PRSS: Prejudiced Random Sensing Strategy for Energy-Efficient Information Collection in the Internet of Things

Peng Sun, Zhi Tian, *Fellow, IEEE,* Zhibo Wang, *Senior Member, IEEE,* and Zhi Wang, *Member, IEEE*

***Abstract*—Compressive Sensing (CS) has been widely used in the Internet of Things (IoT) to achieve efficient information collection. However, existing works have mainly focused on utilizing CS to lower the sampling rate or reduce the number of transmissions, without explicitly accounting for the heterogeneity of energy consumption in IoT environments, resulting from the different locations of IoT sensor nodes. In this paper, capitalizing on the heterogeneity of energy consumption in the IoT, we propose a CS-based prejudiced random sensing strategy (PRSS) to achieve a desirable tradeoff between the overall energy consumption and the sensing accuracy. Specifically, each sensor node participates in sensing via distributed random access based on an assigned sensing probability, which is determined by its energy consumption in sending the sensed data, data collision rate and its contribution to recovery accuracy. We employ the statistical restricted isometry property (StRIP) as a practical indicator of the recovery accuracy and derive a sufficiently good recovery error bound based on it. Then, we devise a novel convex optimization framework to find the most energy-efficient sensing probability assignment strategy with accuracy guarantee. We evaluate PRSS using real-world sea surface temperature (SST) data trace, and results demonstrate that it can significantly reduce energy consumption and prolong network lifetime for the same sensing accuracy compared with benchmark algorithms.**

***Index Terms*—Internet of Things, Wireless Sensor Networks, Heterogeneity, Compressive Sensing, Statistical Restricted Isometry Property, Sensing Probability.**

I. Introduction

With the development of wireless communications and the intellectualization of sensing devices, the Internet of Things (IoT) has drawn significant attention from both industry and academia [1] [2]. The IoT has found extensive applications in many domains, e.g. environmental monitoring, health-care, smart cities and homes [3] [4] [5]. Information collection is the fundamental operation that underpins various IoT applications. Wireless sensor networks (WSNs), as one of the key technologies of the perception layer of the IoT, have been playing a critical role in information collection [6] [7] [8] [9] [10]. Typically, a WSN consists of a fusion center (FC) and a number of distributed sensor nodes. The sensor nodes are required to periodically report their sensed data to the FC, where the information aggregation and extraction tasks are performed. For most WSNs, the network lifetime is determined by the limited energy supply in sensor nodes due to the difficulty in replacing or recharging the batteries. Therefore, achieving energy-efficient information collection becomes one of the dominating issues in WSNs and the IoT.

In the past few years, there have been considerable research interests in improving the energy efficiency of information collection in WSNs and the IoT. Approaches to maximize energy efficiency can be divided into two broad categories. One concentrates on the energy efficiency of protocols, such as topology control [11], sleep scheduling [12] and mobile data collection [13]. The other aims at reducing the amount of data transmission via in-network processing, such as data aggregation. The recently emerged compressive sensing (CS) [14] [15] theory provides a new avenue for promoting energy efficiency in WSNs and the IoT, as it promises perfect recovery of sparse signals using only a small number of random measurements [16]. The spatial correlation of sensor readings in the IoT results in an inherent sparsity of data under a proper transform basis, which lays the foundation for the extensive applications of CS techniques in the IoT.

There are a large number of prior works on investigating how CS can be used to achieve energy-efficient information collection in WSNs and the IoT, e.g., [6], [17], [18], [19], [20], [21], [22], [23], [24], [25]. A CS-based information acquisition framework is proposed for the IoT in [6], which involves the whole process of information collection, including compressed sampling, transmission and accurate reconstruction. The work in [17] [18] presents a comprehensive analysis on the effects of acquiring, processing and communicating CS measurements on network energy efficiency, showing that CS achieves higher energy efficiency in comparison to conventional approaches. In [19], a hybrid CS technique is integrated into clustered WSNs. Based on traditional intra-cluster transmission and CS-based inter-cluster transmission schemes, an analytical model is proposed in order to find the optimal size of clusters that could lead to minimum number of transmissions. Similarly, in [20], a cluster-based compressive sensing data collection algorithm is proposed, where the block diagonal matrices are used as the CS measurement matrices. In [21], adaptive CS is applied to the process of information collection in WSNs by iteratively computing projections in order to maximize the amount of information gain per energy expenditure. In [22], a novel CS-based random sampling scheme is proposed. By

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leveraging a sampler rate indicator feedback scheme, it adjusts the sampling rate to maintain an acceptable reconstruction performance while minimizing the number of samples, by jointly considering the causality of sampling, hardware limitations and the tradeoff between the randomization scheme and computational complexity. In [23], a decentralized networking scheme that combines the concepts of random access and CS is proposed to achieve energy and bandwidth efficiency in underwater WSNs. The concept of sufficient sensing probability is employed to account for the packet loss caused by collisions. The work in [24] develops a novel data gathering scheme based on matrix completion, which takes advantage of the low-rank feature rather than sparsity of sensing data. In [25], based on the compressibility of physical phenomena and the inherent resource heterogeneity in WSNs, a nonuniform compressive sensing (NCS) method is proposed, which is shown to achieve comparable signal approximation accuracy at significantly reduced energy consumption. All these works have mainly focused on utilizing CS to reduce the number of sensor measurements that are sampled and transmitted in the network. In practical IoT environments, however, as different IoT sensor nodes transmit their sensed data to the FC over different communication distances, there exists significant energy consumption heterogeneity. This kind of heterogeneity should be integrated into the design of sparse sensing techniques to achieve an energy consumption balance among different IoT sensor nodes, contributing to more energy-efficient information collection in the IoT.

In this paper, we consider a two-dimensional WSN that measures a physical phenomenon (e.g. temperature, humidity), over a geographical region during a certain time period, for geographical and environmental monitoring purposes. The design objective of this WSN is to obtain a sufficiently accurate approximation of the data field with as little energy expenditure as possible. However, achieving this is challenging. As the need for high sensing accuracy and the desire to reduce energy consumption are two conflicting issues, it is intractable to find a balance between them. For example, uniform random sensing only considers sensing accuracy and is agnostic to the energy consumption heterogeneity in the IoT, resulting in insufficient energy efficiency. While greedy sensing always chooses the subset of sensor nodes with lower energy consumption to participate in sensing and thus often lacks a sufficiently widespread coverage of the entire data field, resulting in poor sensing accuracy. By exploiting the energy consumption heterogeneity in the IoT in the design of sparse sensing techniques, we propose a CS-based prejudiced random sensing strategy (PRSS) to achieve a desirable tradeoff between a minimized energy consumption and a satisfactory sensing accuracy. In PRSS, each sensor node performs sampling and random medium access based on an assigned sensing probability, which is determined by its energy consumption in sending the sensed data to the FC, packet collision rate and its contribution to recovery accuracy.

One technical challenge in PRSS lies in how to predict the recovery accuracy after determining the subset of sensor nodes that participate in sensing. In this paper, instead of using traditional metrics in CS, we employ the statistical restricted isometry property (StRIP) [26], a probabilistic version of the restricted isometry property (RIP), as a practical indicator of the recovery accuracy, as it is easy to calculate. After deriving a sufficiently good recovery error bound based on the StRIP, we devise a novel convex optimization framework to find the most energy-efficient sensing probability assignment strategy with accuracy guarantee. We evaluate the performance of PRSS using real-world SST data trace. Experimental results demonstrate that PRSS can achieve significant energy savings and prolongation of network lifetime for the same sensing accuracy compared to benchmark algorithms.

