Practical Scheduling for Stochastic Event Capture in Wireless Rechargeable Sensor Networks

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***Abstract*—Existing scheduling schemes for stochastic event capture with rechargeable sensors either adopt simplified assumptions on event staying time or provide no performance guarantee. Considering the stochasticity of event staying time, we investigate the sensor scheduling problem aiming to maximize the overall Quality of Monitoring (QoM) in events capture application of wireless rechargeable sensor networks. We first provide a paradigm to calculate the QoM of a point of interests (PoI) and formulate the scheduling problem into an optimization problem. Although we find that that this problem is NP-complete, we prove that the objective function of the optimization problem is monotone submodular. Therefore we can express the problem as a maximization of a submodular function subject to a matroid constraint. Accordingly we can design an approximation algorithm which achieves a factor of $1/2$ of the optimum. We evaluate the performance of our solution through simulations, and simulation results show that our scheme outperforms former works.**

***Index Terms*—Rechargeable sensors; events capture; scheduling; submodularity.**

I. Introduction

Although event capture in WSNs has been studied extensively, there are some new challenges when we consider the same issue in wireless rechargeable sensor networks (WRSNs) [1]. There are works such as [2]–[4] focusing on how to exploit on-line information of event occurrence to optimize the Quality of Monitoring (QoM). Here QoM is defined as the ratio of interesting events captured to all occurred events. These works do not consider the stochastic characteristic of the event staying time. In duty-cycle sensor networks, the works [5], [6] aim to maximize the QoM under the assumption that event staying time follows the exponential distribution. But these solutions do not provide any performance guarantee.

In this paper, we study the scheduling problem for stochastic event capture in WRSNs with more practical considerations. We present effective approximation algorithm with performance guarantee. The contributions of this work are as follows.

- We consider the scheduling problem for stochastic event capture in WRSNs in a more practical way. The stochasticity of event staying time is taken into account. We provide a paradigm to calculate the QoM of a point of interests (PoI) in the presence of single or multiple monitoring sensors.
- We formulate the scheduling problem into an optimization problem. Although this problem is NP-complete, we find that we can express the problem as a maximization of a submodular function subject to a matroid constraint. This formulation allows us to design an approximation algorithm which achieves a factor of $1/2$ of the optimum.
- We conduct extensive simulations to verify the results. For small-scale networks, we compare the performance of the proposed algorithm with that of the optimal solution. For large-scale networks, we show that the proposed algorithm outperforms two other scheduling algorithms.

The remainder of the paper is organized as follows. In Section II, basic assumptions and formal definition of our problem are presented. In Section III, we prove the hardness of the problem and present an approximation algorithm with performance guarantee. Section IV presents simulation results. Before concluding this work in Section VI, we briefly discuss the related work in Section V.

II. Problem Formulation

A. Network Model

We assume that m sensors $V = \{v_1, v_2, \ldots, v_m\}$ distributed in a 2D region cover n PoIs $O = \{o_1, o_2, \ldots, o_n\}$. In particular, suppose that sensor v_i covers a subset of PoIs O_i. Adjacent sensors can cover nonempty PoIs in common. Accordingly, target o_i might be covered by a subset of sensors V_i. A base station serves as a sink, and requires each sensor to report its current energy level and other useful information to it hop by hop on a regular basis. The Collection Tree Protocol (CTP) [7] is used as the routing protocol for sensors. Assume that time is divided into time slots and the duration of a time slot is fixed and given a priori. Every T time slots, the base station determines the periodic schedules for the next T interval of all sensors, and disseminate them to sensors. The periodic schedules followed by sensors are of identical length $\mathcal{L}$. We name such period starting with the scheduling process as *scheduling period*, and let T be a multiple of $\mathcal{L}$. A sensor can schedule itself to be active or inactive in any time slot. Therefore, the schedule of sensor v_i can be expressed by a vector $S_i = (a_{i1}, a_{i2}, \ldots, a_{i\mathcal{L}})$, where component $a_{ij} = 1$ indicates the sensor is active in time slot j while $a_{ij} = 0$ means the opposite. After all, we assume that the reporting processes of sensors take place with so low frequency (e.g., 1 hour) that its energy overhead can be ignored.

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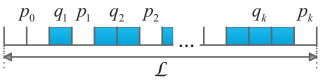

Fig. 1. Illustration of vector regularization

B. Recharging Model and Energy Consumption Model

Much existing work holds that the energy harvesting rates in many cases are of high variability, and the environmental energy model can be cast as a stochastic process [3], [4]. However, for a wide range of application scenarios, such as that correspond to indoor environment, the energy availability has been proved to be time-dependent and predictable [8]–[12]. For instance, by effectively taking into account both the current and past-days weather conditions, [12] obtains a relative mean error of only 10%. Hence, with the knowledge of the accurate harvesting energy prediction of the next scheduling period for a sensor, along with the current residual energy, one can make rational decision on energy budget for the sensor in the next scheduling period. Note that a valid decision should warrant sensors will never run out of energy.

