Energy-Efficient Cooperative Spectrum Sensing by Optimal Scheduling in Sensor-Aided Cognitive Radio Networks

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***Abstract*—A promising technology that tackles the conflict between spectrum scarcity and underutilization is cognitive radio (CR), of which spectrum sensing is one of the most important functionalities. The use of dedicated sensors is an emerging service for spectrum sensing, where multiple sensors perform cooperative spectrum sensing. However, due to the energy constraint of battery-powered sensors, energy efficiency arises as a critical issue in sensor-aided CR networks. An optimal scheduling of each sensor active time can effectively extend the network lifetime. In this paper, we divide the sensors into a number of nondisjoint feasible subsets such that only one subset of sensors is turned on at a period of time while guaranteeing that the necessary detection and false alarm thresholds are satisfied. Each subset is activated successively, and nonactivated sensors are put in a low-energy sleep mode to extend the network lifetime. We formulate such problem of energy-efficient cooperative spectrum sensing in sensor-aided CR networks as a scheduling problem, which is proved to be $\mathcal{NP}$-complete. We employ Greedy Degradation to degrade it into a linear integer programming problem and propose three approaches, namely, Implicit Enumeration (IE), General Greedy (GG), and λ-Greedy (λG), to solve the subproblem. Among them, IE can achieve an optimal solution with the highest computational complexity, whereas GG can provide a solution with the lowest complexity but much poorer performance. To achieve a better tradeoff in terms of network lifetime and computational complexity, a brand new λG is proposed to approach IE with the complexity comparable with GG. Simulation results are presented to verify the performance of our approaches, as well as to study the effect of adjustable parameters on the performance.**

***Index Terms*—Cooperative spectrum sensing, energy efficiency, optimal scheduling, sensor-aided cognitive radio (CR) networks.**

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I. Introduction

SPECTRUM resources are becoming increasingly limited with the emergence of various wireless devices and applications. According to the U.S. Federal Communications Commission [1], the allocated spectrum resources are heavily underutilized in vast temporal, spatial, and spectral dimensions. This is mainly because under existing regulatory policy, frequency bands are statically assigned to licensed/primary users (PUs), and no reutilization is permitted for unlicensed/secondary users (SUs). Cognitive radio (CR) [2]–[4] is proposed to tackle the conflict between spectrum scarcity and underutilization, which enables SUs to opportunistically utilize the channel when PUs are absent, and to vacate it instantly when PUs are in operation to avoid interfering with the licensed usage.

Spectrum sensing is fundamental for CR networks as it detects the state of channel for opportunistic reutilization [5]. There are two important metrics in spectrum sensing: 1) detection probability P_d and 2) false alarm probability P_f [6]. The higher the P_d, the better the PUs are protected; the lower the P_f, the more efficiently the channel can be reutilized by SUs. To increase the detection probability, a collection of signal detection techniques are proposed in [7] and [8]. Among them, the energy detector, which is optimal for detecting a weak unknown signal from a known zero-mean constellation [9], is adopted in this paper.

In CR networks, one architecture is to incorporate the spectrum sensing functionality into individual SU transceiver, which raises the cost and exposes certain security vulnerability. An alternative is to take advantage of dedicated sensors that perform spectrum sensing and report decision to SUs as a service [10]. Local spectrum sensing has a hidden terminal problem, where one single sensor might perform poorly when the channel suffers multipath fading or shadowing. To address this issue, multiple sensors can be coordinated to perform cooperative spectrum sensing [11], [12]. There are two important metrics in cooperative spectrum sensing: 1) cooperative detection probability Q_d and 2) cooperative false alarm probability Q_f [13]. When Q_d is larger than a predefined threshold $\overline{Q}_d$, it is considered that PUs are well protected; similarly, when Q_f is smaller than a threshold $\overline{Q}_f$, we can ensure that the spectrum reutilization opportunities are well captured by SUs. Additionally, a novel mobility scheme has been proposed in [14], which is able to guarantee fairly and effectively data gathering from all nodes.

Sensors have size and weight restrictions, with direct impact on the limited power resources. Since replacing the battery is not feasible in many applications, energy efficiency emerges as a critical issue. As presented in [15], the power consumed by an active sensor is 34 mW, but when the sensor sleeps, it is merely 0.4 mW. Therefore, an optimal scheduling of each sensor active time can effectively extend the network lifetime. For the practical purpose of using the energy-constrained sensor network for spectrum sensing [16], it is crucial to optimally schedule the battery-powered sensors to maximize the network lifetime while ensuring that the necessary detection and false alarm thresholds are satisfied. For example, we can intuitively design a schedule that when a subset of sensors can satisfy the necessary thresholds, all others are allowed to enter a low-energy sleep mode.

In this paper, we study the problem of maximizing the network lifetime by optimally scheduling each sensor active time in a sensor-aided CR network. We divide the sensors into a number of nondisjoint subsets based on their individual channel conditions. Each subset is activated successively, such that at any time only one subset is activated, and all the other sensors are in a low-energy sleep mode. The sensors from the activated subset are responsible for performing spectrum sensing and guarantee that the network satisfies the necessary detection and false alarm thresholds. To the best of our knowledge, this is the first try to consider such problem. Our contributions are as follows.

1) We consider energy-efficient cooperative spectrum sensing in sensor-aided CR networks and formulate it as a scheduling problem, which is proved to be $\mathcal{NP}$-complete.
2) We degrade it into a series of subproblems, reformulated as a linear integer programming problem.
3) We propose three approaches to solve the subproblem.
4) We verify the performance of our approaches through comprehensive simulations.

The remainder of this paper is organized as follows. We present in Section II the background information and related work on spectrum sensing and energy efficiency. In Section III, the energy-efficient cooperative spectrum sensing problem (ECSSP) is formulated and degraded into a series of subproblems. Three approaches are proposed in Section IV to solve the subproblem. In Section V, simulation results are employed to verify the performance of our approaches. We conclude this paper with future work in Section VI.

II. Background Information

A. Spectrum Sensing

We assume that each sensor performs local spectrum sensing independently. Let H_1 denotes the state that the channel is busy, and H_0 for the channel is idle. Using an energy detector, by integrating the received signal in bandwidth W over the sensing period t_s, the sensor s_i will compare the collected energy E_i with a predefined threshold ε_i to decide whether the channel is occupied by PUs [17]: $D_i = \begin{cases} 1, & E_i > \varepsilon_i \\ 0, & \text{otherwise} \end{cases}$.

