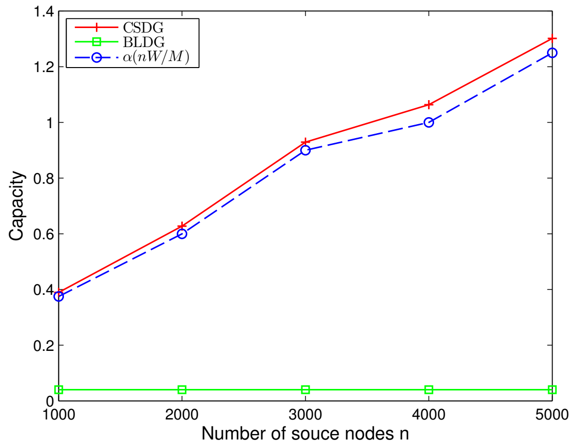

Fig. 8. Capacities of CSDG and BLDG with different number of source nodes n in single-sink networks.

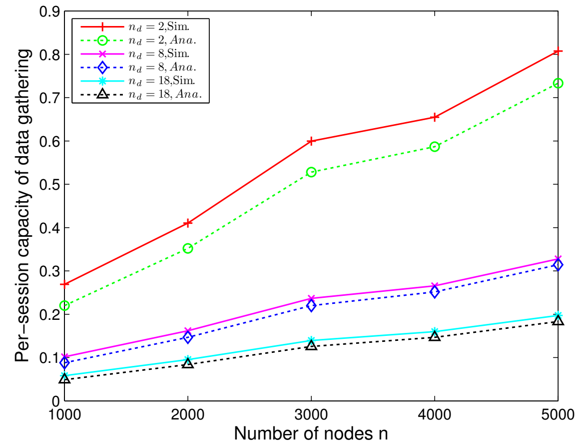

Fig. 9. Per-session capacities of data gathering with different number of nodes n and sessions n_d in multi-sink networks.

coding for correlated and sparse data transmission [23], [24]. Therefore, it is also interesting to compare our scheme with a joint source-channel-network coding scheme based on compressive sensing proposed in [24]. The objective of the scheme is to reconstruct all sources within an allowed distortion level at each receiver for multicast networks under AWGN channels. Both temporal and spatial correlations among source samples are considered in this scheme, while only spatial dependencies among source data are considered in our paper. Actually, in [24], by ignoring temporal precoding, we note that performing spatial precoding and analog random linear network coding among nodes over the network corresponds to using a sparse random matrix for compressive sensing in our scheme, which means only a fraction of sources are transmitting for each measurement. From [24], it can be seen that $k \log n$ source nodes are randomly selected to transmit samples to each receiver for each measurement and the number of random projections needed for data recovery is $M = \Omega(k \log n)$. While from the above discussion, we can see that in our scheme the number of randomly selected source nodes n_s for each session and the number of random projections M needed for data recovery are dependent on the number of sinks n_d, i.e., $n_s = n/n_d$.

V. Numerical Simulations

In this section, we evaluate the capacity performance of the proposed data gathering schemes using MATLAB simulations for both single-sink and multi-sink wireless sensor networks. We generate connected networks by uniformly and randomly placing n nodes in a unit square area, which is divided into cells with side length of $\sqrt{3 \log n/n}$. We assume that TDMA is used at the network MAC layer and each cell is scheduled by using K^2-TDMA scheme, where $K = 5$ is adopted in the simulations. Furthermore, we assume that a packet (measurement) with size length b bits can be transmitted over a channel within the duration t of one time slot. The channel bandwidth W is normalized to one. We assume the sensor data is k-sparse signal with $k = 10$. For the recovery algorithm, we use ℓ_1-magic algorithm.