The main contributions of this paper can be summarized as follows:

- We exploit the heterogeneity of energy consumption in the IoT in the design of sparse sensing techniques. In particular, we propose a CS-based prejudiced random sensing strategy, where each sensor node participates in sensing randomly based on an assigned sensing probability, to achieve a desirable tradeoff between a minimized energy consumption and a superior sensing accuracy.
- By employing the StRIP as a practical indicator of the recovery accuracy, we derive a recovery error bound, which can be demonstrated to be tight in practical network settings.
- We devise a novel convex optimization framework to find the most energy-efficient sensing probability assignment strategy with accuracy guarantee.

The remainder of the paper is organized as follows: In Section II, the network model is introduced, and the overall sparse sensing process is formulated. Section III presents the heterogeneity of energy consumption in the IoT and elaborates the implementation details of PRSS. Section IV provides performance assessment of our scheme and comparisons of energy consumption and network lifetime with benchmark algorithms. Finally, some concluding remarks are provided in Section V.

II. Network Model and Problem Formulation

A. Network Model

As shown in Fig. 1, in the network model considered here, we assume that N sensor nodes have been distributed uniformly at random in a rectangular sensing area, to measure the temporal-spatial field of some physical phenomena (e.g., temperature, humidity, pressure, etc.). An FC is also deployed to collect data samples from sensor nodes and then perform field reconstruction. In this paper, two common positions for the FC are considered: the FC is located at the center of and outside the sensing area[1].

In this paper, we consider a frame-based sensing process. At the beginning of each frame, sensor nodes perform measurements about the physical field. Then, the generated sensor measurements are transmitted to the FC. At the end of the frame, the FC reconstructs the signal field based on the data packets received during that frame. Once the reconstruction

[1]Note that in the following sections, we use FC1 and FC2 to represent that the FC locates at the center of and outside the sensing area, respectively.

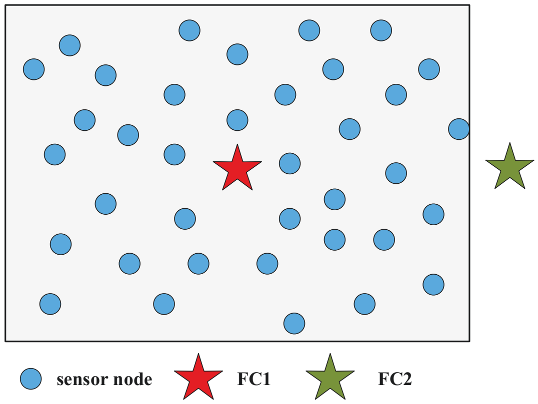


Fig. 1: Network model: N sensor nodes distributed in a rectangular sensing area with two common FC locations.

is accomplished, the current frame is discarded and the next frame starts. The frame length T is assumed to be less than the coherence time T_{coh} of the physical phenomenon, which ensures that the data field remains almost unchanged within each frame.

Thanks to the spatial correlation of the field, sensor readings are inherently sparse under a proper transform basis, which suggests that only a random subset of sensor nodes need to participate in sensing. Therefore, within each frame, two strategies are used for energy saving: 1) during data collection, sparse sensing is adopted in which only a random subset of sensor nodes sample the field and transmit their samples to the FC, and 2) during reconstruction, CS-based sparse signal recovery is performed at the FC to recover the signal field. In order to eliminate the need for downlink transmission from the FC, the random sensor selection is implemented in a decentralized way based on the concept of sensing probability [23]. Specifically, at the beginning of each frame, each sensor node makes a decision about whether it will take part in sensing according to an assigned sensing probability, which is determined by its energy consumption in sending the sensed data to the FC and its contribution to recovery accuracy. The sensing probability assignment strategy among all sensor nodes is optimized to realize the most energy-efficient sensing with accuracy guarantee. Since the process of random sensor selection is decentralized, it is impractical to schedule the medium access of different sensor nodes in a deterministic or cooperative manner. Thus, we employ a simple random access approach instead. Note that in random access, packets from different sensor nodes are subject to collisions when they arrive at the FC in an overlapped time.

B. Problem Formulation

In a specific frame, assume that each sensor node in the network acquires a measurement from the physical field. The sensor measurement, together with the sensor node's location tag, is organized into a data packet of L bits, which is then modulated and transmitted to the FC. Upon receiving a certain number of data packets, the FC demodulates the signal and extracts the measurement information from which it reconstructs the entire signal field.

The measurements of all N sensor nodes in the current frame can be grouped into a data vector $\mathbf{x} = [x_1, x_2, ..., x_N]^T$, where x_i is the measurement of the i-th sensor node. It has been shown in [27] [28] [29] [30] that most physical phenomena have a sparse (compressible) representation in some transform basis, e.g. Fourier, DCT, wavelets etc. In this paper, it is assumed that the vector of Fourier coefficients of $\mathbf{x}$ is sparse. Formally, if we denote by $\mathbf{\Psi}$ the Fourier transform basis, we have $\mathbf{x} = \mathbf{\Psi}\mathbf{s}$, and $\mathbf{s}$ is a sparse vector, which contains only a small number of non-zero coefficients.

With each sensor node assigned a sensing probability, only a random subset of them participate in sensing in each frame, which can be modeled as an active compressive random sub-sampling process in the spatial domain. Assume that M_s sensor nodes turn out to participate in sensing, the generated sensor measurements can be grouped into an M_s-dimensional vector $\mathbf{y}_s$, and it can be obtained by

$$\mathbf{y}_s = \mathbf{\Phi}_s \mathbf{x} \tag{1}$$

where $\mathbf{\Phi}_s$ is an $M_s \times N$ random selection matrix modeling the process of random sensor selection. $\mathbf{\Phi}_s$ is constructed by randomly selecting M_s rows from the N-dimensional identity matrix. As the sensing probability assigned to each sensor node is determined by its energy consumption in transmitting the sensor measurement to the FC and its contribution to recovery accuracy, the sensing probability assignment strategy tends to be heterogeneous. Therefore, unlike traditional uniform random sensing, the structure of $\mathbf{\Phi}_s$ here presents some degree of nonuniformity. Therefore, Eq. (1) can be reformulated as

$$\mathbf{y}_s = \mathbf{\Phi}_s \mathbf{\Psi}\mathbf{s} \tag{2}$$

Once the process of random sensor selection is completed, M_s sensor nodes need to access the shared channel to communicate their measurements to the FC. As stated earlier, there is a probability of packet collisions, and the colliding packets are simply discarded by the FC. Similarly, we model the packet collisions as a passive compressive random sub-sampling process. If we denote the correctly received sensor measurements at the FC by a vector $\mathbf{y}$, we have

$$\mathbf{y} = \mathbf{\Phi}_r \mathbf{y}_s = \mathbf{\Phi}_r \mathbf{\Phi}_s \mathbf{\Psi}\mathbf{s} = \mathbf{A}\mathbf{s} \tag{3}$$

where $\mathbf{\Phi}_r$ is an $M \times M_s$ random selection matrix modeling random access, and $\mathbf{A} = \mathbf{\Phi}_r \mathbf{\Phi}_s \mathbf{\Psi}$ is the equivalent sensing matrix.

Taking the sensing noise into consideration, we have

$$\mathbf{y} = \mathbf{A}\mathbf{s} + \mathbf{e} \tag{4}$$

where $\|\mathbf{e}\|_2 \leq \xi$ represents the sensing noise induced by the limitations in the sensing device.