Besides, the introduction of ultra-capacitor (up to 3000 F) can effectively offset the variability of the harvesting energy, and ensures stable power of harvesting [13]. To a great extent, this approach eliminates the dependence of activities of sensors on environmental energy model. As a result, one can simply assign all the residual energy in the capacitor at the end of the latest scheduling period as the energy budget in the next scheduling period.

Nevertheless, the energy budget determination is out of the focus of this paper, we simply assume that the energy budget of the next scheduling period T for sensor v_i has already been determined, and is denoted as e_T^i. In addition, assume that sensor v_i consumes δ_i energy for sensing and capturing an event in one time slot, but negligible energy if it is inactive, or switching between states provided that the duration of a time slot is set to be long enough. For simplicity, assume $l_i = \frac{e_T^i \mathcal{L}}{\delta_i T}$ for each sensor v_i is integral, which means that the charged power for sensor v_i can be equivalently converted to no more than l_i active time slots in periodic schedule S_i. Thus schedule S_i is subject to $||S_i||_1 \leq l_i$ where $||S_i||_1$ is the L_1 norm of S_i. We call l_i the active time slot budget of sensor v_i.

C. Event Model, QoM Concept and Properties

Events are assumed to occur one after another at a PoI, and have step utility function [14], i.e., the utility reaches one instantaneously once an event is detected. Moreover, an event stays for a while before it disappears. Denote by X the staying time. Similarly, the time duration before another new event occurs, which is called the event arrival time, is denoted by Y. Assume that X and Y at PoI i follow the exponential distribution with means $\frac{1}{\lambda_i}$ and $\frac{1}{\mu_i}$, respectively. This assumption has been widely used in the literature (e.g., [5], [6], [14]–[17]). For simplicity, further assume that $\frac{1}{\lambda_i} = \frac{1}{\lambda}$ and $\frac{1}{\mu_i} = \frac{1}{\mu}$ for $i = 1, 2, \ldots, n$. Another important assumption relevant to events is that the events are *identifiable* among sensors [14] (please see [14] for a justification of the assumption).

For QoM of a single PoI i, we use the widely adopted paradigm [17]. Assume there are m_i stochastic events occurring at PoI i during time t, and all the sensors capture c_i events. The QoM of PoI i can be formally defined as:

$$QoM(i) = \lim_{t\to\infty} \sum_{i=1}^{N} c_i / \sum_{i=1}^{N} m_i \tag{1}$$

Furthermore, define the regularization function which resembles run-length encoding [18] $R : \{0,1\}^{\mathcal{L}} \mapsto N^{\mathcal{L}'}$ ($\mathcal{L}' \leq \mathcal{L}$). Informally, if a vector S is in such a form as Fig. 1 illustrates, then we have $R(S) = (p_0, q_1, p_1, q_2, p_2, \ldots q_k, p_k)$. Note that $p_0 = 0$ (or $p_k = 0$) if the schedule starts with (or ends with) an active time slot.

Let us first consider the QoM of a PoI only covered by one single sensor v_i. The **pdf** of the event staying time X can be expressed by:

$$f(x) = \lambda e^{-\lambda x},\ x > 0,\ mean = \frac{1}{\lambda} \tag{2}$$

According to [17], if a sensor is scheduled to be active for q every p time periodically, then the QoM for this (q, p) duty-cycle schedule is given by $QoM = \frac{q}{p} + \frac{1-e^{-\lambda(p-q)}}{\lambda p}$. We extend this result and present the following lemma (note that $f(x)$ is normalized such that one time unit of x is equal to the duration of one time slot).

Lemma 2.1: The QoM of PoI o_i covered by a single sensor v_j ($V_i = \{v_j\}$), whose schedule S_j can be regularized as $R(S_j) = (p_0, q_1, p_1, q_2, p_2, \ldots q_{k_j}, p_{k_j})$, is given by:

$$QoM(i|S_j) = \frac{\sum_{k=1}^{k_j} q_k}{\mathcal{L}} + \frac{\sum_{k=1}^{k_j-1}(1 - e^{-\lambda p_k}) + 1 - e^{-\lambda(p_0+p_{k_j})}}{\lambda\mathcal{L}} \tag{3}$$

Proof: The proof is similar to that of Theorem 6 in [14]. The key point is that if an event happening in an inactive period p_j is ever captured, then it must be first captured in the next present period q_{j+1}. We omit the detailed proof due to space limitation. ■