A. Capacity of Data Gathering with CS in Single-Sink Networks

We first compare the capacity performance of our data gathering scheme (CSDG) with the baseline data gathering scheme (BLDG) in a single-sink network. In this simulation, we use $M = 80, 100, 100, 120, 120$ measurements to recover $k = 10$ sparse data for different number of source nodes n when n varies from 1000 to 5000 with a step size of 1000, respectively. Fig.8 shows the capacities of these two schemes. From the figure, we observe that the capacity of CSDG increases with the number of sensor nodes, whereas the capacity of BLDG is constant although the number of source nodes increases. This confirms our analytical results derived in Section III. The simulation results also indicate that CSDG can achieve more gains on the capacity over BLDG when n is large. We also plot $\alpha(nW/M)$ with $\alpha = 0.03$ in Fig.8 to verify the scaling law of capacity for CSDG. The simulation result shows that the capacity of CSDG scales as nW/M, which also confirms our theoretical analysis.

B. Capacity of Data Gathering with CS in Multi-Sink Networks

In this simulation, we verify the theoretical result for the capacity of data gathering with CS in a multi-sink network. We simulate the cases where there are $n_d = 2, 8, 18$ sessions in the network, respectively. We select the number of sessions $n_d = 2, 8, 18$ so as to make the number of cells separated by two adjacent horizontal branches in the same session as close as possible to be an integer. We use $M = 80, 100, 100, 120, 120$ measurements to recover $k = 10$ sparse data of each session for $n_d = 2$, and additional 20 and 40 measurements to recover the data of each session for $n_d = 8$ and $n_d = 18$, respectively. Fig.9 shows the per-session capacities with different number of nodes n in the simulation (solid line). From the figure, we observe that the per-session capacity decreases with the number of sessions n_d. This is due to the reason that the load of a cell will increase when more sessions pass the cell, which results in the degradation of the per-session capacity. The simulation results also indicate that the per-session capacity is a increasing function of the number of nodes n. Meanwhile, we plot $\alpha(\frac{n\sqrt{n}W}{Mn_d\sqrt{n_s \log n}})$ with $\alpha = 0.07$ for different number of sessions n_d to verify the analytical results (dotted line). The simulation results confirm that the per-session capacity of our data gathering scheme scales as $\frac{n\sqrt{n}W}{Mn_d\sqrt{n_s \log n}}$.

VI. Conclusion

In this paper, we studied the capacity and delay of data gathering with CS in both single-sink and multi-sink random networks. For the single-sink network, we constructed a routing scheme with pipelining scheduling algorithm for data gathering. We derived the bounds of capacity, and analyzed the delay performance of the proposed data gathering scheme with CS. We showed that the proposed scheme can achieve a capacity gain of $\Theta(\frac{n}{M})$ over the baseline transmission scheme and the delay can also be reduced by a factor of $\Theta(\frac{\sqrt{n \log n}}{M})$. For the multi-sink case, we constructed a simple architecture for multi-session data gathering routing, and derived the capacity and delay performance of the proposed scheme. Finally, we verified our theoretical results for the scaling laws of the capacity through simulations in both single-sink and multi-sink random networks.

Appendix A
Proof of Lemma 1

Proof: We first consider the probability of a given cell c that is used by the three stages of data gathering process. Recall that the length of path for each source node to transmit packets to the router in the horizontal branch is no more than $\frac{1}{2\sqrt{c_0 n_s}}$. Thus, in the first stage, the number of cells that n_s source nodes will pass through is no more than $n_s \cdot \frac{1}{2\sqrt{c_0 n_s}} \cdot \sqrt{\frac{n}{3\log n}} = \sqrt{\frac{n_s n}{12 c_0 \log n}}$. In the second stage, the total number of horizontal branches is $\sqrt{c_0 n_s}$ with each branch containing $\sqrt{\frac{n}{3\log n}}$ cells. Hence, there are no more than $\sqrt{\frac{c_0 n_s n}{3\log n}}$ cells acting as routers in the second stage. In the third stage, there is only one vertical branch in the spanning tree and thus the number of cells is $\sqrt{\frac{n}{3\log n}}$. Notice that there are total $N_c = \frac{n}{3\log n}$ cells in the unit square area. We denote p_1, p_2 and p_3 as the probabilities of the given cell c that is used in the three stages, respectively. Therefore, $p_1 \leq \sqrt{\frac{n_s n}{12 c_0 \log n}}/N_c = \sqrt{\frac{3 n_s \log n}{4 c_0 n}}$, $p_2 \leq \sqrt{\frac{n_s n}{3 c_0 \log n}}/N_c = \sqrt{\frac{3 n_s \log n}{c_0 n}}$ and $p_3 \leq \sqrt{\frac{n}{3\log n}}/N_c = \sqrt{\frac{3\log n}{n}}$. Thus, the probability that a given cell c is used by a data gathering session is $p = \sum_{i=1}^{3} p_i \leq c_1 \sqrt{\frac{n_s \log n}{n}}$, where c_1 is a constant. ■

