Energy-Efficient Spectrum Sensing for IoT Devices

Nhu-Ngoc Dao, Woongsoo Na, Anh-Tien Tran, Diep N. Nguyen, and Sungrae Cho

***Abstract*—Device-to-device communications have been considered as an indispensable enabler, which reduces the traffic burden associated with fifth-generation (5G) mobile networks. In such communications, cognitive spectrum sensing identifies the available spectrum resources for direct interconnections among user devices. Although various sensing techniques have been proposed during the last decade, improving the sensing efficiency (SE), such as energy reduction and positive sensing ratio, remains an open challenge. The problem becomes severe in 5G networks, wherein battery-constrained Internet-of-things devices (IoTDs) are densely interconnected. In this paper, we optimize the SE based on adaptive medium learning with a probabilistic decay feature. The wireless channels that are potentially available for IoTDs are sorted and sensed in the descending order of their probabilities, which indicate the estimated percentage of the availability of the sensed channels. The probabilities learn from the preceding sensing-results, and they decay with time. Numerical results show that the proposed sensing approach achieves significant SE improvement compared to existing algorithms.**

***Index Terms*—spectrum sensing, sensing efficiency, D2D communications, probabilistic sensing, uncertain wireless environment**

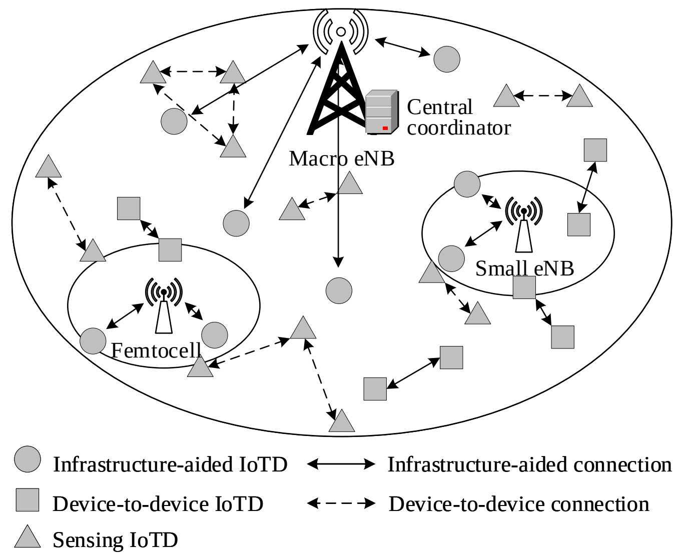

Fig. 1. Cognitive radio for IoTD communications in 5G environments.

I. Introduction

The ever-increasing number of connected devices has been considered as one of the key motivations for the development of fifth-generation (5G) mobile networks. The rapid development of the Internet of Things (IoT) paradigm, with various emerging applications to our life, is the clearest evidence for this status quo. As estimated by Ericsson [1], there will be around 18 billion IoT devices (IoTDs) connected by 2022. The explosion of concurrent IoT connections will definitely overwhelm the 5G spectrum regardless of the allocated bandwidth. As a result, improving the spectrum utilization is an essential challenge that the 5G networks face. To that extent, cognitive radio (CR) has been considered as a great potential solution [2]–[4]. CR introduces opportunistic communications not only for connections between the IoTDs and the networks but also among IoTDs directly by exploiting temporarily available radio channels/spectrum. The temporarily available/idle channels are found through spectrum sensing techniques in which radio devices physically sense wireless channels. Fig. 1 illustrates a prime scenario, wherein dense IoTDs associate with either the eNodeBs (eNBs) or each other. In this environment, infrastructureless connections are established among the IoTDs by utilizing the CR technology [5], [6].

In the 5G environment, two main challenges that force new spectrum sensing technologies to be studied consist of (*i*) a broad spectrum of licensed/unlicensed wireless channels and (*ii*) device-to-device (D2D) communication demands among battery-constrained IoTDs in dense systems. The former makes IoTDs consume a significant amount of time and energy to sense over the entire spectrum, while the latter reveals a problem of energy limitation in the IoTDs. In addition, because the IoTDs are mostly known as small-traffic services (e.g., machine-type communications) [7]–[10], which require a small amount of transmission resource, sensing the entire or a large portion of the 5G spectrum is unnecessary and ineffective. In particular, this leads to poor sensing efficiency (SE) in terms of energy consumption (EC) and positive sensing (PS) ratio. To capture the sensing efficiency, the PS ration is defined as the percentage of the number of sensed channels that are vacant out of the total number of sensed channels. It is seen that 0 ≤ PS ratio ≤ 1. A higher PS ratio implies less channels have to be sensed, i.e., a higher SE. Most existing works on spectrum sensing in 5G [11], [12] overlooked the uncertainty in the set of potential channels (for sensing) and its implication on the SE.

To handle the uncertainty of wireless environment, we propose a novel cognitive spectrum sensing algorithm based on probabilistic sensing and trigger update techniques, namely

This research was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (NRF-2018M1A3A3A02066018).

N.-N. Dao is with the Department of Computer Science and Engineering, Sejong University, Seoul, Korea. (email: nndao@sejong.ac.kr).

W. Na is with the Department of Computer Science and Engineering, Kongju National University, Cheonan 31080, South Korea. (email: wsna@kongju.ac.kr).

A.-T. Tran and S. Cho are with the School of Computer Science and Engineering, Chung-Ang University, Seoul, Korea. (email: attran@uclab.re.kr, srcho@cau.ac.kr).

D. N. Nguyen is with the School of Electrical and Data Engineering, University of Technology Sydney, NSW, Australia. (email: diep.nguyen@uts.edu.au).

Corresponding author: Sungrae Cho.

probabilistic decay featured sensing (PDFS) algorithm. The PDFS adopts a centralized model, wherein a central coordinator (CC) manages and controls the sensing operations in the IoTDs. The IoTDs sense each wireless channel in their proximity with a corresponding probability. The probability estimates the percentage that the wireless channel is considered to be vacant at this moment. This estimation is determined by jointly considering the IoTDs' location and preceding sensing results with respect to the time-dependent decay impact. A new observation of positive (i.e., the channel is idle) or negative (i.e., the channel is busy, not available for secondary use) sensing report will trigger-update the probability accordingly. As a result, the PDFS prioritizes to sense high-probability wireless channels and, therefore, it significantly improves the PS ratio. The main contributions of this paper are summarized as follows:

- At each IoTD, the PDFS dynamically senses a discrete set of wireless channels which have high probabilities of PS. The wireless channels that might lead to negative results are mostly ignored.
- The PDFS improves the SE, hence reduces the energy required for spectrum sensing that is particularly critical for IoTD operations Moreover, overhead reduction of sensing reports and decrease in sensing latency are achieved, resulting in higher channel utilization.
- Extensive simulations confirm that PDFS outperform state-of-the-art sensing algorithms (e.g., [13] and [14]) in both SE and computational complexity.