The detection probability $P_{d,i}$ and false alarm probability $P_{f,i}$ of the sensor s_i are defined as

$$P_{d,i} = \Pr\{D_i = 1|\mathrm{H}_1\} = \Pr\{E_i > \varepsilon_i|\mathrm{H}_1\}$$

$$P_{f,i} = \Pr\{D_i = 1|\mathrm{H}_0\} = \Pr\{E_i > \varepsilon_i|\mathrm{H}_0\}$$

which can be evaluated in terms of $\mathbb{Q}$-function as [18]

$$P_{d,i} = \mathbb{Q}\left(\frac{\varepsilon_i}{2\sqrt{Wt_s}(\gamma_i+1)\sigma_{n,i}^2} - \sqrt{Wt_s}\right) \quad (1)$$

$$P_{f,i} = \mathbb{Q}\left(\frac{\varepsilon_i}{2\sqrt{Wt_s}\sigma_{n,i}^2} - \sqrt{Wt_s}\right) \quad (2)$$

where $\gamma_i = \sigma_{p,i}^2/\sigma_{n,i}^2$ is the received signal to noise ratio (SNR) at the sensor s_i, and $\mathbb{Q}(z) := (1/\sqrt{2\pi})\int_z^{+\infty} e^{-(\tau^2/2)}d\tau$.

B. Cooperative Spectrum Sensing

One of the most crucial issues of local spectrum sensing is the hidden terminal problem, which happens when the channel suffers multipath fading or shadowing. In such cases, one single sensor cannot reliably detect the presence of PUs due to the very low SNR of the received signal at the sensor. To address this issue, multiple sensors can be coordinated to perform cooperative spectrum sensing, which can greatly increase the detection probability [11]–[13]. The cooperation steps are as follows: 1) Each sensor s_i performs local spectrum sensing and makes a binary decision $D_i \in \{0,1\}$ independently. 2) They forward the 1-bit decision to a base station (BS). 3) The BS fuses these decisions to make a final decision.

The above steps are referred to as decision fusion. An alternative is data fusion, i.e., instead of reporting the 1-bit decision to the BS, each sensor directly transmits the value of the collected energy E_i. Decision fusion has the advantage of low bandwidth requirement. In addition, [11] has shown that hard decision performs almost as well as soft decision. Therefore, we only consider decision fusion in this paper.

The decision fusion rule at the BS can be OR, AND, or Majority, which can be generalized as "k-out-of-N" voting-based decision fusion [19]. That is, the final decision is 1 if among N sensors there are at least k of them who detect the presence of PUs: $D = \begin{cases} 1, & \sum_{i=1}^N D_i \geq k \\ 0, & \text{otherwise} \end{cases}$, where N is the number of sensors.

Cooperative detection probability Q_d and cooperative false alarm probability Q_f are defined as

$$Q_d = \Pr\{D = 1|\mathrm{H}_1\} = \Pr\left\{\sum_{i=1}^N D_i \geq k|\mathrm{H}_1\right\}$$

$$Q_f = \Pr\{D = 1|\mathrm{H}_0\} = \Pr\left\{\sum_{i=1}^N D_i \geq k|\mathrm{H}_0\right\}$$

which can be calculated as

$$Q_d = \sum_{i=k}^{N} \left\{ \sum_{j=1}^{C_N^k} \left[\prod_{l=1}^{k} P_{d,x_{j,l}} \times \prod_{l=k+1}^{N} (1 - P_{d,x_{j,l}}) \right] \right\} \quad (3)$$

$$Q_f = \sum_{i=k}^{N} \left\{ \sum_{j=1}^{C_N^k} \left[\prod_{l=1}^{k} P_{f,x_{j,l}} \times \prod_{l=k+1}^{N} (1 - P_{f,x_{j,l}}) \right] \right\} \quad (4)$$

where $C_N^k = N!/(k!(N-k)!)$. Note that the OR rule corresponds to the case of $k = 1$, i.e.,

$$Q_d = 1 - \prod_{i=1}^{N} (1 - P_{d,i}) \quad (5)$$

$$Q_f = 1 - \prod_{i=1}^{N} (1 - P_{f,i}) \quad (6)$$

and the AND rule for that of $k = N$, i.e.,

$$Q_d = \prod_{i=1}^{N} P_{d,i} \quad (7)$$

$$Q_f = \prod_{i=1}^{N} P_{f,i}. \quad (8)$$

C. Related Work

There have been extensive research activities on proposing optimal strategies to improve the spectrum sensing performance [20]–[22]. For example, Liang *et al.* [6] formulate a sensing–throughput tradeoff problem of designing the sensing duration to maximize the achievable throughput of SUs. In [18], Lee and Akyildiz develop a framework for optimizing the sensing parameters to maximize the sensing efficiency with the interference avoidance constraint. These literatures adjust the sensing time to optimize the spectrum sensing performance. However, energy efficiency and network lifetime are not considered. In [23], Peh and Liang show that cooperating all SUs in the network does not necessarily achieve the optimal performance of cooperative spectrum sensing; the best is to coordinate a certain number of them who have the highest SNR. In [24], Zhang *et al.* derive a half-voting fusion rule to optimize the energy threshold and, hence, the cooperation performance. Nevertheless, they do not focus on maximizing the network lifetime.

The problem of energy minimization in sensor-aided CR networks is addressed in [25] and [26]. Given thresholds for cooperative detection and false alarm probabilities, they find the optimal sensing interval and sensor number to minimize energy consumption. However, they are only concerned about how to find one subset of sensors whose energy consumption is minimum. Our work differs from them by dividing sensors into a number of subsets satisfying the necessary thresholds, but does not care about which subset consumes the minimum energy. We focus on activating these subsets successively to maximize the total network lifetime.

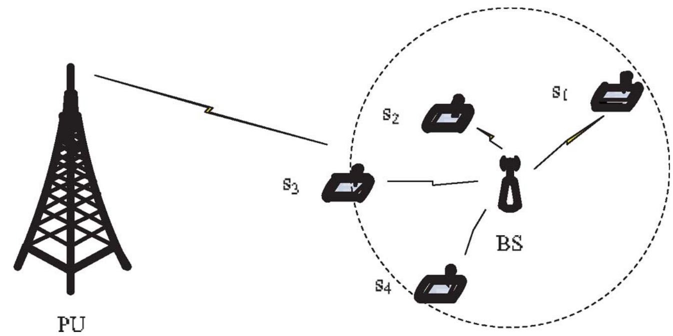

Fig. 1. Sensor-aided CR network model.