Appendix B
Proof of Lemma 2

Proof: Let I_i be an independent variable. Considering a given cell c, if the cell c is used by the flow i then $I_i = 1$, and $I_i = 0$ otherwise. For all the sessions, the number of routing flows N_f passing through the cell c is $N_f = \sum_{i=1}^{n_d} I_i$. Recall that the probability that the cell c is used by a flow is $p \leq c_1 \sqrt{\frac{n_s \log n}{n}}$. Using Binomial Distribution [20, Lemma 3], we have

$$\mathbb{P}(N_f > 2\rho) < \frac{2\rho(1-p)}{(2\rho - n_d \cdot p)^2} < \frac{2(1-p)}{\rho} < \frac{c_2\sqrt{n}}{n_d\sqrt{n_s \log n}} \quad (12)$$

where c_2 is a constant. When $n_d\sqrt{n_s} \geq c_2\sqrt{n \log n}$, $\mathbb{P}(N_f > 2\rho) < \frac{1}{\log n} \to 0$ as $n \to \infty$. This implies that the number of routing flows passing through a cell is at most 2ρ with high probability when $n \to \infty$. ■

Appendix C
Proof of Theorem 4

Proof: Following a similar method for analyzing delay performance in single-sink networks, we calculate the average time taken by the three stages as mentioned previously for each data gathering session in multi-sink networks. In the first stage, each source node should send M measurements to the corresponding horizontal branch and need $\frac{1}{2\sqrt{c_0 n_s}} \cdot \sqrt{\frac{n}{3\log n}} = \Theta(\sqrt{\frac{n}{n_s \log n}})$ hops for each measurement to reach the branch. Also, each cell contains $\Theta(\log n)$ nodes. Hence, the average time it requires for each session in the first stage is $\Theta(MK^2 \cdot \sqrt{\frac{n}{n_s \log n}} \cdot \frac{\log n}{n_d}) = \Theta(M\sqrt{\frac{n}{\log n}} \cdot \frac{\log n}{\sqrt{n_s} n_d})$. Furthermore, due to random deployment of source nodes and sink in a session, the number of hops for the farthest node to transmit a measurement to the sink in the second and third stages is still bounded by $\Theta(\sqrt{\frac{n}{\log n}})$. Therefore, the average delay for each session is $\Theta(M\sqrt{\frac{n}{\log n}} \cdot \frac{\log n}{\sqrt{n_s} n_d} + M\sqrt{\frac{n}{\log n}}) = \Theta(M\sqrt{\frac{n}{\log n}})$ where $\frac{\log n}{\sqrt{n_s} n_d}$ is smaller than 1. ■

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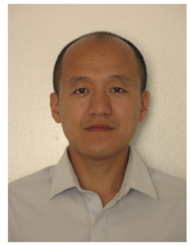
Haifeng Zheng received his B.E. and M.E. degrees in Communication Engineering from Fuzhou University, Fuzhou, China, in 2000 and 2003, respectively. He is currently pursuing the Ph.D. degree in the Department of Electronic Engineering, Shanghai Jiao Tong University, Shanghai, China. Since 2003, he has been a faculty member in the College of Physics and Information Engineering, Fuzhou University, China. His research interests include network capacity, wireless sensor networks, compressive sensing, multimedia communications.