Given the measurement vector $\mathbf{y}$, the random selection matrices $\mathbf{\Phi}_s$, $\mathbf{\Phi}_r$, and the Fourier transform basis $\mathbf{\Psi}$, reconstruction of the data field $\mathbf{x}$ can be realized by solving the following constrained l_1-norm based minimization problem

$$\min \ \|\mathbf{s}\|_1 \quad \text{s.t.} \ \|\mathbf{y} - \mathbf{A}\mathbf{s}\|_2 \leq \xi \tag{5}$$

which can be solved using an efficient solver such as basis pursuit de-noising (BPDN) or various greedy algorithms (e.g. orthogonal matching pursuit, OMP) [31] [32].

III. Details of PRSS

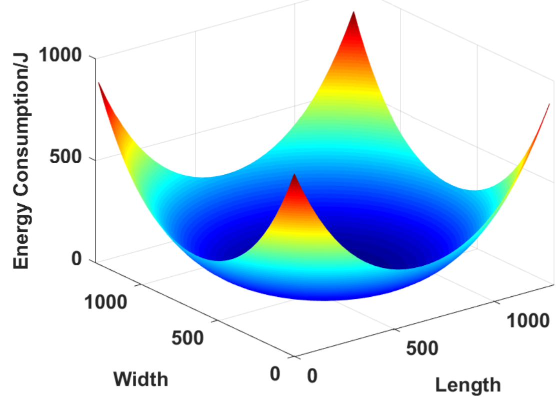
Exploiting the heterogeneity of energy consumption in the IoT in the design of sparse sensing techniques, we propose the prejudiced random sensing strategy (PRSS), which can achieve significantly reduced energy consumption and elongated network lifetime for the same sensing accuracy. In this section, we elaborate the detailed design considerations of PRSS. First, we present the heterogeneity of energy consumption in the IoT. Then we discuss the packet reception model during the random sensor selection and random access process. After that, we analyze the tradeoff between energy consumption and recovery accuracy and derive a sufficiently good recovery error bound. Ultimately, we formulate a convex optimization problem to find the most energy-efficient sensing probability assignment strategy with accuracy guarantee.

A. Heterogeneity of Energy Consumption

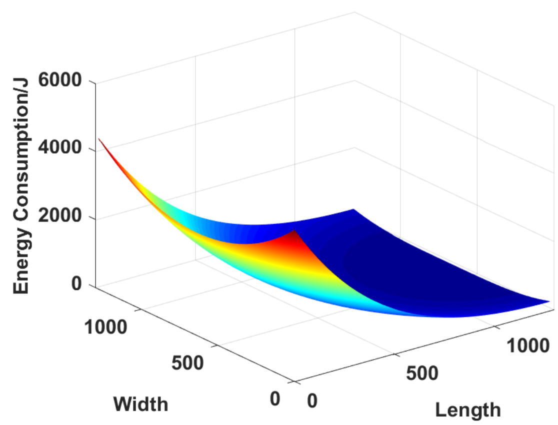
In this paper, we assume that the energy cost for sensing and computation is negligible, which are fairly typical assumptions in WSNs [17]. The overall energy consumption is dominated by radio communications in transmitting and receiving data packets, and it is directly related to the communication distance from the sender node to the destination. In our application scenario, a large number of sensor nodes are deployed to measure the physical field and transmit their measurements to the FC, and each of them has a different communication distance. Using the energy consumption model introduced in [33], the energy consumption E_i in sending L bits of data from the sensor node i to the FC is calculated as

$$E_i = E_0 L + \varepsilon_{amp} L {d_i}^n \tag{6}$$

where E_0 is the energy consumed in the transceiver circuitry at the transmitter, ε_{amp} is the energy consumed by the transmitter antenna for transmitting one meter, d_i is the communication distance from sensor node i to the FC, and n is the path loss exponent. We show the energy consumption maps of the sensing area for the two common FC locations under the following example set of system parameters: The length and width of the sensing area are $L_x = 1280$m and $L_y = 1280$m, respectively. Each transmitted packet contains $L = 400$ bits of data, $E_0 = 50$ nJ$/bit$, n is set to 3.5 in this paper to account for the multi-path effect instead of using a free space model which chooses $n = 2$, and $\varepsilon_{amp} = 100$ pJ$/bit/m^4$. Fig. 2 shows the two energy consumption maps of the rectangular sensing area. As we can observe from the figures, for both FC locations, sensor nodes deployed at different locations in the sensing area consume drastically different amount of energy when sending a data packet to the FC.



(a) The FC locates at the center of the sensing area



(b) The FC locates outside the sensing area

Fig. 2: The energy consumption maps of the rectangular sensing area for the two common FC locations.

B. From Sensing Probability to Reception Rate

To save energy, each sensor node participates in sensing based on an independent Bernoulli distribution, where the sensing probabilities $\mathbf{p} = [p_1, p_2, ..., p_N]^T$ $(0 \le p_i \le 1,\ i = 1, 2, ..., N)$ are determined by the tradeoff between energy consumption and recovery accuracy, as elaborated in Section III.C. Assume that the available network bandwidth is B and each sensor node transmits at a bit-rate equal to the bandwidth, so the packet duration is $T_p = L/B$. When the average sensing probability of all nodes is $p = \frac{1}{N}\sum_{i=1}^{N} p_i$, the average number of nodes that participate in sensing is $M_s = \sum_{i=1}^{N} p_i = pN$. Being assigned a sensing probability p_i, the average packet generation rate for node i is given by $\lambda_i = \frac{p_i}{T - T_p}$. Thus the aggregate arrival rate of data packets at the FC is $\lambda = \sum_{i=1}^{N} \lambda_i = \frac{\sum_{i=1}^{N} p_i}{T - T_p} = \frac{Np}{T - T_p}$. Due to random access, packet collisions will happen. In order to determine the probability of collision, as in [23], we assume that the packet arrival process resembles a Poisson process and model the probability of no collision as the probability that no packet arrives in an interval of length $2T_p$, which is given by

$$\text{Prob}\left\{no\ collision\right\} = e^{-2\lambda T_p} = e^{-2\frac{NpT_p}{T - T_p}} \tag{7}$$

Therefore, the probability that a data packet from sensor node i is successfully received at the FC within a frame length T

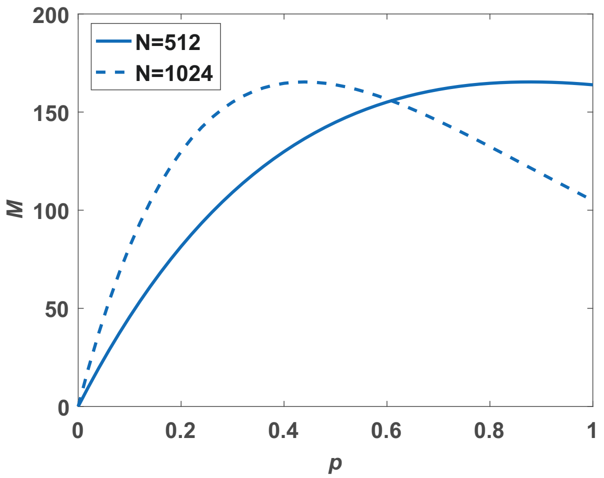


Fig. 3: The average number of correctly received sensor measurements M versus the average sensing probability p with parameters $N = 512$ or $N = 1024$, $T = 180$ s, $L = 400$ bits and $B = 2$ kbps.

is given by

$$q_i = p_i \cdot \text{Prob}\{no\ collision\} = p_i \cdot e^{-2\frac{Np}{T}\frac{T_p}{T_p}} \qquad (8)$$

Stacking q_i of all sensor nodes, we have $\mathbf{q} = [q_1, q_2, ..., q_N]^T$, and the average reception rate among all nodes is denoted by $q = \frac{1}{N}\sum_{i=1}^{N} q_i = pe^{-2\frac{Np}{T}\frac{T_p}{T_p}}$. Let M denote the average number of correctly received data packets at the FC during each frame, then $M = qN = pNe^{-2\frac{Np}{T}\frac{T_p}{T_p}}$.