The remainder of this paper is organized as follows. We present a literature review of cutting-edge sensing algorithms in Section II. Section III clarifies the problem in detail. Section IV describes the sensing efficiency optimization with adaptive medium learning, and we evaluate the performance of the proposed algorithm in Section V. Finally, we draw conclusions and suggest future directions in Section VI.

II. Related Works

Aiming at improving the SE, a variety of cutting-edge sensing algorithms has been proposed in the literature [11], [12]. From an operational model design perspective, the existing algorithms can be classified into two main categories: (*i*) *cooperative* [13]–[18] and (*ii*) *non-cooperative* [19]–[22] models.

In a cooperative model, the CC processes sensing information from all IoTDs to model the status of wireless channels for calculating appropriate sensing parameters, and then dispatches the sensing configurations to the IoTDs. For instance, Na *et al.* [13] proposed a centralized cooperative directional sensing technique to realize fine-grained sensing for IoTDs with directional antennas. The CC collects all reported information via available directional antennas from IoTDs. Based on a joint optimization running on the collected information, the CC assigns optimized sensing parameters (sensing period, sensing power, and sensing beams) to each IoTD. On the other hand, a spatial-temporal sensing nodes selective fusion scheme [14] was proposed to calculate the minimal sensing EC while maintaining the required detection performance. In [15], Xiong *et al.* proposed an adaptive spectrum sensing strategy (ASSS) to improve the SE by strictly considering IoTD traffic parameters. The CC models IoTD traffic-pattern transitions by following discrete-time Markov chain (DTMC) to flexibly decide whether a random or persistent spectrum range should be sensed. To reduce feedback overhead of sensing reports from IoTDs to CC, So *et al.* [16] modified the formal the feedback by applying opportunistic transfer behavior based on a threshold optimized and published by the CC. Only IoTDs that satisfy this threshold are allowed to send feedback data to the CC. Alternatively, because SE maximization cannot be jointly achieved with maximal energy efficiency (EE), Hu *et al.* [17] balanced the SE and EE following two typical strategies: maximizing EE while satisfying SE requirement and vice versa. The corresponding optimal algorithms are developed based on a joint optimization function of sensing duration (SD) and final decision threshold. In [18], an iterative algorithm was proposed to maximize EE by jointly determining the optimal sensing time, data transmission time, and number of IoTDs. The algorithm exploits the impact of transmission power variation to obtain the optimal sensing time and the corresponding probability of sensing false alarm (FA).

Unlike the cooperative system models, adopting non-cooperative models (a.k.a decentralized solutions) forces the IoTDs to individually perform sensing activities and share the results together without the support of a central entity. For instance, Vosoughi *et al.* [19] presented a fully distributed trust-aware consensus-inspired scheme for DCSS that was effective against insistent spectrum sensing data falsification (ISSDF) attacks. This scheme partially removes SE reduction and interference with IoTDs of ISSDF attacks, and boosts flexibility, cost-saving, missed-detection, and FA error rates of cooperative systems. In [20], Hajihoseini *et al.* proposed a distributed diffusion based method to improve convergence rate, reliability against communication link failure, and the performance of spectrum sensing in CR sensor networks. From another perspective, Lu *et al.* [21] proposed a pilot-based IoTD-link channel state information (CSI)-aided sensing strategy to solve CSI mismatch, pilot overhead, and frequency correlation in practical mobile CR ad hoc networks. This strategy was then combined with a multichannel first-come-first-served medium access control (MAC) scheme to resolve IoTDs competition prior to sensing, randomize sensing decisions, and boost the network throughput. Aygun *et al.* [22] proposed a voting-based distributed cooperative sensing algorithm for connected IoTDs based on the probability of FA and missed detection (MD) to converge the spectrum detection error to zero. The algorithm calculates an optimum energy detection threshold to sense the available channels from the IoTDs and selects the one with the highest number of votes.

Although these aforementioned sensing algorithms make significant contributions to improve the SE, a strict consideration of uncertain wireless environment has not been taken into account to provide flexible and adaptable sensing operations.

III. Problem Statement

The SE challenge ($\mathcal{P}$) is expressed as follows: "*Given that there are m wireless channels available in the transmission*

TABLE I
KEY NOTATION DESCRIPTION

Notation	Description
M, S, and N	The sets of available wireless channels, total sensed channels, and vacant sensed channels, respectively.
n	The number of vacant channels that an IoTD requires for its communication.
$\mathbf{e}$	The energy consumed for sensing a wireless channel.
Δ	The differential between S and N.
v_i	the vacancy probability estimated for the i-th channel.
r_i	the sensing result of the i-th channel.
λ	the decay factor that indicates the decay speed of knowledge about channel status.

range of an IoTD, and the IoTD requires n channels for its communication, how to minimize the EC for spectrum sensing activity while satisfying the IoTD requirements". We consider a system model that consists of a central macro eNB and a number of small eNBs/access points/femtocells in the coverage area. All these network devices provide infrastructure-aided communication ability to the users. In this model, the number and locations of small network devices are unknown and mobility realizing an uncertain wireless environment; see Fig. 1. Let M, S, and N denote the sets of available wireless channels, total sensed channels, and vacant sensed channels at each location of IoTD, respectively. It is observed that $N \in S \in M$. In addition, let $\mathbf{e}$ denote the energy consumed for sensing a wireless channel. Table I summarizes the key notations used in this paper. Accordingly, the problem $\mathcal{P}$ is formulated as

$$\mathcal{P} \triangleq \min_{\{x_i\}} \left(\sum_{i}^{M} (x_i \times \mathbf{e}) \right), \tag{1}$$

$$\text{s.t. } \|M\| \geq n, \tag{2}$$

$$n \in \mathbb{N}, \tag{3}$$

$$x_i = \begin{cases} 1 & \text{if } i\text{-th channel is sensed,} \\ 0 & \text{otherwise,} \end{cases} \tag{4}$$