There are works on the energy-efficient coverage problem in wireless sensor networks (WSNs). For example, Zou and Chakrabarty [27] present an efficient technique for the selection of active sensors to reduce energy consumption while providing full coverage and connectivity. In [28], Berman *et al.* formulate the problem of maximizing sensor network lifetime while the monitored area is partially or fully covered. In [29], Cardei *et al.* model the energy-efficient target coverage as a maximum set covering problem and propose two efficient heuristic approaches. Our work extends from these existing literatures in WSNs to prolong the lifetime of a sensor-aided CR network for cooperative spectrum sensing.

III. Energy-Efficient Formulation and Degradation

We consider a sensor-aided CR network composed of randomly deployed sensors and a BS, as shown in Fig. 1. The BS coordinates the sensor network for cooperative spectrum sensing. The outcome detection on whether PUs are occupying the channel will be reported to SUs who want to access the channel.

A. ECSSP

In such sensor-aided CR network, before scheduling, the BS acquires information on the average SNR at each sensor (such information is required only once, after that, each sensor only needs to forward its 1-bit decision for fusion); thus, the detection and false alarm probabilities $P_{d,i}$ and $P_{f,i}$ of the sensor s_i can be evaluated by (1) and (2). The sensing period t_s is assumed to be the same among all sensors. Since the collected energy E_i depends on the sensing period, it makes sense to have the energy threshold ε_i dependent on t_s. Based on the average SNR at each sensor and the same t_s, we assign an optimal ε_i to each sensor to maximize its individual $P_{d,i}$ and meanwhile minimize its individual $P_{f,i}$. Our problem is to schedule each sensor active time for cooperative spectrum sensing while satisfying the necessary detection and false alarm thresholds $\overline{Q}_d$ and $\overline{Q}_f$ to prolong the network lifetime. In general, the scheduling steps are the following: 1) Based on each sensor $P_{d,i}$ and $P_{f,i}$, the BS designs an optimal schedule and broadcasts. 2) Each sensor then alternates between active and sleep modes according to the schedule.

TABLE I
$P_{d,i}$ AND $P_{f,i}$ OF THE SENSOR s_i

	s_1	s_2	s_3	s_4
P_d	0.713	0.894	0.967	0.775
P_f	0.116	0.198	0.314	0.173

1) Definition 1—ECSSP: Given a set of N sensors $C = \{s_1, s_2, \ldots, s_N\}$, find a series of nondisjoint subsets $S_1, S_2, \ldots, S_K$ from C with time coefficients $t_1, t_2, \ldots, t_K \in (0, 1]$, respectively, while guaranteeing that each subset S_j satisfies the necessary detection and false alarm thresholds $\overline{Q}_d$ and $\overline{Q}_f$ to maximize the network lifetime $t_1 + t_2 + \cdots + t_K$. For each sensor s_i, it appears in $S_1, S_2, \ldots, S_K$ with total time of at most 1, which is assumed as the lifetime of each sensor.

ECSSP can be mathematically formulated as

$$\max_{t_j, x_{ij}} t_1 + t_2 + \cdots + t_K \tag{9}$$

$$\text{s.t.} \quad \begin{cases} Q_{d,j} \geq \overline{Q}_d, & \text{for } j = 1, 2, \ldots, K \\ Q_{f,j} \leq \overline{Q}_f, & \text{for } j = 1, 2, \ldots, K \\ \sum_{j=1}^{K} x_{ij} t_j \leq 1, & \text{for } i = 1, 2, \ldots, N \end{cases} \tag{10}$$

where $t_j \in (0, 1]$, $x_{ij} \in \{0, 1\}$ ($x_{ij} = 1$ if and only if $s_i \in S_j$). Since [19] has proved that the OR rule always outperforms the AND and Majority rules in energy detector-based cooperative spectrum sensing, we only focus on ECSSP with OR rule in (5) and (6) to achieve energy efficiency, which is formulated as

$$\max_{t_j, x_{ij}} t_1 + t_2 + \cdots + t_K \tag{11}$$

$$\text{s.t.} \quad \begin{cases} 1 - \prod_{i=1}^{N} (1 - x_{ij} P_{d,i}) \geq \overline{Q}_d, & \text{for } j = 1, 2, \ldots, K \\ 1 - \prod_{i=1}^{N} (1 - x_{ij} P_{f,i}) \leq \overline{Q}_f, & \text{for } j = 1, 2, \ldots, K \\ \sum_{j=1}^{K} x_{ij} t_j \leq 1, & \text{for } i = 1, 2, \ldots, N \end{cases} \tag{12}$$

where $t_j \in (0, 1]$, $x_{ij} \in \{0, 1\}$ ($x_{ij} = 1$ if and only if $s_i \in S_j$).

Theorem 1: ECSSP is $\mathcal{NP}$-complete.

Proof: See the Appendix. ■

Let us consider a numerical example of ECSSP with four sensors s_1, s_2, s_3, and s_4, as in Fig. 1. The detection and false alarm probabilities $P_{d,i}$ and $P_{f,i}$ of the sensor s_i have been evaluated as in Table I. Assume the cooperative detection and false alarm thresholds $\overline{Q}_d = 0.9$ and $\overline{Q}_f = 0.3$. We find out the maximum number of subsets satisfying the necessary thresholds, i.e., $S_1 = \{s_1, s_2\}$, $S_2 = \{s_1, s_4\}$ and $S_3 = \{s_2, s_4\}$, as shown in Table II. Since each sensor has been assumed to have the same lifetime of 1, the maximum network lifetime is proved to be 1.5, which can be obtained by assigning each of the three feasible subsets with 0.5 active time respectively, as in Fig. 2. If no scheduling is performed, the network lifetime is only 1. However, with optimal scheduling, the network lifetime is improved by 50%.

Note that both cooperative detection and false alarm probabilities rise with an increase of sensor number in (5) and (6), where the OR rule is adopted for decision fusion. This characteristic leads to the following tips: 1) If a subset does not satisfy $Q_d \geq \overline{Q}_d$, we can add more sensors into the subset to make it satisfied. 2) However, if a subset does not satisfy $Q_f \leq \overline{Q}_f$, adding sensors will make no sense. Therefore, as shown in Table II, for example, when $\{s_3\}$ dose not satisfy $Q_f \leq \overline{Q}_f$, there is no need to consider the subset that consists of $\{s_3\}$ anymore. Such approach wipes off some unnecessary calculations. Despite high computational complexity, the algorithm, which we call Implicit Enumeration (IE), can find out all feasible subsets.