As a PoI might be covered by multiple sensors, we develop a solution to deal with this situation. We further suppose $S_i = (a_{i1}, a_{i2}, \ldots, a_{i\mathcal{L}})$ and $S_j = (a_{j1}, a_{j2}, \ldots, a_{j\mathcal{L}})$ are two different vectors, then we define the OR operation of vectors as follows:

$$S_i \vee S_j = (a_{i1} \vee a_{j1}, a_{i2} \vee a_{j2}, \ldots, a_{i\mathcal{L}} \vee a_{j\mathcal{L}}) \tag{4}$$

Lemma 2.2: The QoM of PoI o_i covered by multiple sensors $V_i = \{v_{1'}, v_{2'}, \ldots, v_{n'}\}$, whose schedule is $S_{j'}$ ($j' = 1', 2', \ldots, n'$) respectively, is given by:

$$QoM(i|S_{1'}, S_{2'}, \ldots, S_{n'}) = QoM(i| \bigvee_{v_{j'} \in V_i} S_{j'}) \tag{5}$$

In other words, the QoM under multiple sensors can be equivalently viewed as under single sensor with a combined schedule, $\bigvee S_{j'}$, of every sensor.

Proof: Clearly, assuming that an event is first captured by time slot $a_{j'k}$ of sensor $v_{j'}$, regardless of whether the event occurs at $a_{j'k}$ or not, it must also be captured by v_a as $a_{j'k} \in \bigvee_{v_{j'} \in V_i} S_{j'}$; and vice versa. Then the result follows. ■

Note that this lemma holds only under the assumption that the events are identifiable among all sensors. According to Lemma 2.1 and 2.2, the QoM of a PoI can be calculated as follows.

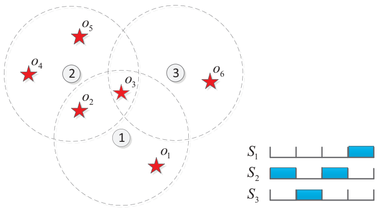

Fig. 2. An example of scheduling

Corollary 2.1: The QoM of PoI o_i is given by:

$$QoM(i) = QoM(i| \bigvee_{v_j \in V_i} S_j) \tag{6}$$

For simplicity of exposition, we call $\widehat{S}_i = \bigvee_{v_j \in V_i} S_j$ the *equivalent monitoring schedule* for PoI o_i. When there is no ambiguity, we still use a_{ij} to denote the j_{th} time slot state in $\widehat{S}_i$ of PoI o_i. Moreover, according to Eq. (3), it is obvious that even if $\widehat{S}_i$ is cyclically shifted, e.g., $\widehat{S}_i$ changes from $(1,0,0,0)$ to $(0,0,1,0)$, the QoM of o_i remains unchanged. We call this property of $\widehat{S}_i$ as *cyclic shift symmetry* and formally state this observation in the following corollary.

Corollary 2.2: The equivalent monitoring schedule $\widehat{S}_i$ of any PoI o_i exhibits cyclic shift symmetry in terms of QoM.

D. Problem Statement

We first present a simple example before delving into the details. As shown in Fig. 2, suppose there are 3 sensors covering totally 6 PoIs in the region. The sensor schedule length $\mathcal{L} = 4$, and the active time slot budget for v_1, v_2 and v_3 are 1, 2 and 1 respectively. Further, it can be seen that the sensor schedules are set to $S_1 = (0,0,0,1)$, $S_2 = (1,0,1,0)$ and $S_3 = (0,1,0,0)$, respectively. Therefore, the equivalent monitoring schedule $\widehat{S}_i$ for each PoI can be determined, e.g., $\widehat{S}_2 = S_1 \vee S_2 = (1,0,1,1)$. In addition, assume $\lambda = 1$ for the exponential distribution of the staying time. Consequently, the QoMs of PoI o_1, o_2, o_3, o_4, o_5 and o_6 are 0.4876, 0.9080, 1, 0.8161, 0.8161 and 0.4876, respectively. In fact, this schedule yields an optimal overall QoM.

Considering the finite active time slot budget l_i of sensors, we wish to find the optimal scheduling of every sensor in order to maximize the overall QoM of all PoIs. We assign a normalized weight w_i to each PoI o_i. Then QoM can be written as a weighted sum of the individual QoMs. As a result, our problem can be formally stated as follows:

$$\begin{aligned} (P_1): \quad & \text{maximize} \quad && \sum_{i=1}^{N} w_i QoM(i) \\ & \text{subject to} && ||S_i||_1 \le l_i \quad \forall i = 1,2,\dots,m, \end{aligned}$$

Note that $QoM(i)$ can be calculated according to Corollary 2.1 and Lemma 2.1. During this procedure, the equivalent monitoring schedule $\widehat{S}_i$ for each PoI o_i should be calculated based on those schedules of sensors covering o_i.