where $\|M\|$ is the size of M. Constraint (2) ensures that there are sufficient number of vacant channels to satisfy the IoTD; otherwise, all the channels in M must be sensed, and an optimal solution is unnecessary. On the other hand, it is obtained that $S = \{x_i | x_i = 1\}$. As defined in Section I, the PS ratio is given by

$$\text{PS} = \frac{\|N\|}{\|S\|}. \tag{5}$$

It is seen that the minimization of $\mathcal{P}$ and the maximization of PS are equivalent and they are obtained if and only if the differential (Δ) between S and N (i.e., $\Delta = \|S\| - \|N\|$) is minimum. Therefore, $\mathcal{P}$ can be expressed as

$$\mathcal{P} \triangleq \min_{S} \Delta, \tag{6}$$

$$\text{s.t. } (2), (3), (4),$$

$$\|N\| \geq n. \tag{7}$$

Because of the uncertainty of the environment, there is insufficient information for the IoTD to make an efficient sensing decision. In other words, $\mathcal{P}$ is a problem with insufficient conditions and it is unresolvable directly. However, from a heuristic approach perspective, the optimal solution for problem $\mathcal{P}$ can be approximately achieved if vacant channels are prioritized to be selected for sensing.

IV. SENSING EFFICIENCY OPTIMIZATION

Aiming at the target "*vacant channels should be selected for sensing*," we propose the PDFS approach, adopting the following methodology:

1) Develop a time-dependent function to estimate the vacancy probabilities of wireless channels in every location.
2) In a location, IoTDs decide to sense the wireless channels on the basis of the estimated vacancy probabilities in a descending order. The IoTDs terminate their sensing operations when either their requirements are fulfilled or all the channels are sensed.

To enable the above methodology, PDFS approach has been designed as a centralized model, wherein a CC at the macro eNB performs the vacancy probability estimation and dispatches appropriate sensing policies to the IoTDs. In the scope of this paper, we consider the channel availability and all channels that are sensed and detected vacant are equally considered to be assigned. However, it is worthy noting that our design can adopt any channel selection/allocation strategy, e.g., the channel quality.

A. Vacancy Probability Estimation

Regarding the location dependency, we rasterize the coverage area of the macro eNB into a location matrix. The vacancy probability vector $\mathcal{V}$ is estimated for each matrix element, which reflects our knowledge about the channels' status. Initially, $\mathcal{V}_j$ at location j-th is given by

$$\mathcal{V}_j = \{v_{ij}\}, \quad i = 1, 2, 3, \ldots, M_j, \tag{8}$$

where the vacancy probability v_{ij} of the i-th channel at location j-th is primitively specified by the following policy:

$$v_{ij} \begin{cases} = 0.5 & \text{if there is no information of the } i\text{-th channel,} \\ \in [0, 0.5) & \text{if the } i\text{-th channel is occupied or previous sensing on this channel is negative,} \\ \in (0.5, 1] & \text{otherwise.} \end{cases} \tag{9}$$

On the contrary, it is seen that the channels' status also depends on the time of the IoTDs. To handle the time dependency, we transform $\mathcal{V}_j$ into a time-dependent function $\mathcal{V}_j[t] = \{v_{ij}[t]\}$, which decays the knowledge of the channel status backward at Ø as t tends to ∞.

In addition, from (9), it is observed that $v_{ij}[0] = 0.5, \forall i, j$. We select this value as a convergence point when applying decay feature to the vacancy probability. Hence, the vacancy probability of the i-th channel is

$$v_{ij}[t] = 0.5 - (0.5 - v_{ij}[t-1]) \times e^{-\lambda t}, \tag{10}$$

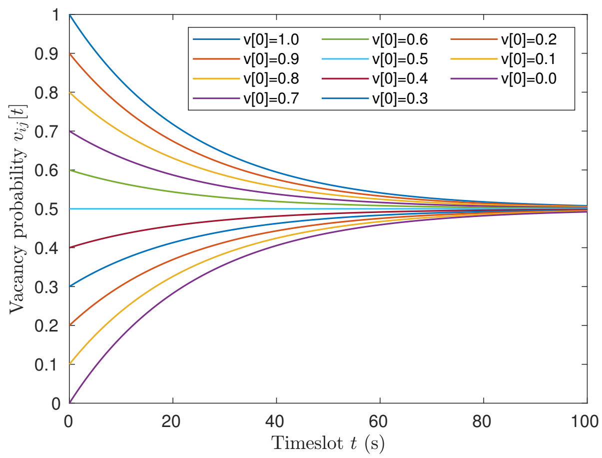

Fig. 2. Time-dependent vacancy probability $v_{ij}[t]$ for various values of $v_{ij}[0]$ with a decay factor λ equal to 0.05.

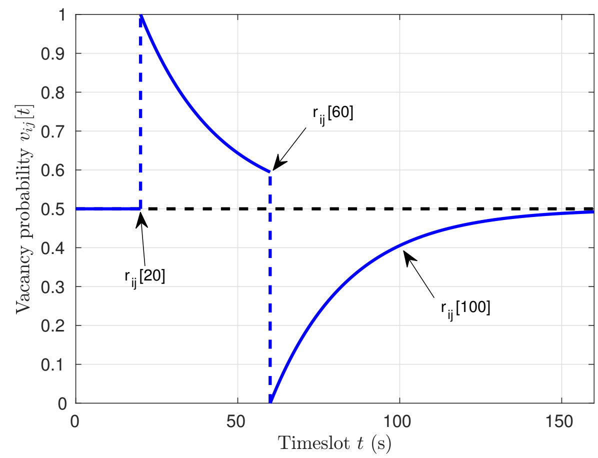

Fig. 3. An example of trigger-update policy on time-dependent vacancy probability $v_{ij}[t]$ with $v_{ij}[0] = 0.5$ when $r_{ij}[20] = 1$, $r_{ij}[60] = 0$, and $r_{ij}[100] = \varnothing$.

where decay factor λ represents the decay speed of the truthfulness about the channel status observed. In general, λ is selected on the basis of IoT service life-time distribution, which usually adopts the Poisson point process (PPP) [23]–[25]. The λ selection ensures that the decay duration approximates the mean of IoTs' service life-time when $v_{ij}[t] \sim 0.5$. Fig. 2 plots the time-dependent vacancy probability $v_{ij}[t]$ for various values of $v_{ij}[0]$ with a decay factor λ equal to 0.05. It is seen that the vacancy probability decreases to approximately 0.5 after 100 timeslots.