For example, assume $N = 512$ (or $N = 1024$), $T = 180$ s, $L = 400$ bits and $B = 2$ kbps, the average number of correctly received sensor measurements M versus the average sensing probability p is shown in Fig. 3. As we can observe from the figure, the number of received sensor measurements M increases monotonically with p when p is small. However, as a larger average sensing probability p means a higher probability of packet collisions, after a certain critical point, M remains stable (when $N = 512$) or even descend (when $N = 1024$).

C. Predicting the Recovery Accuracy Based on the StRIP

A key step in our PRSS is to judiciously decide on $\mathbf{p}$ by simultaneously taking into account the heterogeneity of energy consumption, packet collisions in random access and recovery accuracy. There are two commonly used strategies to determine $\mathbf{p}$. One is uniform random sensing, where all sensor nodes are treated equally. Specifically, each sensor node is assigned an identical sensing probability, i.e. $p_i = p,\ i = 1, ..., N$. Uniform random sensing is widely used in traditional sparse sensing techniques due to its simplicity and robustness in practice. However, it is agnostic to the heterogeneity of energy consumption in WSNs, and hence does not achieve maximum energy saving. The other is greedy sensing that selects one sensor node after another, always picking the node which consumes the least energy in transmitting the sensor measurement to the FC. In other words, $p_i = 1$ if E_i is among the M_s lowest, otherwise $p_i = 0$. The problem of greedy sensing is that it excessively prioritizes the subset of sensor nodes with smaller energy consumption (closer to the FC), so it often loses a sufficiently wide-spread and balanced coverage of the entire data field, resulting in poor recovery accuracy. As a result, there is a need to find the best possible tradeoff between these two approaches.

To address the tradeoff problem between recovery accuracy and the overall energy consumption, we need to quantitatively analyze these two factors. Given a network topology and an energy consumption model, we can obtain the energy consumption map of the network without difficulty. Thus, the energy consumption of a particular sensing strategy is easy to calculate. However, it is intractable to numerically determine the exact recovery accuracy, as the ground truth of the data field is usually unavailable. Even though some metrics of sensing matrix (e.g. the RIP) have been proposed to prove theoretical recovery accuracy guarantees, they are impractical in our application scenario. The reasons are two fold: 1) Verifying the RIP of a sensing matrix is NP-hard and computationally intensive; 2) They only provide a loose lower bound on the recovery accuracy, resulting in a waste of resources. To sum up, we need to find a practical metric of the sensing matrix that can predict recovery accuracy in an efficient manner.

In this paper, rather than the sophisticated RIP, the statistical RIP (StRIP) which is proposed in [26] is employed as a practical indicator for quantifying recovery accuracy. As a probabilistic version of the RIP, the StRIP is much easier to be verified and can still provide a sufficiently good recovery accuracy guarantee. There are three basic conditions which can be used to verify whether an $M \times N$ matrix $\mathbf{\Phi}$ satisfies the StRIP [26], i.e.,

1) (St1) The rows of $\mathbf{\Phi}$ are orthogonal, and all row sums are zero.
2) (St2) The columns of $\mathbf{\Phi}$ form a group under pointwise multiplication.
3) (St3) Bounded column sum: for $j = 2, 3, ..., N$

$$\left|\sum_{i=1}^{M} \phi_{i,j}\right|^2 \leq M^{2-\eta} \qquad (9)$$

where η satisfies $0 < \eta \leq 1$ and $\phi_{i,j}$ is the i-th row and j-th column element of $\mathbf{\Phi}$.

In our application scenario, the sensing matrix $\mathbf{A}$ is constructed by randomly selecting M rows from the $N \times N$ Fourier basis matrix $\mathbf{\Psi}$. In order to verify whether $\mathbf{A}$ satisfies the StRIP, we need to check the three basic conditions mentioned above. It is straightforward to show that conditions St1 and St2 are satisfied. Thus, the condition St3 is of critical significance. For clarity, we first define a term called *Maximum Column Sum (MCS)* based on St3. For any sensing matrix $\mathbf{A}$, its *MCS* is defined as

$$\mu(\mathbf{A}) = \max_{j=2,...,N} \left|\sum_{i=1}^{M} a_{ij}\right|^2 \qquad (10)$$

where a_{ij} is the i-th row and j-th column element of $\mathbf{A}$.

Based on the main results of StRIP in [26], we obtain the following lemma, which bridges the *MCS* and the RIP condition.

LEMMA 1. *Statistical RIP*
For a structured sensing matrix $\mathbf{A} = \mathbf{\Phi}_r \mathbf{\Phi}_s \mathbf{\Psi}$ *of size* $M \times N$ *as in (3), suppose that there exists* $\frac{1}{2} < \eta \leq 1$ *such that*

$$\mu\left(\mathbf{A}\right) \leq M^{2-\eta}. \tag{11}$$

Then, for all k*-sparse vectors* $\mathbf{s} \in \mathbb{R}^N$ *where* $k < 1 + (N-1)\,\varepsilon$, *if* $M \geq \left(c\frac{k \log N}{\varepsilon^2}\right)^{1/\eta}$ *for some constant* c, *then the inequalities*

$$(1-\varepsilon)\left\|\mathbf{s}\right\|^2 \leq \left\|\frac{1}{\sqrt{M}}\mathbf{A}\mathbf{s}\right\|^2 \leq (1+\varepsilon)\left\|\mathbf{s}\right\|^2 \tag{12}$$

hold with probability exceeding $1-\delta$ *(with respect to all* k*-sparse vectors uniformly drawn from the space* $\mathbb{R}^N$*), with* $\delta = 4e^{-\frac{[\varepsilon \quad (k \quad 1)/(N \quad 1)]^2 M^\eta}{32k}}$. *In other words,* $\frac{1}{\sqrt{M}}\mathbf{A}$ *satisfies RIP of order* k*, with isometry constant* ε.

According to Lemma 1, when δ becomes smaller, there will be a higher probability for $\frac{1}{\sqrt{M}}\mathbf{A}$ to satisfy RIP. Under the fixed signal sparsity k, a larger η produces a smaller δ, which requires a smaller *MCS* $\mu\left(\mathbf{A}\right)$. This indicates that a sensing matrix with a smaller *MCS* satisfies RIP with a higher probability.

Note that our structured sensing matrix $\mathbf{A}$ encompasses two random selection matrices due to random sampling and random access, while existing work considers one random matrix only, such as Theorem 1 in [34]. Expanding the literature, we provide the following Theorem 1 on the error performance of the recovery scheme in (5).