III. Scheduling to Maximize QoM of Stochastic Event Capture in WRSNs

In this section, we first show that the scheduling problem is NP-complete. Then we come up with an approximation algorithm with performance guarantee.

A. Hardness Analysis of the Scheduling Problem

We prove that the scheduling problem is NP-complete as stated in the following theorem.

Theorem 3.1: The scheduling problem is NP-complete.

Proof: We place the detailed proof in the Appendix for a better flow of the paper. ■

B. Reformulation of the Scheduling Problem

We first give some definitions to be used in our discussions.

Definition 3.1: Let S be a finite ground set. A real-valued set function $f: 2^S \mapsto \mathbb{R}$ is *normalized*, *nondecreasing* (or *monotonic*) and *submodular* if and only if it satisfies the following conditions, respectively [19]: (i) $f(\emptyset) = 0$; (ii) $f(A) \le f(B)$ for any $A \subseteq B \subseteq S$, or equivalently: $f(A \cup \{e\}) - f(A) \ge 0$ for any $A \subseteq S$ and $e \in S \backslash A$; and (iii) $f(A \cup \{e\}) - f(A) \ge f(B \cup \{e\}) - f(B)$ for any $A \subseteq B \subseteq S$ and $e \in S \backslash B$.

Definition 3.2: [19] A *matroid* $\mathcal{M}$ is a tuple $\mathcal{M} = (S, \mathcal{I})$, where S is a finite ground set and $\mathcal{I} \subseteq 2^S$ is a collection of independent sets, such that: (i) $\emptyset \in \mathcal{I}$; (ii) If $X \subseteq Y \in \mathcal{I}$, then $X \in \mathcal{I}$; and (iii) If $X, Y \in \mathcal{I}$, and $|X| < |Y|$, then $\exists y \in Y \backslash X$ such that $X \cup \{y\} \in \mathcal{I}$.

Definition 3.3: [19] Given $S = \bigcup_{i=1}^{k} S'_i$ is the disjoint union of k sets, $l_1, l_2, \dots, l_k$ are positive integers, a *partition matroid* $\mathcal{M} = (S, \mathcal{I})$ is a matroid where $\mathcal{I} = \{X \in S : |X \cap S'_i| \le l_i \text{ for } i = 1,2,\dots,k\}$.

We will demonstrate that the problem P_1 fits perfectly well in the realm of maximizing a monotone submodular function subject to a partition matroid. We start with a definition of ground set S. Denote by $\mathbf{a}_{ij}$ the activating time slot a_{ij} of sensor v_i, then S is given by:

$$S = \{\mathbf{a}_{11}, \mathbf{a}_{12}, \dots, \mathbf{a}_{1\mathcal{L}}, \dots, \mathbf{a}_{m1}, \mathbf{a}_{m2}, \dots, \mathbf{a}_{m\mathcal{L}}\} \tag{7}$$

The sensor schedule S_i can be equivalently defined as a subset of S, namely $S_i = \{\mathbf{a}_{i1'}, \mathbf{a}_{i2'}, \dots, \mathbf{a}_{i\mathcal{L}'}\}$ if and only if $a_{ij'} = 1\,(j' = 1', 2', \dots, \mathcal{L}')$. We use these two definitions interchangeably if there is no confusion. Further, S can be partitioned into m disjoint sets, $S'_1, S'_2, \dots, S'_m$, which is given by $S'_i = \{\mathbf{a}_{i1}, \mathbf{a}_{i2}, \dots, \mathbf{a}_{i\mathcal{L}}\}$. S'_i is called *candidate schedule* of sensor v_i, as any feasible schedule S_i is the subset of S'_i. It is obvious that any scheduling policy X, consisting of all sensor schedule S_i, namely $X = \{S_1, S_2, \dots, S_m\}$, is subject to $|X \cap S'_i| = |S_i| \le l_i$. Then we can write the independent sets as $\mathcal{I} = \{X \subseteq S : |X \cap S'_i| \le l_i \text{ for } i = 1,2,\dots,m\}$.

On the other hand, it can be easily proved that $\mathcal{M} = \{S, \mathcal{I}\}$ is a matroid by verifying the three properties proposed in Def. 3.2. Hence we have the following lemma.

Lemma 3.1: The constraint in the scheduling problem P_1 can be written as a partition matroid on the ground set S.

We rewrite the optimization problem in P_1 as following:

$$\begin{aligned} (P_2): \quad & \text{maximize} \quad && f(X) = \sum_{i=1}^{N} w_i QoM(i| \bigvee_{v_j \in V_i} S_j) \\ & \text{subject to} && X \in \mathcal{I} \\ & && S_i = X \cap S'_i \quad \forall i = 1,2,\dots,m, \end{aligned}$$

Algorithm 1 Greedy Algorithm

Input: The sensors set $V = \{v_1, v_2, \dots, v_m\}$, the PoIs set $O = \{o_1, o_2, \dots, o_n\}$, the objective function $f(\cdot)$, the ground set S, the candidate schedule S_i', active time slot budget $l_1, l_2, \dots, l_m$.