To immediately reflect the channel status observed, we use a *trigger-update* policy to renew the vacancy probability of wireless channels. In particular, whenever the CC receives a sensing report from the IoTDs, the vacancy probability is updated accordingly. Let $\mathcal{R}_j = \{r_{ij} \mid i = 1, 2, \ldots, M_j\}$ denote the sensing report observed, where r_{ij} is the sensing result of the i-th channel at location j-th. Here, r_{ij} is given by

$$r_{ij} = \begin{cases} 0 & \text{if the } i\text{-th channel is sensed and it is occupied,} \\ 1 & \text{if the } i\text{-th channel is sensed and it is vacant,} \\ \varnothing & \text{otherwise.} \end{cases} \tag{11}$$

Among the channels in which r_{ij} values are equal to 1, several channels will be assigned to the IoTD for its communication requirements afterward. Because these channels will be occupied by the IoTD, their corresponding r_{ij} values are updated to 0 in order to reflect the upcoming occupation. Finally, the CC performs trigger updates on every element $r_{ij}[t]$ of the current $\mathcal{V}_j[t]$ based on the received sensing report $\mathcal{R}_j$ as follows:

$$v_{ij}[t] = \begin{cases} r_{ij} & \text{if } r_{ij} \neq \varnothing, \\ v_{ij}[t] & \text{otherwise; see Equation (10).} \end{cases} \tag{12}$$

Fig. 3 illustrates an example of the trigger-update policy on a time-dependent vacancy probability $v_{ij}[t]$ with $v_{ij}[0] = 0.5$. The value of $v_{ij}[t]$ remains 0.5 when $t \in [0, 20)$. When $t = 20$, $v_{ij}[t]$ is reset to 1 because the corresponding $r_{ij}[20] = 1$, indicating that the wireless channel is vacant at timeslot 20. Similarly, $v_{ij}[t]$ jumps to 0 at timeslot 60 because the corresponding $r_{ij}[60] = 0$, owing to the channel occupation. In particular, when $r_{ij}[100] = \varnothing$ at timeslot 100, the vacancy probability $v_{ij}[t]$ keeps its decay trend similar to the previous behavior because the channel was not sensed.

B. Cognitive Sensing Operation

The pseudocodes of operations in the CC and IoTDs are demonstrated in Algorithms 1 and 2, respectively. Referring to these algorithms, two typical procedures are derived, which are for IoTD broadcasting and D2D communications in the network.

1) IoTD Broadcasting Communication: In broadcasting communication, IoTD requests CR resources to broadcast their data to every IoTD in their proximity. Prime examples of broadcasting applications include shopping advertisement, notification alarm, and tourist information kiosk positioning [26], [27]. Such one-way communications do not require responses from the receivers. Therefore, once the CC obtains a cognitive broadcasting request of ϵ wireless channels from an IoTD, the CC responds by sending the current vacancy probability set $\mathcal{V}_j[t]$ according to the IoTD location; see Equations (10) and (12). In its turn, the IoTD contiguously senses the wireless channels with their probability $v_{ij}[t]$ values in a descending order. The sensing operation is terminated when either ϵ vacant channels are detected, or all of the channels are sensed. The corresponding sensing results are stored into the sensing report $\mathcal{R}_j$ following the definition in (11). When the CC receives the sensing report, ϵ vacant channels are assigned to the IoTD for its broadcasting communication. Accordingly, the current vacancy probability set $\mathcal{V}_j[t]$ is updated by Equation (12). Corresponding pseudocodes are presented in Algorithm 1 except Lines 5–9 and Algorithm 2 except Lines 3–4.

2) IoTD D2D Communication: In D2D communications (1:1, 1:k, or k:k models), multiple IoTDs request CR resources for mutual communication. There are various peer-aware applications such as content sharing, multiplayer gaming, and

Algorithm 1 Central Coordinator Operation

1: Initiate $\mathcal{V}_j = \{v_{ij} = 0.5 | \forall i\}$;
2: Activate decay feature to $\forall i, j$ as in Eq. (10);
3: **if** IoTD broadcast resource request receive **then**
4:     Send the current set $V_j[t]$ according to the IoTD location;
5: **if** IoTD D2D resource request receive **then**
6:     Calculate the temporary sets as in Eq. (13);
7:     **if** IoTD participates in k pairs of communications **then**
8:         Calculate the temporary set as in Eq. (14);
9:     Send the current set $V_j[t]$ according to the IoTDs' location;
10: **if** a sensing report receive **then**
11:     Update $v_{ij}[t] | \forall i, j$ as in Eq. (12);
12:     Assign ϵ vacant channels to the IoTD as its request;
13:     Reset $v_{ij}[t] = 0 | \forall i, j \in \{\text{the } \epsilon \text{ channels}\}$;

Algorithm 2 IoTD Operation

1: **if** broadcast resources are needed **then**
2:     Send a broadcast resource request to the CC;
3: **if** D2D resources are needed **then**
4:     Send a D2D resource request to the CC;
5: **if** a probability set $\mathcal{V}_j$ is received **then**
6:     Descending ($\mathcal{V}_j$);
7:     **repeat** $v_{ij} \in \mathcal{V}_j$
8:         Sense the i-th wireless channel by its probability as in v_{ij};
9:     **until** $\forall v_{ij}$ are sensed `OR` ϵ vacant channels are found
10:     Update the sensing report $\mathcal{R}_j$ by Eq. (11);
11:     Send the $\mathcal{R}_j$ to the CC;
12: **if** a vacant channel list assignment is received **then**
13:     Use the assigned channels for communications;

relay-transmission assistant. In such communications, multiple IoTDs might be located at different locations, which generally possess different vacancy probability sets $\mathcal{V}_j[t]$. Hence, when the CC receives D2D communications from IoTDs, the current vacancy probability sets of each IoTD pair are temporarily averaged in advance. These temporary sets $\bar{\mathcal{V}}_A[t]$ and $\bar{\mathcal{V}}_B[t]$ between IoTDs A and B are given by

$$\bar{\mathcal{V}}_A[t] = \bar{\mathcal{V}}_B[t] = \left\{ \frac{v_{ij}^A[t] + v_{ij}^B[t]}{2},\ i = 1, 2, 3, \ldots, M, \forall j \right\}. \tag{13}$$

If an IoTD participates in k pairs of communications, its temporary set $\bar{\mathcal{V}}_j[t]$ is given by

$$\bar{\mathcal{V}}_j[t] = \left\{ \max_{t=1,2,\ldots,k} (\bar{v}_{ij}^t[t]),\ i = 1, 2, \ldots, M \right\}, \tag{14}$$

where $\bar{v}_{ij}^t[t]$ is the temporary vacancy probability of the i-th channel on the t-th pair.