TABLE II
SUBSETS FEASIBLE FOR NECESSARY DETECTION AND FALSE ALARM THRESHOLDS

	$\{s_1\}$	$\{s_2\}$	$\{s_3\}$	$\{s_4\}$
Q_d	0.713✗	0.894✗	0.967✓	0.775✗
Q_f	0.116✓	0.148✓	0.314✗	0.173✓
	$\{s_1, s_2\}$	$\{s_1, s_4\}$	$\{s_2, s_4\}$	
Q_d	0.970✓	0.935✓	0.976✓	
Q_f	0.247✓	0.269✓	0.295✓	
	$\{s_1, s_2, s_4\}$			
Q_d	0.993✓			
Q_f	0.377✗			

B. Greedy Degradation

Note that for a solution $\{t_j, x_{ij}\}$, we can always find a sufficiently small granularity $\omega \in (0, 1]$ such that each t_j can be expressed as an integral multiple of ω. Therefore, we can first find out the least weighted subset (as defined in Section III-C, where the weight is inversely associated with the sensor residual lifetime) S_1 satisfying the necessary detection and false alarm thresholds and place it at the first ω, update the residual lifetime and weight that each sensor belongs to S_1, and again choose the second least weighted subset S_2 at the second ω, so forth until there is none subset feasible for the constraints. The least weighted subset ensures that we try to select the least number of sensors with the most residual lifetime to satisfy the thresholds at each iteration. The algorithm is referred to as Greedy Degradation, which returns suboptimal solution to ECSSP.

The granularity ω is in fact a time interval for how long the subset S_j is active. For example, if $\omega = 0.2$, it means each sensor can participate in at most five subsets. If $\omega = 1$, it corresponds to disjoint subsets, because each sensor can only participate in one subset.

Algorithm 1: Greedy Degradation
1: Given $C = \{s_1, s_2, \ldots, s_N\}$
2: Given $l_1 = l_2 = \cdots = l_N = 1$
3: $w_i = \text{func}(l_i)$, for $i = 1, 2, \ldots, N$
4: $j = 0$
5: **while** the feasible least weighted subset (by solving LWSP in Section III-C) $S \neq \emptyset$ **do**
6: $j = j + 1$
7: $S_j = S$
8: **for** each $s_i \in S_j$ **do**

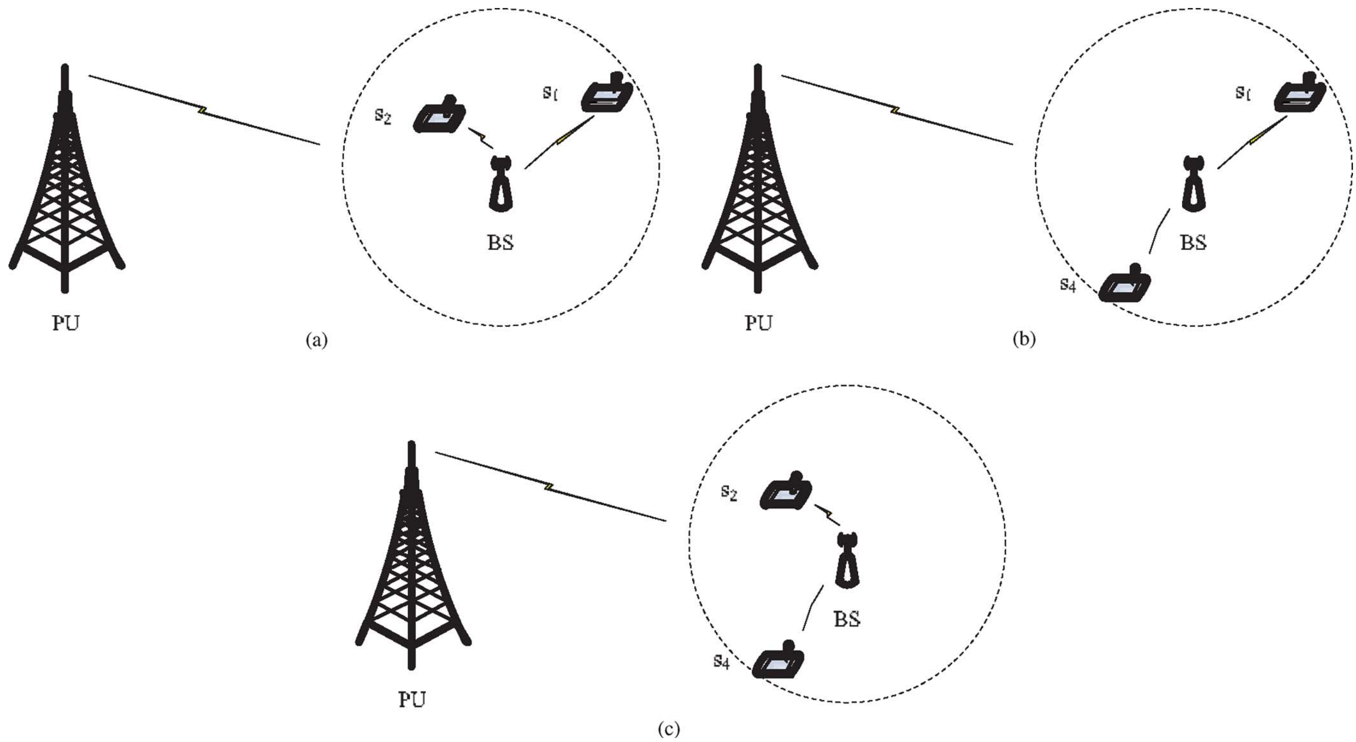

Fig. 2. Three feasible subsets: $S_1 = \{s_1, s_2\}$, $S_2 = \{s_1, s_4\}$, and $S_3 = \{s_2, s_4\}$ with 0.5 active time, respectively. (a) $S_1 = \{s_1, s_2\}$. (b) $S_2 = \{s_1, s_4\}$. (c) $S_3 = \{s_2, s_4\}$.