Output: The sensor schedules $S_1, S_2, \dots, S_m$.

```
D = S; S_i = ∅;
for i = 1, 2, ..., m; X = ∅;
k = 1;
while k ≤ m × 𝓛 do
    a_ij = arg max_{d∈D} f_X(d);
    if f_X(a_ij) = 0 then
        break;
    end if
    X ← X + a_ij;  S_i ← S_i + a_ij; (namely set S_ij = 1)
    D ← D\a_ij; S_i' ← S_i'\a_ij;
    if ||S_i||_1 = l_i then
        D ← D\S_i';
    end if
    k = k + 1;
end while
```

The new optimization function $f(X)$ bears a desirable property as is stated in the following lemma.

Lemma 3.2: The objective function $f(X)$ in the optimization problem P_2 is a monotone submodular function.

Proof: We prove this lemma in the Appendix for a better flow of the paper. ■

C. Approximation Algorithm

Having proved that the objective function of our problem is monotone submodular, now we can resort to a simple greedy algorithm to find an optimized QoM. The details of the algorithm can be found in Alg. 1. It can be seen that at each step the algorithm adds one element with the highest marginal value to set.

Theorem 3.2: The greedy scheduling algorithm can achieve 1/2-approximation.

Proof: According to the classical results obtained by [20] and Lemma 3.1 and 3.2, the result follows. ■

IV. Performance Evaluation

We present simulation results to verify our findings. Unless otherwise stated, we use the following simulation setups: (i) the event staying time $X \in \text{exponential}(\lambda)$, $\lambda = 1$; (ii) each sensor has a sensing range $r = 1\,m$; (iii) The weight $w_i = 1$ for each PoI o_i.

A. Performance Evaluation in Small-scale Sensor Networks

We compare our proposed approximation algorithm with the optimal solution for small-scale networks in this section.

We randomly distribute sensors in a $3\,m \times 3\,m$ region in this scenario. As for PoIs, the deployment region is discretized into square cells of dimensions $0.5\,m \times 0.5\,m$, and each vertex of each cell is a PoI. We vary the number of sensors between 4 and 8, and only record the data where the total number of covered PoIs is 36, so as to make the comparisons reasonable among different cases with different number of sensors. We compute the overall QoMs of the schedules output by the greedy for three scenarios: (1) sensor schedule length $\mathcal{L} = 8$, and the active time slot budget $l_i = 1$ for every sensor v_i; (2) $\mathcal{L} = 5$, and $l_i = 1$; (3) $\mathcal{L} = 5$, and l_i is randomly selected from $\{1, 2\}$. Note that the optimal solution is obtained by

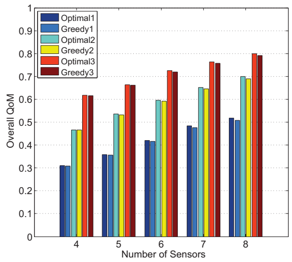

Fig. 3. Greedy vs optimal

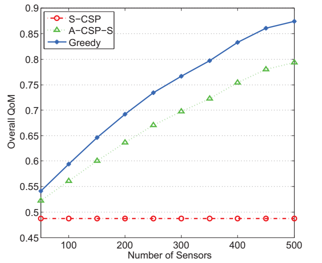

Fig. 4. Greedy vs S-CSP & A-CSP-S

enumerating all possible scheduling policies under the same active time slot budgets constraints.

The simulation results are shown in Fig. 3, where Optimal1 and Greedy1 refer to the first scenario, and Optimal2 and Greedy2 refer to the second, and so on. It can be seen that for networks with small size, the performance of our proposed greedy is quite close to that of the optimal solution. The overall QoM of both optimal and greedy algorithms rises when the number of sensors increases. Another observation is that the overall QoM grows with a larger active time slot budget l_i.

B. Performance Evaluation in Large-scale Sensor Networks

We compare our algorithm to CSP proposed in [5], an energy-efficient protocol for stochastic events capture which accommodates both synchronous and asynchronous networks, in large-scale sensor networks.

Generally, there are two versions of CSP: S-CSP for synchronous networks, where all the sensors employ the same (q, p) schedule and start their on periods at the same time; and A-CSP for asynchronous networks, where each sensor employs the same (q, p)-periodic schedule, but start their on periods independently at a uniformly random point in time within the period p. Since A-CSP is only suitable for asynchronous networks, we extend it to synchronous networks in discrete time model by letting each sensor start their on periods independently at a random time slot in the schedule of length $\mathcal{L}$, which we call A-CSP-S. In addition, to make the comparison between CSP and our scheme feasible, we assume that there is no sensor whose sensing region is completely covered by those of its active neighbors, which means each sensor should not go sleep. Note that, in essence, A-CSP-S is a randomized algorithm.