The temporary sets of vacancy probability respond to the IoTDs. In their turns, the IoTDs sense the wireless channels with the received probabilities, and then report the sensing results to the CC. Based on the sensing reports received from the IoTDs, the CC performs resource allocation algorithms to distribute the vacant channels among IoTDs. Corresponding pseudocodes are presented in Algorithm 1 except Lines 3–4 and Algorithm 2 except Lines 1–2. Depending on the utilized resource allocation algorithms, the IoTDs might perform additional sensing operations. The selection of the resource allocation algorithm is beyond the scope of this paper; for reference, plenty of such algorithms are introduced in [3], [28].

C. Practical Implementation

In terms of computational complexity, the main workload of vacancy probability estimation is generated by Equation (10) to determine $\mathcal{V}_j[t]$. In Equation (10), the $e^{-\lambda t}$ element has a time complexity of $O(10^\alpha)$, where α indicates the number of fractional digits of $-\lambda t$. As derived from our thorough experiment analysis, α should be 2 in order to provide appropriate algorithmic results; meanwhile, a larger α has an insufficient impact on the result with a much higher computational cost. From a space complexity perspective, the memory size occupied by $\mathcal{V}_j[t]$ is deterministic, and this memory is updated regularly after a timeslot duration or after a sensing report is received. That is, the space complexity of the vacancy probability estimation is $O(1)$. It is worth noting that the $\mathcal{V}_j[t]$ estimation is performed by the CC, which has a significant computational resource.

For cognitive sensing operation, IoTDs receive a vacancy probability set from the CC, and then sense the wireless channels with their probability $v_{ij}[t]$. The sensing results are stored in a sensing report $\mathcal{R}_j$ with a constant dimension. Therefore, both time and space complexities of the cognitive sensing operation are $O(1)$. In other words, the proposed sensing algorithm can be implemented in lightweight IoTDs without any significant computational issues.

Regarding to security exploitation, in the case a malicious agent tries to exploit the decay function to optimally select signaling for resources at optimal time points to ensure maximal resources occupation, the malicious agent must have knowledge of time points and demand which are going to be. However, in practical cognitive radio systems (e.g., Spectrum Access Systems (SAS) [29] in the United States by the Federal Communications Commission (FCC) and Licensed Shared Access (LSA) [30] by the European Telecommunications Standards Institute (ETSI) in Europe), the number, locations, and demand of other users are confidential, i.e., unknown. For that, it is impractical for any device/user to predict the trigger update points in all channels. In other words, our design is practically protected from being compromised.

V. Performance Evaluations

A. Simulation Model

To evaluate SE improvements of the proposed PDFS algorithm, a simulation network topology of 1 km × 1 km dimension was developed on the `OPNET` framework [31]. A central coordinator located at the macro eNB manages all the cognitive communications in the topology. The IoTDs are locationed randomly. Among these IoTDs, the number of infrastructure-aided IoTDs are in the range of (0, 500) devices, which have an operational duration of (5, 50) s. During each timeslot, there are random requests from 10% IoTDs, resulting in average broadcast and D2D communications of (0, 20) and (0, 30), respectively. Detailed simulation configurations are described in Table II.

The proposed PDFS algorithm was compared to the optimal directional cognitive sensing (ODCS) scheme [13] and spatial-temporal cognitive sensing (STCS) scheme [14] to reflect the sensing performance in both directional and omnidirectional

TABLE II
SIMULATION CONFIGURATIONS.

Parameter	Value
Topology size	1 km × 1 km
IoTD locations	Random
Number of wireless channels	32
Number of infrastructure-aided IoTDs	0 – 500
Number of IoTD broadcast communication requests	0 – 200
Number of IoTD D2D communication requests	0 – 300
Sensing energy consumption per wireless channel	0.3 mJ (directional antenna) 0.5 mJ (omni antenna)
Sensing range	150 m
Operational duration of IoTDs	5 – 50 s
Number of active IoTDs per timeslot	10%
Sensing duration per wireless channel	0.1 ms
Decay factor λ	0.05
Decay timeslot	100 ms
Simulation duration	1000 s

sensing environments. The ODCS scheme provides selective channel sensing by deactivating wireless beam transceivers that might result in collisions. Meanwhile, the STCS scheme assumes a random sensing rate that temporarily depends on the location.

The simulations were conducted for 1000 s for each system configuration set. Typically, this setting results in 10,000 output samples per evaluation. For a comprehensive comparison, the SE performances were evaluated by three key metrics:

- SD, which determines the time taken by the IoTDs for sensing activities. The SD metric represents *sensing time efficiency*.
- PS ratio, as illustrated by Equation (5). The PS ratio indicates *sensing decision accuracy*.
- EC, which is the amount of energy consumed by the IoTDs for sensing operations. The EC metric indicates *sensing energy efficiency*.

B. Numerical Results

Regarding the sensing time efficiency, Fig. 4 depicts the total SD of the IoTDs consumed in 1000 s for their cognitive communications. It is observed that the total SD metrics in all three simulated schemes are directly proportional to the IoTD density in the network. This is because larger number of IoTDs results in high channel occupation as well as collision. Therefore, infrastructureless IoTDs must reduce their channel utilization time and re-sense vacant channels more frequently. For instance, the numerical results show that the IoTDs take (1.5, 1.9, 2.3) and (15.3, 17.1, 26.7) ms for sensing activities when the number of IoTDs in the network are 5 and 50 devices, respectively, by applying the (PDFS, ODCS, STCS) schemes. Although these schemes possess the same behavior, the proposed PDFS scheme performs better than the ODCS and STCS schemes by 10.53% and 42.70%, respectively, in terms of SD reduction. The PDFS scheme prioritizes sensing highly possible vacant channels by learning

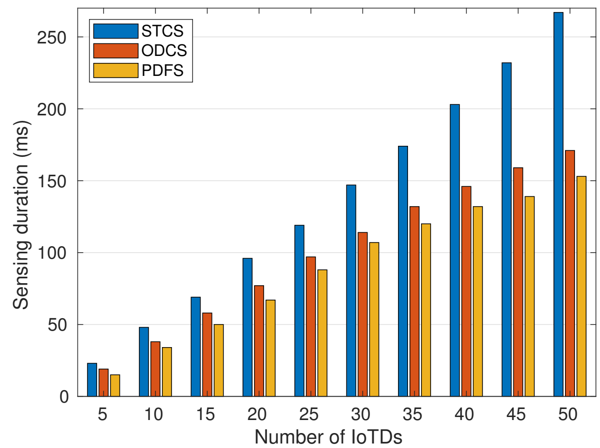

Fig. 4. Total sensing duration for all IoTDs in the network.