9: $l_i = l_i - \omega$
10: $w_i = \text{func}(l_i)$
11: **if** $l_i < \omega$ **then**
12: $C = C \backslash \{s_i\}$
13: **end if**
14: **end for**
15: **end while**
16: $G = j$
17: **if** $G == 0$ **then**
18: **return** $\emptyset$
19: **else**
20: **return** $S_1, S_2, \ldots, S_G$
21: **end if**

The Greedy Degradation algorithm takes, as the inputs, C the set of available sensors, ω the granularity, and l_i and w_i the residual lifetime and weight of each sensor and returns feasible subsets $S_1, S_2, \ldots, S_G$. The function "$w_i = \text{func}(l_i)$" in lines 3 and 10 represents a mapping function from l_i to w_i, which is monotonically decreasing to show the inverse relationship. The algorithm forms feasible subsets step by step, from line 5 to 15. The set C maintains the available sensors whose residual lifetime is at least ω; thus, they can participate in additional subsets. When a feasible subset S_j is formed, the residual lifetime and weight of each sensor belonging to S_j are updated in lines 9 and 10. Once a sensor depletes its lifetime, it is removed from the available set from line 11 to 13. The total network lifetime will be $\omega \times G$, which is obtained by assigning each feasible subset with the active interval ω.

C. Least Weighted Subset Problem (LWSP)

Greedy Degradation degrades ECSSP into a series of subproblems, where the least weighted subset of sensors satisfying the necessary detection and false alarm thresholds is selected from the available set at each iteration.

Definition 2: LWSP: Given a set of M available sensors $C = \{s_1, s_2, \ldots, s_M\}$ and a set of weight coefficients $w_i > 0$ corresponding to each sensor s_i, find out a subset S from C satisfying the necessary detection and false alarm thresholds $\overline{Q}_d$ and $\overline{Q}_f$ with a minimum total weight.

LWSP can mathematically be formulated as

$$\min_{x_i} \sum_{i=1}^{M} x_i w_i \tag{13}$$

$$\text{s.t.} \quad \begin{cases} 1 - \prod_{i=1}^{M} (1 - x_i P_{d,i}) \geq \overline{Q}_d \\ 1 - \prod_{i=1}^{M} (1 - x_i P_{f,i}) \leq \overline{Q}_f \end{cases} \tag{14}$$

where $x_i \in \{0, 1\}$ ($x_i = 1$ if and only if s_i is selected).

Note that (14) is nonlinear. Thus, we perform the following equivalent transformation:

$$(14) \Leftrightarrow \begin{cases} \sum_{i=1}^{M} \ln(1 - x_i P_{d,i}) \leq \ln(1 - \overline{Q}_d) \\ \sum_{i=1}^{M} \ln(1 - x_i P_{f,i}) \geq \ln(1 - \overline{Q}_f) \end{cases}$$

$$\Leftrightarrow \begin{cases} \sum_{i=1}^{M} x_i \ln(1 - P_{d,i}) \leq \ln(1 - \overline{Q}_d) \\ \sum_{i=1}^{M} x_i \ln(1 - P_{f,i}) \geq \ln(1 - \overline{Q}_f) \end{cases}$$

$$\Leftrightarrow \begin{cases} \sum_{i=1}^{M} x_i a_i \geq 1 \\ \sum_{i=1}^{M} x_i b_i \leq 1 \end{cases}$$

where

$$\begin{cases} a_i = \frac{\ln(1-P_{d,i})}{\ln(1-\overline{Q}_d)} > 0 \\ b_i = \frac{\ln(1-P_{f,i})}{\ln(1-\overline{Q}_f)} > 0 \end{cases}, \quad \text{for } i = 1, 2, \ldots, M.$$

The proof of $\ln(1 - x_i P_{d,i}) = x_i \ln(1 - P_{d,i})$ is as follows: since x_i can only be 0 or 1, 1) when $x_i = 0$, then $\ln(1 - x_i P_{d,i}) = \ln 1 = 0 = x_i \ln(1 - P_{d,i})$; and 2) when $x_i = 1$, then $\ln(1 - x_i P_{d,i}) = \ln(1 - P_{d,i}) = x_i \ln(1 - P_{d,i})$. Based on it, LWSP can be reformulated as a linear integer programming problem

$$\min_{x_i} \sum_{i=1}^{M} w_i x_i \tag{15}$$

$$\text{s.t.} \quad \begin{cases} \sum_{i=1}^{M} a_i x_i \geq 1 \\ \sum_{i=1}^{M} b_i x_i \leq 1 \end{cases} \tag{16}$$

where $w_i, a_i, b_i > 0$, $x_i \in \{0, 1\}$.

IV. Solution to Least Weighted Subset Problem

Note that LWSP is a variation of the Knapsack problem (KP), a known $\mathcal{NP}$-complete problem. We propose three approaches, namely, IE, GG, and λG to solve it, which in turn solve the ECSSP. Among them, IE can obtain the optimal solution with the highest complexity, whereas GG solves it worst with the lowest complexity. A brand new λG is proposed to approach the performance of IE with complexity comparable with GG.

A. IE

We have described the IE of finding out all the feasible subsets satisfying (16) in Section III-A. Selecting the least weighted subset from them is apparently the optimal solution to LWSP. Unfortunately, IE has a complexity of $O(2^M)$, which implies that the running time grows exponential to the sensor number.

Algorithm 2: IE

```
1: Given w = [w_1, w_2, ..., w_M]
2: Given a = [a_1, a_2, ..., a_M]
3: Given b = [b_1, b_2, ..., b_M]
4: x = zeros(1, M)
5: y = zeros(2^M, M)
6: i = 1
7: j = 0
8: [y, j] = Recursion(a, b, x, y, i, j)
9: if j = 0 then
10:    return zeros(1, M)
11: end if
12: for k = 1 to j do
13:    v_k = w * y(k, :)'
14: end for
15: find y(k, :)* with minimum v_k*
16: x = y(k, :)*
17: return x
```

```
1: function [y, j] = Recursion(a, b, x, y, i, j)
2: x(i) = 1
3: if b * x' <= 1 then
4:    if a * x' >= 1 then
5:       j++
6:       y(j, :) = x
7:    end if
8:    if i < M then
9:       [y, j] = Recursion(a, b, x, y, i + 1, j)
10:   end if
11: end if
12: x(i) = 0
13: if i < M then
14:    [y, j] = Recursion(a, b, x, y, i + 1, j)
15: end if
```

The IE algorithm takes as the inputs the weight coefficients w and the constraint coefficients of each sensor a and b and returns the optimal subset x ($x_i = 1$ if and only if s_i is selected), where $x = \text{zeros}(1, M)$ if there is none feasible subset. "$[y, j] = \text{Recursion}(a, b, x, y, i, j)$" in line 8 is a recursive function, which returns all feasible subsets satisfying (16) y and the number of them j.