Throughout the simulation, sensors are distributed randomly in a $20\,m \times 20\,m$ region. The sensor schedule length $\mathcal{L}$ is set to 4, and the active time slot budget $l_i = 1$ for any sensor v_i. Further, the distance between adjacent PoIs is increased with the average number of sensors increasing from 50 to 500, such that the number of covered PoIs maintains 500 all the time. As for A-CSP-S, we simulate the algorithm for 50 times and record the mean value of the outputs. As shown in Fig. 4, our proposed greedy algorithm always achieves the highest QoM. In addition, A-CSP-S performs much better than S-CSP.

V. Related Work

We briefly review the related work in this section. Jaggi *et al.* [2] exploited the temporal correlations in the event occurrences to develop efficient activation policies. Ren *et al.* [3] focused on general renewal processes, where the event arrival time can be drawn from an arbitrary probability distribution. Tang *et al.* [8] assumed that the utility function is monotone submodular, and provided a polynomial time algorithm which guarantees a constant approximation. These methods are utility-based and do not apply to stochastic event capture. In duty-cycle sensor networks, Yau *et al.* [14] considered the impact of stochastic event arrival time and staying time on QoM. He *et al.* [15] extended the results of periodic coverage problem by incorporating the energy constraints of mobile sensors, as well as the energy consumption of sensor movement. As for static sensors, He *et al.* [5] considered the energy efficiency and the coordination issues between sensors in synchronous and asynchronous networks. He *et al.* discussed a complementary problem in [6] with respect to connectivity. In [17], Jiang *et al.* used readers capable of mobility and functioning as energy distributors and data collectors to charge sensors. These results provide no performance guarantee and cannot be applied to optimal scheduling in WRSNs in terms of QoM maximization.

VI. CONCLUSION

In this paper, we consider the scheduling problem in order to maximize the QoM of stochastic event capture in WRSNs. Specifically, we propose an approximation algorithm with constant approximation ratio. Simulation results show that our algorithm has performance close to the optimal, and outperforms the former work. Nevertheless, our work mainly focuses on a few types of events, we will extend our work to accommodate general cases in the future.

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APPENDIX

A. Proof of Theorem 3.1

Proof: To show that problem P_1 is NP-complete, we consider its decision version. Denote by bipartite graph $G = (V, O, E)$ the coverage graph in Fig. 5 where V and O denote the set of sensors and PoIs respectively, and E denotes the set of edges between sensors and PoIs. If there is an edge between sensor v_i (depicted in a circle) and PoI o_j (depicted in a rounded rectangle), it means that v_i covers o_j. Given the sensor schedule length $\mathcal{L}$, and a real number $Q \geq 0$, we need to answer whether there exists any scheduling policy of the sensors, such that $||S_i||_1 \leq l_i$ for any sensor v_i, and the objective function in the problem P_1 satisfies: $\sum_{i=1}^{N} w_i QoM(i) \leq Q$.

Denote by Ω the set of weights w_i for all PoIs, and L the set of l_i. Then the above problem instance can be denoted as $SDP(O, V, E, L, \mathcal{L}, \Omega, Q)$. As in [21], we reduce an NP-complete problem called 2-Disjoint Set Cover Problem to the decision version of the scheduling problem (we call it scheduling decision problem hereafter).

Consider a bipartite graph $G = (A, B, E)$ with edges E between two disjoint vertex sets A and B. For each element $b_i \in B$, it has neighborhoods in A which is denoted by $N(b_i)$. Assume that $A = \bigcup_{b_i \in B} N(b_i)$. Then it is proved to be NP-complete in [22] to determine whether there exist two disjoint sets $B_1, B_2 \subset B$ such that $|B_1| + |B_2| = |B|$

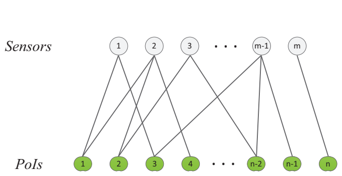

Fig. 5. PoI coverage illustration

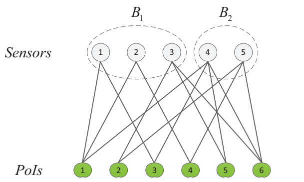

Fig. 6. Reduction from 2-Disjoint set cover problem

and $A = \bigcup_{b_i \in B_1} N(b_i) = \bigcup_{b_i \in B_2} N(b_i)$. For simplicity, we denote the above problem instance as $2DSC(A, B, E)$.