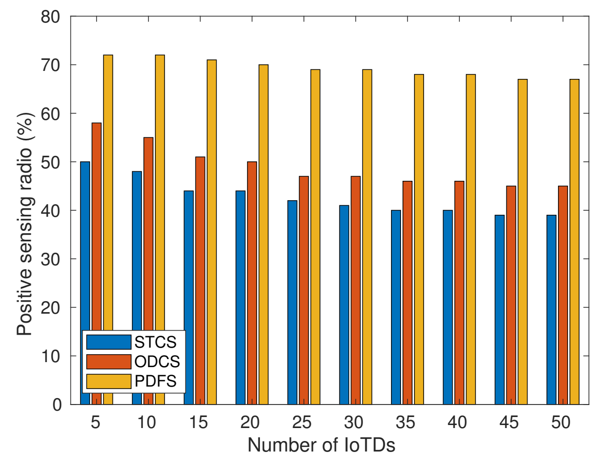

Fig. 5. Positive sensing ratio versus the number of IoTDs.

environmental conditions, while the ODCS scheme deactivates several adjacent channels among IoTDs to avoid interference, and the STCS scheme detects vacant channels on the basis of random sensing.

In terms of sensing decision accuracy, Fig. 5 shows a significant improvement of the PDFS scheme compared to the others. The average PS ratio achieved by the PDFS scheme is 69.30%. This is a 20.30% and 26.60% increase over the average PS ratio achieved by the ODCS and STCS schemes, respectively. In addition, when the number of IoTDs in the network increases from 5 to 50, the PS ratios of the PDFS scheme only decreases by 6.94%; meanwhile, the ratios in the other schemes decrease by approximately 22.01%. The rationale behind these improvements is that the ODCS and STCS schemes cannot adapt well to the environmental dynamic as the PDFS scheme does.

From the sensing energy efficiency perspective, Fig. 6 illustrates the total EC the IoTDs generated during the 1000-second simulation when the IoTD density is adjusted. It is clearly seen that the total EC increases if the number of IoTDs in the network increases. As shown in Fig. 4, the increase in IoTD density expands the SD and leads to higher sensing

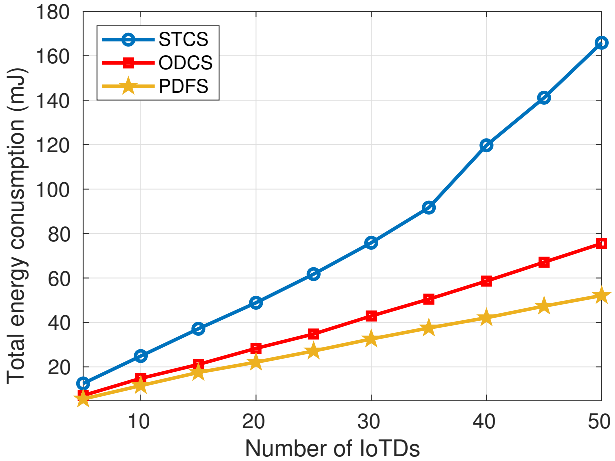

Fig. 6. Total energy consumption depending on IoTD density.

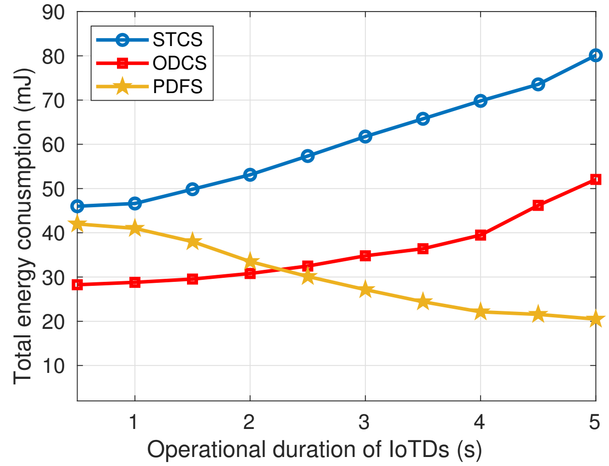

Fig. 7. Total energy consumption depending on operational duration of IoTDs.

faults. These effects make the IoTDs consume significant energy for their sensing activities. Nevertheless, the proposed PDFS scheme outperforms the other schemes by reducing the total EC up to 31.03% (ODCS scheme) and 68.58% (STCS scheme).

In addition, Fig. 7 plots the relation between the total EC and the operational duration of IoTDs. Based on an analysis of Figs. 4 and 6, without loss of generality, we fixed the number of IoTDs to be 25 devices, which were randomly locationed in the network. The graph shows two inverse directions: one is proportional to the operational duration of IoTDs (i.e., STCS and ODCS schemes) and vice versa (i.e., the proposed PDFS scheme). It is true that a longer operational duration of the IoTDs results in more channel resource usage. In other words, there are fewer vacant channels in the network. Therefore, the STCS and ODCS schemes consume significant energy to sense a large amount of channels in order to detect vacant ones. On the contrary, the PDFS scheme senses channels in the proximity with their vacancy probabilities. Note that the vacancy probability of 0.5 is equivalent to a random sensing. Therefore, when the operational duration of the IoTDs is short, the vacancy probabilities quickly decay to 0.5. Hence, this behavior makes the PDFS scheme have similar performance to that of the STCS scheme. However, when the operational duration of the IoTDs increases, the vacancy probabilities reveal the advantages of medium learning. Accordingly, the wireless channels are only sensed by their appropriate probabilities in descending order, i.e., a smaller number of highly possible vacant channels is sensed by the PDFS scheme. This results in a decrease in the total EC. Numerical evaluation demonstrates that the PDFS scheme is able to reduce the total EC up to 60.65% and 74.43% compared to the ODCS and STCS schemes, respectively.