B. GG

Consider a classic KP, i.e., a profitable packing of items into the knapsack [30]: $\begin{matrix} \max \sum_{j=1}^{n} p_j x_j \\ \text{s.t. } \sum_{j=1}^{n} w_j x_j \leq c \end{matrix}$, where $p_j, w_j > 0$, $x_j \in \{0, 1\}$, c for a constant. The greedy algorithm is to consider the profit to weight ratio (called efficiency) of each item as $e_j := p_j / w_j$ and try to put the items with the highest efficiency into the knapsack. Clearly, these items generate the highest profit while consuming the lowest amount of capacity. Although the greedy algorithm cannot always obtain the optimal solution, its complexity, and hence running time, is much lower than IE.

Note that (16) can be relaxed as follows: (16) $\Rightarrow \sum_{i=1}^{M} a_i x_i \geq \sum_{i=1}^{M} b_i x_i \Rightarrow \sum_{i=1}^{M} (a_i - b_i) x_i \geq 0$; thus, the LWSP can be relaxed into a problem similar to the classic KP, i.e.,

$$\min_{x_i} \sum_{i=1}^{M} w_i x_i \tag{17}$$

$$\text{s.t.} \quad \sum_{i=1}^{M} (a_i - b_i) x_i \geq 0 \tag{18}$$

where $w_i, a_i, b_i > 0$, $x_i \in \{0, 1\}$.

Based on [30], GG starts with an empty subset and simply goes through the sensors in decreasing order of efficiency, adding them one by one into the subset until (16) is satisfied. We consider the efficiency of each sensor as

$$e_i := \frac{a_i - b_i}{w_i} \tag{19}$$

which has a complexity of $\mathrm{O}(M \log M)$, mainly due to sorting the sensors in decreasing order of efficiency such as $(a_1 - b_1)/w_1 \geq (a_2 - b_2)/w_2 \geq \cdots \geq (a_M - b_M)/w_M$.

Algorithm 3: GG

sort w, a, b as $(a_1 - b_1)/w_1 \geq (a_2 - b_2)/w_2 \geq \cdots \geq (a_M - b_M)/w_M$
$x = \mathrm{zeros}(1, M)$
for $i = 1$ to M **do**
  $x_i = 1$
  if $b * x' \leq 1$ **then**
    if $a * x' \geq 1$ **then**
      return x
    end if
  else
    return $\mathrm{zeros}(1, M)$
  end if
end for

The GG algorithm takes as the inputs the weight coefficients w and the constraint coefficients of each sensor a and b and returns a suboptimal subset x ($x_i = 1$ if and only if s_i is selected), where $x = \mathrm{zeros}(1, M)$ means that there is no feasible subset.

C. λG

To improve the performance of GG, we define a different kind of efficiency for the greedy algorithm. For example, by means of Lagrange multiplier, we can incorporate one constraint into the objective function $\min_{x_i} \sum_{i=1}^{M} w_i x_i + \lambda(\sum_{i=1}^{M} b_i x_i - 1) \Leftrightarrow \min_{x_i} \sum_{i=1}^{M} (w_i + \lambda b_i) x_i$, where $\lambda \geq 0$ to have $\sum_{i=1}^{M} b_i x_i \leq 1$. Thus, the LWSP can be transformed into another problem also similar to the classic KP, i.e.,

$$\min_{x_i} \sum_{i=1}^{M} (w_i + \lambda b_i) x_i \tag{20}$$

$$\text{s.t.} \quad \sum_{i=1}^{M} a_i x_i \geq 1 \tag{21}$$

where $w_i, a_i, b_i > 1, \lambda \geq 1, x_i \in \{1, 1\}$.

Based on [30], λG starts with an empty subset and simply goes through the sensors in decreasing order of efficiency, adding them one by one into the subset until (16) is satisfied. We consider the efficiency of each sensor as

$$e_i := \frac{a_i}{(w_i + \lambda b_i)} \tag{22}$$

which has a complexity of $\mathrm{O}(M \log M)$.

Algorithm 4: λG

Given $C = \{s_1, s_2, \ldots, s_M\}$
Given λ
for each $s_i \in C$ **do**
  $e_i = a_i/(w_i + \lambda b_i)$
end for
$S = \emptyset$
while S cannot satisfy (16) **do**
  if $S == C$ **then**
    $S = \emptyset$
    break
  end if
  for $s_i \in C \backslash S$, find s_i^* with maximum e_i^*
  $S = S \cup s_i^*$
end while
return S

The λG algorithm takes as inputs the set of the available sensors C, the weight coefficients w, and the constraint coefficients of each sensor a and b, and returns the suboptimal subset S, where $S = \emptyset$ means there is no feasible subset.

We then have a new problem on how to choose an appropriate λ to obtain the best suboptimal solution to LWSP. Note that λ is actually used to coordinate the proportions of w_i and b_i in the decreasing order sorting of $a_i/(w_i + \lambda b_i)$. Considering two extreme cases, i.e., $\lambda = 0$, b_i has no effect on the sorting of a_i/w_i and $\lambda = +\infty$, w_i has no role in the sorting of a_i/b_i. Since λ will affect the efficiency value and hence the order of sensors being selected, it is important to optimize the value of λ.

Assume two arbitrary efficiency values $a_i/(w_i + \lambda b_i)$ and $a_j/(w_j + \lambda b_j)$, the critical λ which may change the decreasing-order sorting of these two efficiency values is obtained by letting $a_i/(w_i + \lambda b_i) = a_j/(w_j + \lambda b_j)$. Thus, we calculate all these critical values of λ, i.e.,

$$\lambda(i, j) = \frac{a_j w_i - a_i w_j}{a_i b_j - a_j b_i} \tag{23}$$

where $i = 1, 2, \ldots, M$, and $j = i + 1, \ldots, M$. There are a total of $M(M-1)/2$ values for λ. The best suboptimal solution to LWSP can be obtained by considering those λ's of positive value [recall $\lambda \geq 0$ as specified in (20) and (21)], and the two extreme cases of 0 and $+\infty$. By applying these values of λ to the λG algorithm, the best suboptimal solution can be obtained with a complexity of $\mathrm{O}(M^3 \log M)$.

V. Simulation

Simulation results are presented to verify the performance of our approaches as well as to study the effect of adjustable parameters on the performance. We simulate a stationary sensor-aided CR network whose sensors are randomly deployed, with sensor number N and granularity ω as adjustable parameters.