Shilin Xiao (M'11) received his M.S. degree from the University of Electronic Science and Technology of China, Chengdu, China, in 1988 and Ph.D. degree from Shanghai Jiao Tong University (SJTU), Shanghai, China, in 2003. From 1988 to 1999, he worked with the Guilin Institute of Optical Communications. Since 2000, he has joined the State Key Laboratory of Advanced Optical Communication Systems and Network, SJTU. Currently, he is a professor with the Department of Electronic Engineering, SJTU. His major research interests include optical communications, optical switching and passive optical networks. He has published more than 90 papers in technical journals and conferences. He is a senior member of the Chinese Institute of Electronics and the Optical Society of China.



Xinbing Wang (M'06-SM'12) received the B.S. degree (with hons.) in automation from Shanghai Jiao Tong University, Shanghai, China, in 1998, the M.S. degree in computer science and technology from Tsinghua University, Beijing, China, in 2001, and the Ph.D. degree with a major in electrical and computer engineering and minor in mathematics from North Carolina State University, Raleigh, in 2006. Currently, he is a professor with the Department of Electronic Engineering, Shanghai Jiao Tong University. His research interests include resource allocation and management in mobile and wireless networks, TCP asymptotics analysis, wireless capacity, cross-layer call admission control, asymptotics analysis of hybrid systems, and congestion control over wireless ad hoc and sensor networks. Dr. Wang has been a member of the Technical Program Committees of several conferences including ACM MobiCom 2012, ACM MobiHoc 2012, 2013, IEEE INFOCOM 2009-2013.

Xiaohua Tian (S'08-M'11) received his B.E. and M.E. degrees in communication engineering from Northwestern Polytechnical University, Xi'an, China, in 2003 and 2006, respectively. He received the Ph.D. degree in the Department of Electrical and Computer Engineering (ECE), Illinois Institute of Technology (IIT), Chicago, in Dec. 2010. He is currently a postdoc in Department of Electronic Engineering in Shanghai Jiao Tong University, China. His research interests include wireless networking, Internet of Things and next-generation Internet. He serves as the guest editor of International Journal of Sensor Networks, publicity co-chair of the 7th International Conference on Wireless Algorithms, Systems, and Applications (WASA 2012). He also serves as the Technical Program Committee member for IEEE GLOBECOM 2011-2013, IEEE ICC 2013 and WASA 2011.

Mohsen Guizani (S'85-M'89-SM'99-F'09) is currently a Professor and the Associate Vice President for Graduate Studies at Qatar University, Doha, Qatar. He was the Chair of the Computer Science Department at Western Michigan University from 2002 to 2006 and Chair of the Computer Science Department at University of West Florida from 1999 to 2002. He also served in academic positions at the University of Missouri-Kansas City, University of Colorado-Boulder, Syracuse University and Kuwait University. He received his B.S. (with distinction) and M.S. degrees in Electrical Engineering; M.S. and Ph.D. degrees in Computer Engineering in 1984, 1986, 1987, and 1990, respectively, from Syracuse University, Syracuse, New York. His research interests include Computer Networks, Wireless Communications and Mobile Computing, and Optical Networking. He currently serves on the editorial boards of six technical Journals and the Founder and EIC of "Wireless Communications and Mobile Computing" Journal published by John Wiley (http://www.interscience.wiley.com/jpages/1530-8669/). He is the author of eight books and more than 300 publications in refereed journals and conferences. He guest edited a number of special issues in IEEE Journals and Magazines. He also served as member, Chair, and General Chair of a number of conferences. Dr. Guizani served as the Chair of IEEE Communications Society Wireless Technical Committee (WTC) and Chair of TAOS Technical Committee. He was an IEEE Computer Society Distinguished Lecturer from 2003 to 2005. Dr. Guizani is an IEEE Fellow and a Senior member of ACM.