VI. Concluding Remarks

By utilizing probabilistic decay features to sensing decisions during each medium scanning iteration, the proposed PDFS algorithm provides significant SE improvement in terms of time and energy efficiencies as well as PS ratio for establishing cognitive D2D communications in 5G mobile networks. In addition, the PDFS algorithm possesses low computational complexity, which is even applicable to lightweight IoTDs. Despite these advantages, the centralization architecture of the PDFS algorithm might generate a control overhead between the central controller and the IoTDs. Therefore, a decentralization transformation and/or overhead reduction should be studied in the future. Moverover, owing to the nature of channel competition for resource occupation, security issues (e.g., sensing signal jamming, flooding, and spoofing attacks) should be comprehensively investigated in future study.

References

[1] Ericsson, "Internet of Things forecast," (cited March 25, 2019). [Online]. Available: https://www.ericsson.com/en/mobility-report/internet-of-things-forecast

[2] F. Boccardi, R. W. Heath, A. Lozano, T. L. Marzetta, and P. Popovski, "Five disruptive technology directions for 5G," *IEEE Communications Magazine*, vol. 52, no. 2, pp. 74–80, 2014.

[3] M. El Tanab and W. Hamouda, "Resource allocation for underlay cognitive radio networks: A survey," *IEEE Communications Surveys & Tutorials*, vol. 19, no. 2, pp. 1249–1276, 2017.

[4] C. Yang, J. Li, M. Guizani, A. Anpalagan, and M. Elkashlan, "Advanced spectrum sharing in 5G cognitive heterogeneous networks," *IEEE Wireless Communications*, vol. 23, no. 2, pp. 94–101, 2016.

[5] F.-H. Tseng, H.-c. Chao, J. Wang *et al.*, "Ultra-dense small cell planning using cognitive radio network toward 5G," *IEEE Wireless Communications*, vol. 22, no. 6, pp. 76–83, 2015.

[6] I. Kakalou, K. E. Psannis, P. Krawiec, and R. Badea, "Cognitive radio network and network service chaining toward 5G: Challenges and requirements," *IEEE Communications Magazine*, vol. 55, no. 11, pp. 145–151, 2017.

[7] I. Farris, A. Orsino, L. Militano, A. Iera, and G. Araniti, "Federated IoT services leveraging 5G technologies at the edge," *Ad Hoc Networks*, vol. 68, pp. 58–69, 2018.

[8] Z. Dawy, W. Saad, A. Ghosh, J. G. Andrews, and E. Yaacoub, "Toward massive machine type cellular communications," *IEEE Wireless Communications*, vol. 24, no. 1, pp. 120–128, 2017.

[9] N.-N. Dao, M. Park, J. Kim, J. Paek, and S. Cho, "Resource-aware relay selection for inter-cell interference avoidance in 5G heterogeneous network for Internet of things systems," *Future Generation Computer Systems*, vol. 93, pp. 877–887, 2019.

[10] N.-N. Dao, D.-N. Vu, A. Masood, W. Na, and S. Cho, "Reliable broadcasting for safety services in dense infrastructureless peer-aware communications," *Reliability Engineering & System Safety*, vol. 193, p. 106655, 2020.

[11] L. Zhang, M. Xiao, G. Wu, M. Alam, Y.-C. Liang, and S. Li, “A survey of advanced techniques for spectrum sharing in 5G networks,” *IEEE Wireless Communications*, vol. 24, no. 5, pp. 44–51, 2017.

[12] F. Hu, B. Chen, and K. Zhu, “Full spectrum sharing in cognitive radio networks toward 5G: A survey,” *IEEE Access*, vol. 6, pp. 15 754–15 776, 2018.

[13] W. Na, J. Yoon, S. Cho, D. Griffith, and N. Golmie, “Centralized cooperative directional spectrum sensing for cognitive radio networks,” *IEEE Transactions on Mobile Computing*, vol. 17, no. 6, pp. 1260–1274, 2018.

[14] Z. Zhang, X. Wen, H. Xu, and L. Yuan, “Sensing nodes selective fusion scheme of spectrum sensing in spectrum-heterogeneous cognitive wireless sensor networks,” *IEEE Sensors Journal*, vol. 18, no. 1, pp. 436–445, 2018.

[15] T. Xiong, Z. Li, Y.-D. Yao, and P. Qi, “Random, persistent, and adaptive spectrum sensing strategies for multiband spectrum sensing in cognitive radio networks with secondary user hardware limitation,” *IEEE Access*, vol. 5, pp. 14 854–14 866, 2017.

[16] J. So and R. Srikant, “Improving channel utilization via cooperative spectrum sensing with opportunistic feedback in cognitive radio networks,” *IEEE Communications Letters*, vol. 19, no. 6, pp. 1065–1068, 2015.

[17] H. Hu, H. Zhang, and Y.-C. Liang, “On the spectrum-and energy-efficiency tradeoff in cognitive radio networks,” *IEEE Transactions on Communications*, vol. 64, no. 2, pp. 490–501, 2016.

[18] F. A. Awin, E. Abdel-Raheem, and M. Ahmadi, “Designing an optimal energy efficient cluster-based spectrum sensing for cognitive radio networks,” *IEEE Communications Letters*, vol. 20, no. 9, pp. 1884–1887, 2016.

[19] A. Vosoughi, J. R. Cavallaro, and A. Marshall, “Trust-aware consensus-inspired distributed cooperative spectrum sensing for cognitive radio ad hoc networks,” *IEEE Transactions on Cognitive Communications and Networking*, vol. 2, no. 1, pp. 24–37, 2016.

[20] A. Hajihoseini and S. A. Ghorashi, “Distributed spectrum sensing for cognitive radio sensor networks using diffusion adaptation,” *IEEE Sensors Letters*, vol. 1, no. 5, pp. 1–4, 2017.

[21] Y. Lu and A. Duel-Hallen, “Channel-aware spectrum sensing and access for mobile cognitive radio ad hoc networks,” *IEEE Transactions on Vehicular Technology*, vol. 65, no. 4, pp. 2471–2480, 2016.