THEOREM 1. *Recovery Error Bound*
Consider the signal sampling and reconstruction scheme in (3)-(5), where $\mathbf{x} = \mathbf{\Psi}\mathbf{s}$ *is a sparse (compressible) signal in the Fourier transform domain and* ξ *is the bounded noise level. For any* $\forall k < \frac{N}{16}$, *there exists* $c > 0$ *such that if* $\mu\left(\mathbf{A}\right) < \min\,\{\sigma_1, \sigma_2, \sigma_3\}$, *then the following inequality*

$$\left\|\mathbf{x} - \hat{\mathbf{x}}\right\|_2 \leq \frac{C_k \xi}{\sqrt{MN}} \tag{13}$$

holds with probability exceeding 0.99, *where* $\hat{\mathbf{x}}$ *is the recovered data field,* C_k *is a constant which is only dependent on the RIP constant,* $\sigma_1 = M^{\frac{3}{2}}$, $\sigma_2 = M^{2-\log_M(16ck\log N)}$ *and* $\sigma_3 = M^{2-\log_M\left[3067.6k\left(\frac{N \quad 1}{N \quad 4k+3}\right)^2\right]}$.

Remark: As stated in Theorem 1, as long as $\mu\left(\mathbf{A}\right)$ is sufficiently small, the recovery error is upper bounded with an overwhelming probability. Therefore, *MCS* can be employed as an indicator of the recovery accuracy. More importantly, *MCS* of a sensing matrix is easy to calculate and Theorem 1 can be verified efficiently. Note that the recovery error bound is sufficiently tight in our application scenario of large-scale WSNs. Specifically, in (13), ξ is the bounded noise level, which is a constant after determining the sensing devices and is usually small under the request of high recovery accuracy. Thus, the recovery error bound is dependent on the coefficient $\frac{C_k}{\sqrt{MN}}$. When the restricted isometry constant

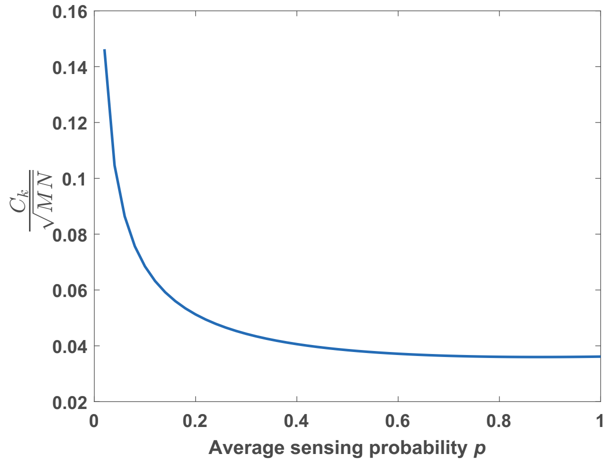


Fig. 4: $\frac{C_k}{\sqrt{MN}}$ versus the average sensing probability p.

$\varepsilon_{4k} = \frac{1}{4}$, $C_k \approx 10.47$ [16], the value of $\frac{C_k}{\sqrt{MN}}$ is usually small for a WSN with hundreds to thousands of sensor nodes. For example, assume $N = 512$, $T = 180$ s, $L = 400$ bits and $B = 2$ kbps, $\frac{C_k}{\sqrt{MN}}$ versus the average sensing probability p is shown in Fig. 4.

As noted in the figure, under a reasonable p, $\frac{C_k}{\sqrt{MN}}$ is small. In particular, if we set $p \geq 0.2$ in order to achieve an acceptable sensing accuracy, then $\frac{C_k}{\sqrt{MN}} \leq 0.05$. Therefore, we can say that the recovery error bound provided in Theorem 1 is sufficiently tight in our application scenario of large-scale WSNs and the requirement of high sensing accuracy. The complete proof of Theorem 1 is presented in the Appendix.

D. Optimal Sensing Probability Assignment Strategy

According to Theorem 1, we can always find a constant α such that when $\mu\left(\mathbf{A}\right) \leq \alpha$, a given level of recovery accuracy is met with high probability. Since $\mathbf{A}$ depends on the sensor selection matrix, we may identify a number of candidate subsets of sensor nodes to participate in sensing, such that each candidate subset results in sufficiently accurate recovery of the data field at the FC. Therefore, the next important step is to pick out the most energy-efficient subset from those candidate subsets. Given the energy consumption map of all sensor nodes $\mathbf{E} = \left[E_1, E_2, ..., E_N\right]^T$, where E_i is defined by the energy consumption model in (6), this process can be formulated as the following optimization problem

$$\begin{aligned} \min \quad & \mathbf{E}^T\mathbf{p} \\ \text{s.t.} \quad & \begin{cases} p = \frac{1}{N}\sum\limits_{i=1}^{N} p_i, \\ \mathbf{q} = \mathbf{p} \cdot e^{-2\frac{N p T_p}{T \quad T_p}}, \\ \mathbf{1}^T\mathbf{q} = M, \\ \left|\mathbf{q}^T\mathbf{\Psi}(:,j)\right|^2 \leq \alpha \quad (j = 2, ..., N), \\ p_i \in \{0, 1\} \quad\quad\quad (i = 1, ..., N). \end{cases} \end{aligned} \tag{14}$$

where p is the average sensing probability, $\mathbf{q} = \left[q_1, q_2, ..., q_N\right]^T$ is the reception rate vector of all sensor nodes, $\mathbf{1} = \left[1, 1, ..., 1\right]^T$, M is the average number of correctly received collision-free data packets at the FC, and $\mathbf{\Psi}(:,j)$ is the j-th column vector of the Fourier basis matrix $\mathbf{\Psi}$.

Note that the objective function in (14) indicates the total energy consumption to be minimized, the third constraint in (14) ensures the number of correctly received sensor measurements for signal recovery at the FC, and the fourth one is the *MCS* constraint for recovery performance guarantee. Considering the contradiction relation between a lower energy consumption and a smaller *MCS*, the number of received measurements M is employed as a proxy to pursue a balance between them. Here p_i encodes whether the i-th sensor node is selected to participate in sensing. When the number of sensor nodes N and the average sensing probability p are small, global optimization techniques, such as the branch-and-bound method, can be used to solve (14). However, this problem has been shown to be NP-hard and it incurs exponentially growing computational complexity in the network size N, which is inapplicable to our application scenario of large-scale WSNs. To address this issue, a widely used heuristic approach for solving the original 0-1 programming problem with a low computational complexity is to modify the binary constraints $p_i \in \{0,1\}$ into $0 \leq p_i \leq 1$, and then solve the resulting relaxed linear programming problem, which leads to

$$\begin{aligned} \min \quad & \mathbf{E}^T\mathbf{p} \\ \text{s.t.} \quad & \begin{cases} p = \frac{1}{N}\sum\limits_{i=1}^{N} p_i, \\ \mathbf{q} = \mathbf{p} \cdot e^{-2\frac{NpT_p}{T}\frac{}{T_p}}, \\ \mathbf{1}^T\mathbf{q} = M, \\ |\mathbf{q}^T\mathbf{\Psi}(:,j)|^2 \leq \alpha \quad (j=2,...,N), \\ 0 \leq p_i \leq 1 \qquad\quad (i=1,...,N). \end{cases} \end{aligned} \tag{15}$$

This problem is different from (14) in that p_i can be fractional. Note that this relaxation operation has been demonstrated to be rational and feasible in [35] and has found extensive applications such as antenna selection in multi-antenna wireless communication systems [36]. More importantly, it can be solved efficiently, for example, using interior-point methods. It typically requires a few tens of iterations, and each iteration can be carried out with a complexity of $\mathcal{O}(N^3)$ operations.

The solution to (15) is a sensing probability assignment strategy, which means that sensor node i participates in sensing with a probability of p_i. This implies that the subset of sensor nodes that actually take part in sensing in each frame is a random event. Therefore, the optimization result only manifests that the expected energy consumption is minimized while the expected *MCS* is bounded. Although this is not an absolute performance guarantee, the recovery error is still upper-bounded with a high probability and the expected energy consumption reflects the average performance of a given sensing probability assignment strategy.