First, we evaluate the performance of Greedy Degradation for ECSSP compared with random selection, where the feasible subset at each iteration is randomly selected. We consider ten different networks whose sensors are random deployment with $N = 20$ and $\omega = 0.1$. In Fig. 3, it can be observed that the network with Greedy Degradation always has a longer lifetime than that with random selection. This is because Greedy Degradation selects the least weighted subset at each iteration, which ensures that we use the least number of sensors with the

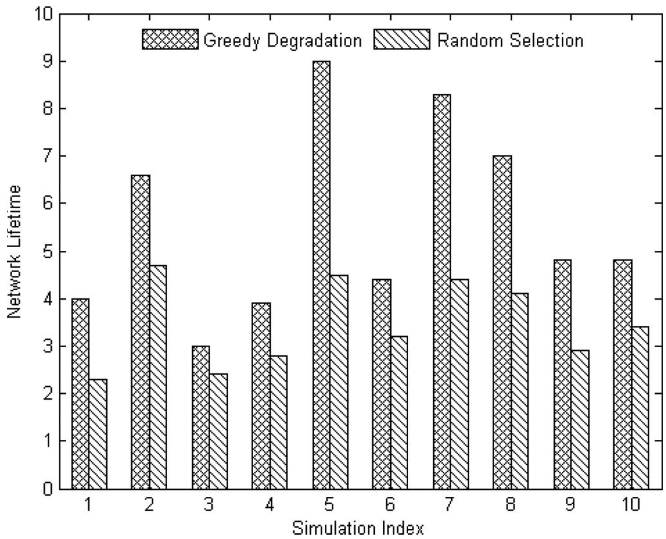

Fig. 3. Comparison between Greedy Degradation and random selection when $N = 20$ and $\omega = 0.1$.

most residual lifetime at the very beginning; hence, the network lifetime can be extended.

Next, we compare the performance of the three approaches to LWSP. In Fig. 4, we show that IE can obtain the optimal solution at the cost of the highest complexity, GG provides the lowest complexity but the shortest network lifetime, and λG approaches IE with complexity comparable with GG.

Finally, we investigate how the adjustable parameters affect the performance. Typically, we consider the following.

1) The sensor number N varies from 2 to 20, with a step size of 1, when $\omega = 0.1$, to study the effect of sensor density. In Fig. 5, the network lifetime computed by three approaches is presented respectively as functions of the sensor number. It can be observed that the network lifetime by three approaches increases with an increase in sensor density. This is because, in general, the more sensors are deployed in the area, the more feasible subsets satisfy the necessary detection and false alarm thresholds.
2) The granularity ω varies from 1 to 1^{-10}, with binary logarithm decrement of 1, when $N = 10$, to study the effect of iterations. In Fig. 6, we show the convergence of the network lifetime with a decrease of granularity. It is observed that when the granularity becomes sufficiently small, which leads to an increase number of iterations, the network lifetime will increase to a fixed value. For example, with ten sensors, we obtain the network lifetime up to 5 by IE when the granularity approaches 2^{-10}.

VI. Conclusion

Due to the energy constraint of battery-powered sensors, energy efficiency is desirable for cooperative spectrum sensing in sensor-aided CR networks. Through optimal scheduling of each sensor active time, we can effectively extend the network lifetime. We divide the sensors into a number of nondisjoint feasible subsets, such that only the sensors from the current active subset are responsible for sensing, while all the others are in a low-energy sleep mode. Such scheduling problem is

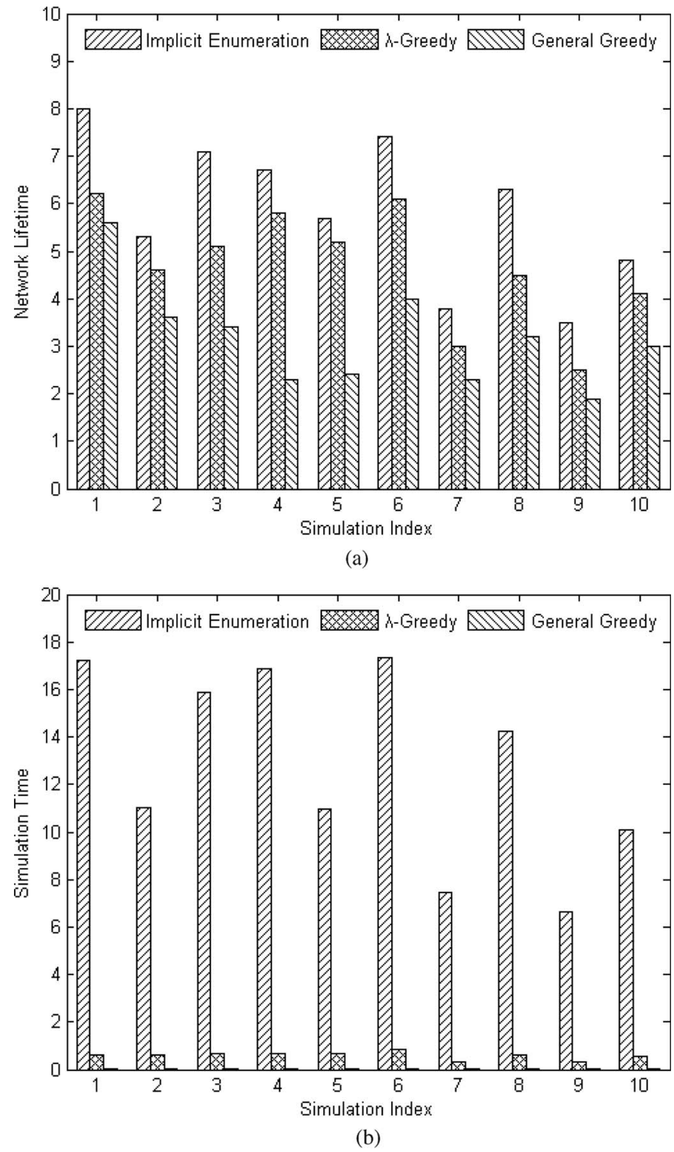

Fig. 4. Comparison among IE, GG, and λG when $N = 20$ and $\omega = 0.1$. (a) Comparison in network lifetime. (b) Comparison in simulation time.

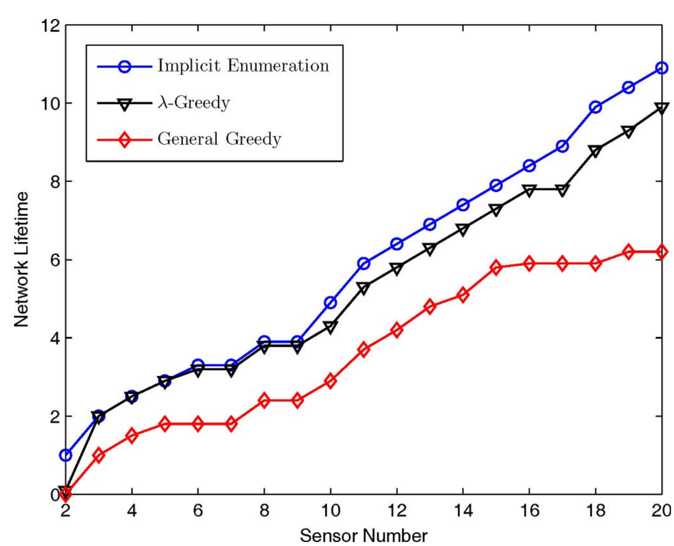

Fig. 5. Network lifetime versus sensor number when $\omega = 0.1$.