First of all, it is easy to see that $SDP(O, V, E, L, \mathcal{L}, \Omega, Q)$ is in the class NP. Next we show that given a unit time oracle for scheduling decision problem we can solve 2-Disjoint Set Cover Problem in polynomial time.

Consider an oracle which can solve any problem instance $SDP(O, V, E, L, \mathcal{L}, \Omega, Q)$ in unit time. Then solving an problem instance $2DSC(A, B, E)$ is equivalent to solving $SDP(A, B, E, \{1, 1, \ldots, 1\}, 2, \{1/|A|, 1/|A|, \ldots, 1/|A|\}, 1)$. Consider A to be the set of PoIs, B to be the set of sensors, and E to be the edges representing coverage relationship between sensors and PoIs. The sensor schedule length $\mathcal{L}$ is set to be 2 and the active time slot budget of all sensors is equal to 1. The PoI weights are assumed to be $1/|A|$ for all PoIs. We check if the overall QoM can be greater or equal to 1. If it is the case, the overall QoM has to be equal to 1 because QoM for each PoI is at most 1. This can only happens if the equivalent monitoring schedule $\widehat{S}_i$ for any PoI o_i is equal to $(1, 1)$. It means there exist 2 disjoint set covers B_1 and B_2, while the entire sensors in B_1 are active in its first time slot and that in B_2 are active in its second time slot. Illustration is provided in Fig. 6.

Conversely, if there exist two disjoint set covers, we can set the sensors in the first set cover to be active in the first time slot, and that in the second set cover to be active in the second time slot. By doing so, the SDP instance will be satisfied since every PoI o_i is continuously covered as $\widehat{S}_i = (1, 1)$, and the overall QoM is equal to 1. In summary, our scheduling problem is NP-complete. ■

B. Proof of Lemma 3.2

Proof: According to Def. 3.1, we have to check if the three conditions hold for $f(X)$. First of all, it is obvious that $f(\emptyset) = 0$ holds. This is because all the sensors are actually inactive for all time slots under such a situation.

Secondly, we consider the monotonicity property of $f(X)$. Given set $A \subseteq S$ and $e_1 \in S \backslash A$. Assume that $e_1 = \mathbf{a}_{ij}$, then $f(A + e_1)$ can be regarded as the resulting overall QoM obtained by activating the time slot a_{ij} of sensor v_i based on the original scheduling policy. Consequently, the equivalent monitoring schedule of PoI o_k, which is covered by v_i ($o_k \in O_i$), may be changed. For simplicity of exposition, denote the original and changed equivalent monitoring schedule of o_k as $\widehat{S}_k^{<A>}$ and $\widehat{S}_k^{<A+e_1>}$, respectively. In particular, the time slot a_{kj} is activated for $\widehat{S}_k^{<A+e_1>}$. To save space, we only consider the case where $\mathbf{a}_{ij} \notin \widehat{S}_k^{<A>}$ (We say $\mathbf{a}_{ij} \in \widehat{S}_k^{<A>}$ if the j_{th} time slot of $\widehat{S}_k^{<A>}$ is active, namely $a_{kj} = 1$, to simplify the notation). It is obvious that if $\widehat{S}_k^{<A>}$ is an empty schedule, we have $QoM(\widehat{S}_k^{<A+e_1>}) > QoM(\widehat{S}_k^{<A>}) (= 0)$. Otherwise, from Corollary 2.2, we can cyclically shift $\widehat{S}_k^{<A>}$

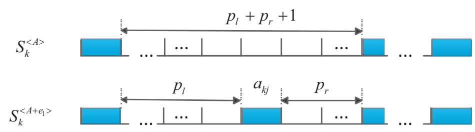

Fig. 7. Proof of monotonicity

and $\widehat{S}_k^{<A+e_1>}$ in the same way, such that the nearest active time slot ahead of a_{kj} is moved to the first position in the schedule, while the QoM remains unchanged. As is illustrated in Fig. 7, assume that there are successive p_l and p_r ($p_l \geq 0, p_r \geq 0, p_l + p_r + 1 \leq \mathcal{L} - 1$) inactive time slots ahead and behind of a_{kj} in $\widehat{S}_k^{<A+e_1>}$. Accordingly, there are successive $p_l + p_r + 1$ inactive time slots in the same locations including a_{kj}. Follows from Eq. (3), we have:

$$
\begin{aligned}
& QoM(k|\widehat{S}_k^{<A+e_1>}) - QoM(k|\widehat{S}_k^{<A>}) \\
=& (\frac{1}{\mathcal{L}} + \frac{1 - e^{-\lambda p_l} + 1 - e^{-\lambda p_r}}{\lambda \mathcal{L}}) - (\frac{1 - e^{-\lambda(p_l + p_r + 1)}}{\lambda \mathcal{L}}) \\
=& \frac{1}{\lambda \mathcal{L}}[\lambda + 1 - e^{-\lambda p_l} + 1 - e^{-\lambda p_r} - (1 - e^{-\lambda(p_l + p_r + 1)})] \\
>& \frac{1}{\lambda \mathcal{L}}[(1 - e^{-\lambda})(1 - e^{-\lambda p_l}) + (1 - e^{-\lambda(p_r + 1)})(1 - e^{-\lambda p_r})] > 0.
\end{aligned}
$$