Remark: A critical parameter in the convex optimization formulation is α, which reflects the value of *MCS*. The value of α has a direct impact on the optimized sensing probability assignment strategy. The larger value of α we choose, the more greedily the corresponding sensing probability assignment strategy behaves (assigning higher sensing probabilities to sensor nodes closer to the FC). In an extreme case, it becomes equivalent to the greedy sensing scheme. Conversely, the smaller the value of α, the fairer the sensing probability assignment strategy becomes among all sensor nodes, which promises better recovery accuracy. Note that when α becomes smaller than a certain threshold, each sensor node will be assigned an identical sensing probability (uniform random sensing). Therefore, we can control the behavior of the optimized sensing probability assignment strategy by adjusting the value of α. It is worth noting that the value of α should not exceed an upper limit value α_H for a given average sensing probability p, i.e., $\alpha \leq \alpha_H$, with α_H denoting the expected *MCS* of greedy sensing, to ensure that a comparable recovery accuracy is achieved with respect to uniform random sensing. On the other side, if the value of α is chosen too small (note that $\alpha \geq 0$ is a necessity to make the problem feasible), all sensor nodes will take the same probability to sense, which is equivalent to uniform random sensing and violates the desire to promote energy efficiency. Thus, we request that $\alpha \geq \alpha_L$.

Given an average sensing probability p, if we could find a proper value of α from the interval $[\alpha_L, \alpha_H]$, the sensing probability assignment strategy produced by the above convex optimization problem can satisfy the two requirements: 1) the recovery error bound provided by it is better or equal to that of uniform random sensing according to Theorem 1; 2) the expected energy consumption of $\mathbf{p}$ is the lowest among all sensing probability assignment strategies in the solution space of the convex optimization problem.

To illustrate how to choose a good value for α, we need to present the tradeoff curves of recovery accuracy versus energy consumption based on the two energy consumption maps in Fig. 2. Note that the data set used here and in the experiments in Section IV is the SST data trace provided by the Jet Propulsion Laboratory, California Institute of Technology, which is accessible at *https://ourocean.jpl.nasa.gov/*. We assume that totally 1024 sensor nodes are deployed at a 32×32 equally spaced grid to measure the SST field in the 1280×1280 m^2 rectangular sensing area, and the measurements generated by 256 randomly selected sensors are used as the ground truth, i.e. $N = 256$. For clarity, we first define the two performance metrics. We employ the normalized mean squared error $NMSE$ as the accuracy metric. Suppose $\hat{\mathbf{x}}$ is the recovered data field, $NMSE$ is defined as follows

$$NMSE = \frac{\|\mathbf{x} - \hat{\mathbf{x}}\|_2^2}{\|\mathbf{x}\|_2^2},$$

then the recovery accuracy is calculated as $1 - NMSE$. Furthermore, the energy consumption of the network is measured by the energy consumption ratio, which is calculated as the proportion of the total energy consumption owing to those nodes that actually participate in sensing over the total energy consumption if all nodes participate, i.e.

$$\text{Energy Consumption Ratio} = \frac{\sum_{\text{sensing } i} E_i}{\sum_{\text{all } i} E_i}.$$

The results are in Fig. 5. We insert an arrow in each curve to indicate the variation of α from α_L to α_H. As

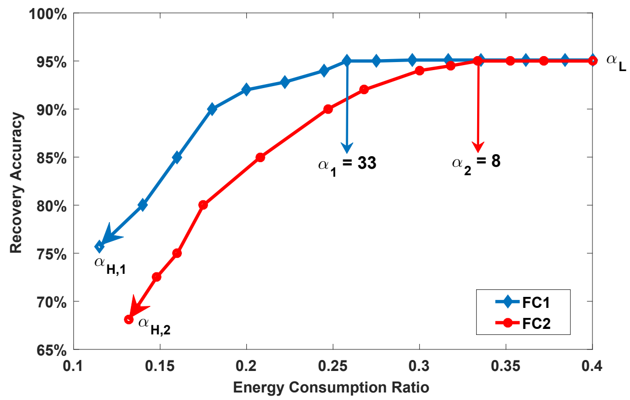


Fig. 5: The impact of the parameter α on the tradeoff between recovery accuracy and energy consumption when the average sensing probability p is set to 0.4.

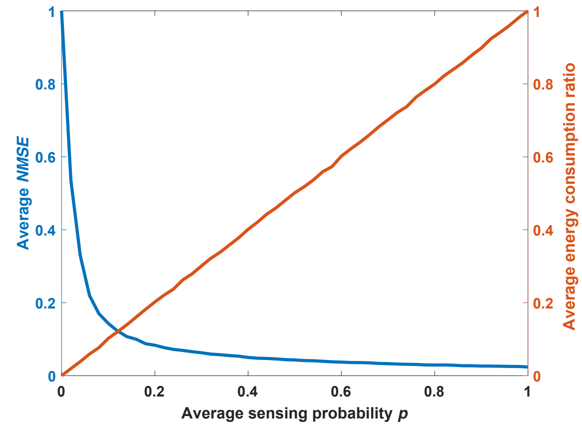


Fig. 6: The average *NMSE* and average energy consumption ratio versus average sensing probability p.

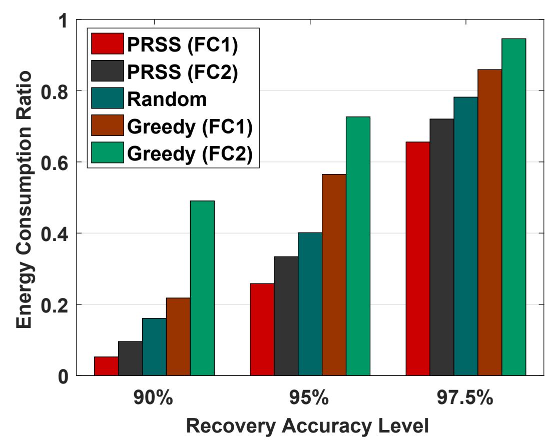


Fig. 7: The comparison of energy consumption ratio among the three schemes under different accuracy levels.

we can observe from the figure, when $\alpha = \alpha_L$ (at the beginning), PRSS bears a similar behavior to uniform random sensing, and it approximates greedy sensing when α grows to α_H. In particular, when the FC locates at the center of the sensing area, with the growth of α initially, the energy consumption ratio declines while the recovery accuracy stays at the same level. However, when α becomes larger than 33, the recovery accuracy sharply drops. When the FC locates outside the sensing area, the recovery accuracy declines when α grows larger than 8. Apparently, it is desired to identify the threshold value, which is the most appropriate choice for the parameter α in the convex optimization problem, such that we can obtain the most energy-efficient sensing probability assignment strategy with accuracy guarantee. Note that we can utilize historical data to tune the parameters.

IV. Performance Evaluation

In this section, we evaluate the performance of the proposed PRSS using real-world SST data trace, and make a comparison with two benchmark algorithms, i.e. uniform random sensing and greedy sensing.