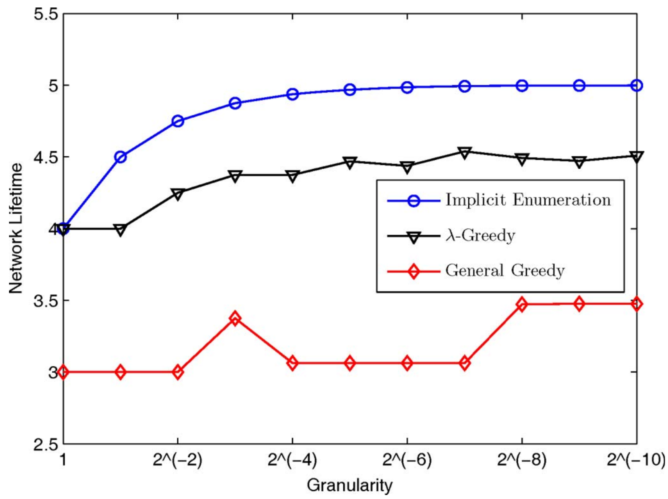

Fig. 6. Network lifetime versus granularity when $N = 10$.

proved to be $\mathcal{NP}$-complete. After degrading it into a series of subproblems, we propose three approaches to solve it. Simulation results demonstrate the tradeoff between network lifetime and computational complexity. Energy-efficient scheduling for multichannel spectrum sensing will be considered as our future work.

Appendix
Energy-Efficient Formulation Is $\mathcal{NP}$-Complete

For simplicity, ECSSP of (11) and (12) can be reformulated as

$$\max_{t_j, x_{ij}} \sum_{j=1}^{K} t_j \tag{24}$$

$$\text{s.t.} \quad \begin{cases} \sum_{i=1}^{N} a_i x_{ij} \geq 1, & \text{for } j = 1, 2, \ldots, K \\ \sum_{i=1}^{N} b_i x_{ij} \leq 1, & \text{for } j = 1, 2, \ldots, K \\ \sum_{j=1}^{K} t_j x_{ij} \leq 1, & \text{for } i = 1, 2, \ldots, N \end{cases} \tag{25}$$

where $a_i, b_i > 0$, $t_j \in (0, 1]$, $x_{ij} \in \{0, 1\}$. The details are elaborated upon in Section III-C.

To prove that ECSSP is $\mathcal{NP}$-complete, we transform it to a decision problem (i.e., to be answered by "yes" or "no") by comparing the objective value with a threshold value. For example, ECSSP-DECISION is defined as

$$\begin{cases} \text{whether there exists } \{t_j, x_{ij}\} \text{ with} & \\ \sum_{j=1}^{K} t_j \geq \bar{t} & \\ \sum_{i=1}^{N} a_i x_{ij} \geq 1, & \text{for } j = 1, 2, \ldots, K \\ \sum_{i=1}^{N} b_i x_{ij} \leq 1, & \text{for } j = 1, 2, \ldots, K \\ \sum_{j=1}^{K} t_j x_{ij} \leq 1, & \text{for } i = 1, 2, \ldots, N \\ t_j \in [0, 1], x_{ij} \in \{0, 1\}. & \end{cases}$$

Lemma 1: ECSSP $\in \mathcal{NP}$, i.e., ECSSP-DECISION can be verified in polynomial time.

Proof: Consider that we are given a series of subsets $S_1, S_2, \ldots, S_K$ with time coefficients $t_1, t_2, \ldots, t_K$ and a threshold value $\bar{t}$. We can verify the following in polynomial time.

1) $\sum_{j=1}^{K} t_j \geq \bar{t}$.
2) Each subset S_j satisfies the necessary detection and false alarm thresholds.
3) For each sensor s_i, it appears in $S_1, S_2, \ldots, S_K$ with total time of at most 1.

■

Lemma 2: ECSSP is $\mathcal{NP}$-hard, i.e., ECSSP-DECISION can be reduced from a known $\mathcal{NP}$-complete problem in polynomial time.

Proof: KP is a known $\mathcal{NP}$-complete problem [30]. KP-DECISION is defined as

$$\begin{cases} \text{whether there exists } \{x_i\} \text{ with} \\ \sum_{i=1}^{N} p_i x_i \geq \bar{p} \\ \sum_{i=1}^{N} w_i x_i \leq c \\ x_i \in \{0, 1\}. \end{cases}$$

To show the $\mathcal{NP}$-hardness of ECSSP, we reduce from KP-DECISION. We restrict ECSSP-DECISION by allowing only instances in which $K = 1$. That is

$$\begin{cases} \text{whether there exists } \{t, x_i\} \text{ with} & \\ t \geq \bar{t} & \\ \sum_{i=1}^{N} a_i x_i \geq 1 & \\ \sum_{i=1}^{N} b_i x_i \leq 1 & \\ t x_i \leq 1, & \text{for } i = 1, 2, \ldots, N. \\ t \in [0, 1], x_i \in \{0, 1\} & \end{cases}$$

Setting $a_i = p_i/\bar{p}$, $b_i = w_i/c$ for $i = 1, 2, \ldots, N$, we notice that KP-DECISION has a feasible solution if the corresponding ECSSP-DECISION has a feasible solution. Therefore, ECSSP can be reduced from KP, and the reduction runs in polynomial time. ■

From the above, since ECSSP belongs to class $\mathcal{NP}$ and is $\mathcal{NP}$-hard, we can conclude that it is $\mathcal{NP}$-complete [31].

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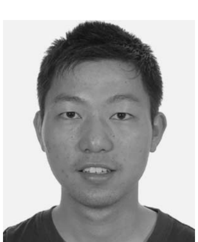

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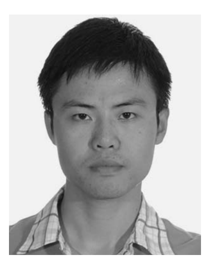

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