Note that the first inequality holds since $e^{-\lambda} > (1 - \lambda)$ for any $\lambda > 0$. Then we have:

$$
\begin{aligned}
f_A(e_1) =& f(A + e_1) - f(A) \\
=& \sum_{o_k \in O_i} w_k [QoM(k|\widehat{S}_k^{<A+e_1>}) - QoM(k|\widehat{S}_k^{<A>})] \geq 0.
\end{aligned}
$$

The monotonicity property of $f(X)$ holds.

Thirdly, we verify the diminishing returns property of $f(X)$. Given set $A \subseteq B \subseteq S$ and $e_1 \in S \backslash B$. Assume that $e_1 = \mathbf{a}_{ij}$, Similarly, we assume that the original equivalent monitoring schedules for o_k in A and B are $\widehat{S}_k^{<A>}$ and $\widehat{S}_k^{<B>}$, while the changed ones are $\widehat{S}_k^{<A+e_1>}$ and $\widehat{S}_k^{<B+e_1>}$, respectively. Due to space limit, we only consider the case where $\mathbf{a}_{ij} \notin \widehat{S}_k^{<A>}$ and $\mathbf{a}_{ij} \notin \widehat{S}_k^{<B>}$, and $\widehat{S}_k^{<A>} \neq \emptyset$. Similar to the analysis of monotonicity of $f(X)$, we assume that after cyclic shift the number of nearest successive inactive time slot ahead of and behind of a_{kj} in $\widehat{S}_k^{<A+e_1>}$ are $p_l^{<A>}$ and $p_r^{<A>}$ respectively, while that in $\widehat{S}_k^{<B+e_1>}$ are $p_l^{<B>}$ and $p_r^{<B>}$ respectively. An important observation is that since $A \subseteq B$, we have $\widehat{S}_k^{<A>} = \bigvee_{v_i \in V_k} S_i^{<A>} = \bigvee_{v_i \in V_k} |A \cap S_i'| \subseteq \bigvee_{v_i \in V_k} |B \cap S_i'| = \bigvee_{v_i \in V_k} S_i^{<B>} = \widehat{S}_k^{<B>}$. Thus it is easy to see that $p_l^{<A>} \geq p_l^{<B>}$ and $p_r^{<A>} \geq p_r^{<B>}$. Hence:

$$
\begin{aligned}
& [QoM(k|\widehat{S}_k^{<A+e_1>}) - QoM(k|\widehat{S}_k^{<A>})] - [QoM(k|\widehat{S}_k^{<B+e_1>}) \\
& - QoM(k|\widehat{S}_k^{<B>})] \\
=& \frac{1}{\lambda \mathcal{L}}[\lambda + 1 - e^{-\lambda p_l^{<A>}} + 1 - e^{-\lambda p_r^{<A>}} - (1 - \\
& e^{-\lambda(p_l^{<A>} + p_r^{<A>} + 1)})] - \frac{1}{\lambda \mathcal{L}}[\lambda + 1 - e^{-\lambda p_l^{<B>}} + 1 - e^{-\lambda p_r^{<B>}} \\
& - (1 - e^{-\lambda(p_l^{<B>} + p_r^{<B>} + 1)})] \\
=& \frac{1}{\lambda \mathcal{L}}\{(1 - e^{-\lambda p_l^{<A>}})(e^{-\lambda p_r^{<B>}} - e^{-\lambda p_r^{<A>}}) + (1 - e^{-\lambda p_r^{<B>}}) \\
& (e^{-\lambda p_l^{<B>}} - e^{-\lambda p_l^{<A>}}) + (1 - e^{-\lambda})(e^{-\lambda(p_l^{<B>} + p_r^{<B>})} \\
& - e^{-\lambda(p_l^{<A>} + p_r^{<A>})})\} > 0.
\end{aligned}
$$

Then we have:

$$
\begin{aligned}
& f_A(e_1) - f_B(e_1) \\
=& \sum_{o_k \in O_i} w_k \{[QoM(k|\widehat{S}_k^{<A+e_1>}) - QoM(k|\widehat{S}_k^{<A>})] \\
& - [QoM(k|\widehat{S}_k^{<B+e_1>}) - QoM(k|\widehat{S}_k^{<B>})]\} \geq 0.
\end{aligned}
$$

We conclude that $f(X)$ is indeed submodular. Summing up all the analyses above, the result follows. ■