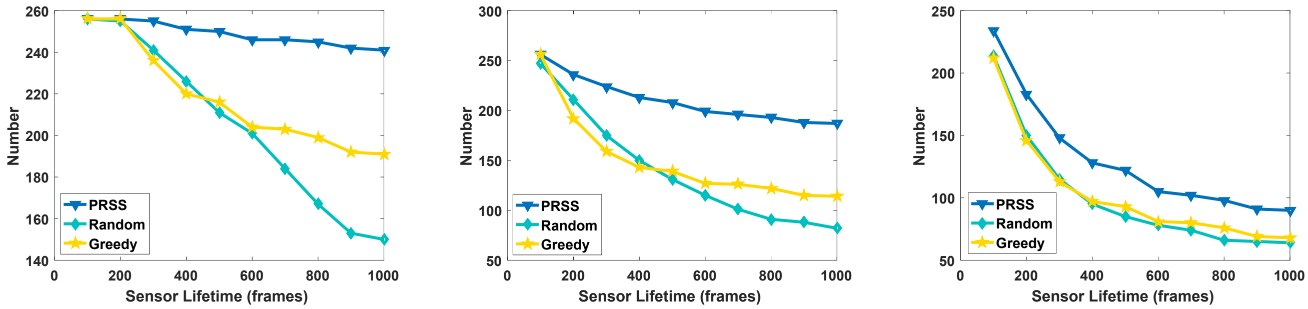
A. Experimental Settings

In environmental monitoring application scenarios of the IoT, a satisfactory sensing quality (reflected by recovery accuracy) is an essential requirement. Furthermore, the network lifetime is also of crucial importance since recharging or replacing batteries of sensor nodes is difficult in practical IoT deployments. Therefore, a figure of merit for network performance is the energy expenditure per successfully delivered bit of information. In this paper, we consider two performance metrics. One is the average energy consumption of the network needed to sense a physical field at the given accuracy level, and the other is network lifetime. Conventionally, network lifetime is defined as the time duration elapsed from the network operation starts until the first node (or the last node) in the network depletes its energy (dies) [33]. However, this simple definition is inapplicable to our problem. In light of a sensor network based on CS, the network lifetime should be defined as the time interval from the beginning till the time beyond which successful recovery is no longer available. For simplicity, we investigate the number of nodes whose lifetimes surpass a given threshold value which varies from 100 to 1000 frames.

B. Energy Consumption and Network Lifetime Comparisons

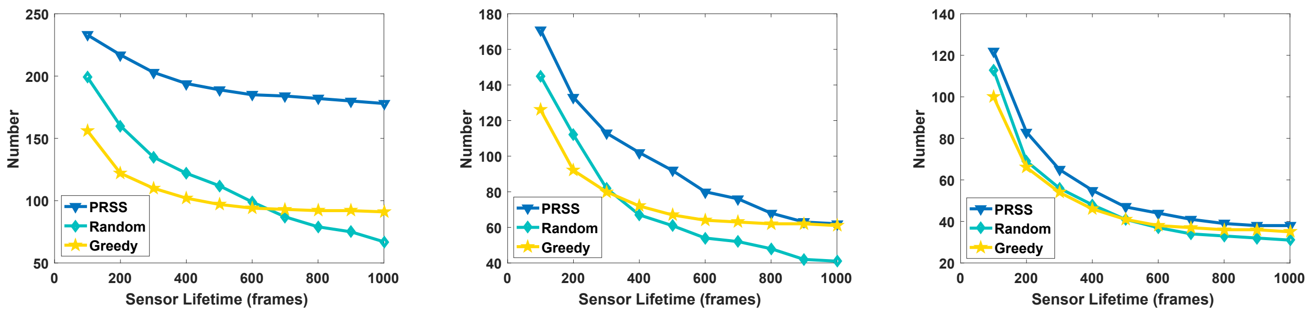
Before presenting the energy consumption and network lifetime comparison results, we first seek to determine a proper average sensing probability p, which meets the given accuracy level with the least energy consumption. Taking the uniform random sensing scheme as an example, the average *NMSE* and the average energy consumption ratio versus the average sensing probability p is shown in Fig. 6. As noted in the figure, as p increases, *NMSE* first drops sharply and then remains relatively stable, while the average energy consumption ratio rises linearly in p. Therefore, in order to save energy, we should choose the smallest value of p conditioned that the given accuracy level is satisfied.

To assess the energy consumption of PRSS, we compare it with the two benchmark algorithms for the two common



(a) $NMSE = 10\%$ (b) $NMSE = 5\%$ (c) $NMSE = 2.5\%$

Fig. 8: Network lifetime comparisons under different accuracy levels when the FC locates at the center of the sensing area.



(a) $NMSE = 10\%$ (b) $NMSE = 5\%$ (c) $NMSE = 2.5\%$

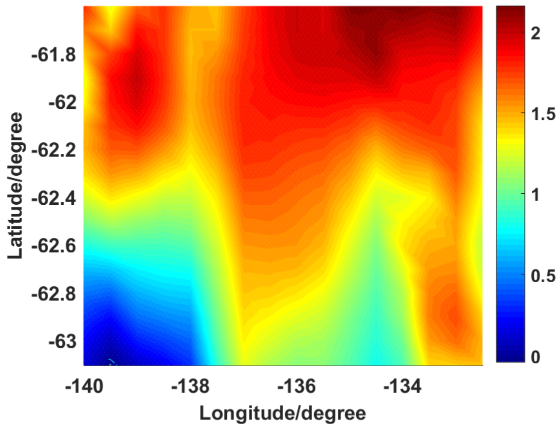
Fig. 9: Network lifetime comparisons under different accuracy levels when the FC locates outside the sensing area.

FC locations. Fig. 7 presents the energy consumption ratio of the three schemes under three different accuracy levels ($NMSE = 10\%/5\%/2.5\%$, representing adequate/ high/ excellent recovery accuracy).

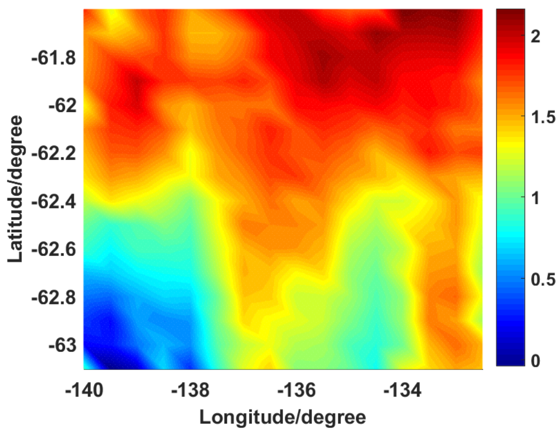
Since uniform random sensing is agnostic to the heterogeneity of energy consumption in the network, it yields the same energy consumption ratio for the two different FC locations. By contrast, PRSS and greedy sensing determine the subset of participating sensors based on the energy consumption dispersion, so the results are different for the two FC locations. As we can observe from Fig. 7, wherever the FC locates, PRSS outperforms both uniform random sensing and greedy sensing under all accuracy levels. Specifically, when the FC locates at the center of the sensing area, PRSS consumes 67.4% and 75.9% less energy than uniform random sensing and greedy sensing under the 90% accuracy level. At $NMSE = 5\%$, PRSS saves 35.6% and 54.3% energy compared to the two benchmark algorithms, respectively. The energy saving of PRSS shrinks at the excellent accuracy level ($NMSE = 2.5\%$), since it requires a large number of sensor nodes to participate in sensing. Nevertheless, the energy consumption ratio is still 16.1% and 23.7% lower than uniform and greedy baselines, respectively. When the FC locates outside the sensing area, the energy consumption ratio of PRSS rises slightly, and the gap between PRSS and uniform random sensing narrows. Besides, greedy sensing presents a much higher energy consumption ratio under all accuracy levels. This is because the energy consumption map increases monotonically from one side of the region to the other, resulting in a stronger spatial correlation. As a result, the recovery accuracy decreases earlier when α grows, as shown in Fig. 5.