[22] B. Aygun and A. M. Wyglinski, “A voting-based distributed cooperative spectrum sensing strategy for connected vehicles,” *IEEE Transactions on Vehicular Technology*, vol. 66, no. 6, pp. 5109–5121, 2017.

[23] N.-N. Dao, J. Lee, D.-N. Vu, J. Paek, J. Kim, S. Cho, K.-S. Chung, and C. Keum, “Adaptive resource balancing for serviceability maximization in fog radio access networks,” *IEEE Access*, vol. 5, pp. 14 548–14 559, 2017.

[24] S. Andreev, O. Galinina, A. Pyattaev, K. Johnsson, and Y. Koucheryavy, “Analyzing assisted offloading of cellular user sessions onto D2D links in unlicensed bands,” *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 1, pp. 67–80, 2015.

[25] R. Zhang, M. Wang, X. Shen, and L.-L. Xie, “Probabilistic analysis on QoS provisioning for internet of things in LTE-A heterogeneous networks with partial spectrum usage,” *IEEE Internet of Things Journal*, vol. 3, no. 3, pp. 354–365, 2016.

[26] N.-N. Dao, Y. Kim, S. Jeong, M. Park, and S. Cho, “Achievable multi-security levels for lightweight IoT-enabled devices in infrastructureless peer-aware communications,” *IEEE Access*, vol. 5, pp. 26 743–26 753, 2017.

[27] W. Na, Y. Lee, J. Yoon, J. Park, and S. Cho, “Fully distributed multicast routing protocol for IEEE 802.15.8 peer-aware communication,” *International Journal of Distributed Sensor Networks*, vol. 11, no. 8, p. 531710, 2015.

[28] G. I. Tsiropoulos, O. A. Dobre, M. H. Ahmed, and K. E. Baddour, “Radio resource allocation techniques for efficient spectrum access in cognitive radio networks,” *IEEE Communications Surveys & Tutorials*, vol. 18, no. 1, pp. 824–847, 2016.

[29] FCC 16-55, “Order on reconsideration and second report and order,” Federal Communications Commission, Washington, D.C., United States, Tech. Rep., April 2016.

[30] ECC Report 205, “Licensed shared access (LSA),” European Telecommunications Standards Institute, Sophia Antipolis CEDEX, France, Tech. Rep., February 2014.

[31] OPNET modeler 14.5, Available: http://www.opnet.com, Accessed in February 23, 2019.

Nhu-Ngoc Dao is an assistant professor at the Department of Computer Science and Engineering, Sejong University, Seoul, Republic of Korea. He received his M.S. and Ph.D. degrees in computer science with the School of Computer Science and Engineering, Chung-Ang University, Republic of Korea, in 2016 and 2019, respectively. He received the B.S. degree in electronics and telecommunications from the Posts and Telecommunications Institute of Technology, Viet Nam, in 2009. Prior to be with the Sejong University, he was a postdoc researcher at the Institute of Computer Science, University of Bern, Switzerland from 2019 to 2020. His research interests include network softwarization, fog/edge computing, and Internet of things. Dr. Dao is a Member of IEEE.

Woongsoo Na received the B.S., M.S., and Ph.D. degrees in computer science and engineering from Chung-Ang University, Seoul, South Korea, in 2010, 2012, and 2017, respectively. He is currently an Assistant Professor with the Department of Computer Science and Engineering, Kongju National University, Chenan, South Korea. He was an Adjunct Professor with the the School of Information Technology, Sungshin Womens University, Seoul, South Korea, from 2017 to 2018, and a Senior Researcher with Electronics and Telecommunications Research Institute, Daejeon, South Korea, from 2018 to 2019. His current research interests include mobile edge computing, flying ad hoc networks, wireless mobile networks, and beyond 5G.

Anh-Tien Tran received his B.S. degree in Electronics and telecommunications from Danang University of Science and Technology, Viet Nam, in 2018. He is currently pursuing the Ph.D. degree in computer science from Chung-Ang University, South Korea, in 2018. His research interests include wireless network and fog computing.

Diep N. Nguyen is a faculty member of the Faculty of Engineering and Information Technology, University of Technology Sydney (UTS). He received M.E. and Ph.D. in Electrical and Computer Engineering from the University of California San Diego (UCSD) and The University of Arizona (UA), respectively. Before joining UTS, he was a DECRA Research Fellow at Macquarie University, a member of technical staff at Broadcom (California), ARCON Corporation (Boston), consulting the Federal Administration of Aviation on turning detection of UAVs and aircraft, US Air Force Research Lab on anti-jamming. He has received several awards from LG Electronics, University of California, San Diego, The University of Arizona, US National Science Foundation, Australian Research Council, including nominations for the outstanding RA (2013) awards, the best paper award at the WiOpt conference (2014), Discovery Early Career Researcher Award (DECRA, 2015), outstanding Early Career Researcher award (SEDE, University of Technology Sydney, 2018). His recent research interests are in the areas of computer networking, wireless communications, and machine learning application, with emphasis on systems' performance and security/privacy. Dr. Nguyen is a Senior Member of IEEE.

Sungrae Cho is a professor with the school of computer sceinces and engineering, Chung-Ang University (CAU), Seoul. Prior to joining CAU, he was an assistant professor with the department of computer sciences, Georgia Southern University, Statesboro, GA, USA, from 2003 to 2006, and a senior member of technical staff with the Samsung Advanced Institute of Technology (SAIT), Kiheung, South Korea, in 2003. From 1994 to 1996, he was a research staff member with electronics and telecommunications research institute (ETRI), Daejeon, South Korea. From 2012 to 2013, he held a visiting professorship with the national institute of standards and technology (NIST), Gaithersburg, MD, USA. He received the B.S. and M.S. degrees in electronics engineering from Korea University, Seoul, South Korea, in 1992 and 1994, respectively, and the Ph.D. degree in electrical and computer engineering from the Georgia Institute of Technology, Atlanta, GA, USA, in 2002.

His current research interests include wireless networking, ubiquitous computing, and ICT convergence. He has been a subject editor of IET Electronics Letter since 2018, and an editor of Ad Hoc Networks Journal (Elsevier) from 2012 to 2017. He has served numerous international conferences as an organizing committee chair, such as IEEE SECON, ICOIN, ICTC, ICUFN, TridentCom, and the IEEE MASS, and as a program committee member, such as IEEE ICC, MobiApps, SENSORNETS, and WINSYS.