As network lifetime is important for environmental monitoring applications of the IoT, we now make a comparison about it among the three sensing approaches. As an alternative, we investigate the number of sensor nodes whose lifetimes reach a given threshold value. We assume that the initial energy of each sensor node is 25 KJ (energy provided by two AA batteries [37]) and that the lifetimes of sensor nodes are measured in frames, and in each frame the FC conducts one field reconstruction based on the received sensor measurements. A sensor node is considered dead when it is no longer able to complete one data transmission. Leveraging the energy consumption model in (6), we obtain the results in Fig. 8 and Fig. 9 for the two FC locations.

The results are self-explanatory. Specifically, when the FC locates at the center of the sensing area, PRSS provides the overwhelming majority of sensor nodes with elongated lifetimes. For example, at $NMSE = 10\%$, there are 241 sensor nodes (note that $N = 256$) which sustain a lifetime of more than 1000 frames when using PRSS. However, the numbers become 150 and 191 when using uniform random sensing and greedy sensing, respectively. When a high accuracy is required ($NMSE = 5\%$), the number of sensor nodes whose lifetimes are longer than 1000 frames is 187, 82, 114 in PRSS, uniform random sensing and greedy sensing respectively. At the excellent accuracy level ($NMSE = 2.5\%$), there are still



(a) The map of the original SST field



(b) The map of the reconstructed SST field

Fig. 10: The SST field is sensed employing PRSS with $p = 0.28$, $T = 180$ s and $T_p = 0.2$ s.

90 sensors which stay alive for more than 1000 frames in PRSS, while there are only 64 and 68 sensors survive this long in uniform random sensing and greedy sensing. Because the sensor nodes have a longer average lifetime, we can say that PRSS sustains a prolonged network lifetime compared to the two benchmark algorithms. Consistent results are observed from Fig. 9 when the FC locates outside the sensing area. Regardless of the required accuracy level, there is a larger number of sensor nodes which have a relatively long lifetime in PRSS than in uniform random sensing and greedy sensing.

C. One Example of Field Reconstruction

To visually illustrate the field reconstruction process, we utilize PRSS to sense an SST data field collected on January 7th, 2017 UTC at latitudes $[-63.1050°, -61.6050°]$ and longitudes $[-140.0050°, -132.5050°]$, which is shown in Fig. 10(a). This data field is inherently sparse in the Fourier domain. Assume an average sensing probability $p = 0.28$, a desired frame length $T = 180$ s, a packet duration $T_p = 0.2$ s, and suppose the FC locates at the center of the sensing region. Following the implementation procedures in Section III, each sensor node i is assigned a sensing probability p_i based on the solution to the convex optimization problem in (15). Then, the reconstructed SST field is shown in Fig. 10(b). Note that in this network design, the parameter α is chosen 85 to achieve the most energy-efficient field sensing with accuracy guarantee. As a result, 95% recovery accuracy is achieved consuming 47.5% and 42.1% less energy compared to the two benchmark algorithms.

V. Conclusion

In this paper, by exploiting the heterogeneity of energy consumption in the IoT in the design of sparse sensing techniques, we propose a CS-based prejudiced random sensing strategy (PRSS), where each sensor node participates in sensing via random medium access based on an assigned sensing probability, to achieve a desirable tradeoff between energy consumption and sensing accuracy. Specifically, we employ the StRIP as a practical indicator of the recovery accuracy and derive a sufficiently good recovery error bound based on it. Then, we devise a novel convex optimization framework to find the most energy-efficient sensing probability assignment strategy with accuracy guarantee. Performance evaluation using real-world SST data trace demonstrates that PRSS can achieve significant energy saving and elongation of network lifetime in the IoT compared to the two benchmark algorithms.

Appendix
Proof of Theorem 1

Given $\mu(\mathbf{A}) \leq M^{2-\eta}$, we let $\delta_{4k} = 4e^{-\frac{[\varepsilon_{4k}-(k-1)/(N-1)]^2 M^{\eta}}{32k}}$ and $\varepsilon_{4k} = \frac{1}{4}$. Assume that all the constraints in Theorem 1 are satisfied. In particular:

1) To satisfy $\eta > \frac{1}{2}$, we have $\mu(\mathbf{A}) < M^{\frac{3}{2}}$.
2) To satisfy $M \geq \left(c\frac{k\log N}{\varepsilon^2}\right)^{1/\eta}$, we have $\eta \geq \log_M(16ck\log N)$, then $\mu(\mathbf{A}) < M^{2-\log_M(16ck\log N)}$.
3) To satisfy $\delta_{4k} = 4e^{-\frac{[\varepsilon_{4k}-(k-1)/(N-1)]^2 M^{\eta}}{32k}} < 0.01$, we have $\eta \geq \log_M\left[3067.6k\left(\frac{N-1}{N-4k+3}\right)^2\right]$, then $\mu(\mathbf{A}) < M^{2-\log_M\left[3067.6k\left(\frac{N-1}{N-4k+3}\right)^2\right]}$.

Under the constraint of $k < \frac{N}{16}$, we have $4k < 1+(N-1)\varepsilon_{4k}$.

According to Lemma 1, the sensing matrix $\frac{1}{\sqrt{M}}\mathbf{A}$ satisfies RIP of order $4k$ with probability more than 0.99 and the restricted isometry constant is $\varepsilon_{4k} = \frac{1}{4}$. Then according to Theorem 1 in [34], we have

$$\|\mathbf{s}-\hat{\mathbf{s}}\|_2^2 \leq \left(\frac{C_k}{\sqrt{M}}\xi\right)^2,$$

which is equivalent to

$$(\mathbf{s}-\hat{\mathbf{s}})^H(\mathbf{s}-\hat{\mathbf{s}}) \leq \left(\frac{C_k}{\sqrt{M}}\xi\right)^2.$$

Note that the Fourier basis matrix $\mathbf{\Psi}$ satisfies $\mathbf{\Psi}^H\mathbf{\Psi} = \frac{1}{N}\mathbf{I}_{N\times N}$, where $\mathbf{I}_{N\times N}$ is the N-dimensional identity matrix. Then we have

$$N(\mathbf{s}-\hat{\mathbf{s}})^H\mathbf{\Psi}^H\mathbf{\Psi}(\mathbf{s}-\hat{\mathbf{s}}) \leq \left(\frac{C_k}{\sqrt{M}}\xi\right)^2,$$

i.e.

$$N(\mathbf{x}-\hat{\mathbf{x}})^H(\mathbf{x}-\hat{\mathbf{x}}) \le \left(\frac{C_k}{\sqrt{M}}\xi\right)^2,$$

which can be reformulated as

$$N\left\|\mathbf{x}-\hat{\mathbf{x}}\right\|_2^2 \le \left(\frac{C_k}{\sqrt{M}}\xi\right)^2.$$

Therefore, the inequality $\left\|\mathbf{x}-\hat{\mathbf{x}}\right\|_2 \le \frac{C_k}{\sqrt{MN}}\xi$ holds.

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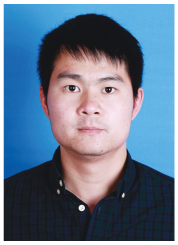

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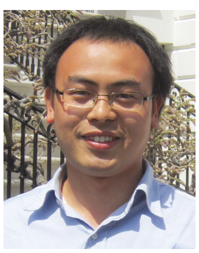

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