Energy-Efficient Joint Optimization of Spectrum Sensing and Energy Harvesting in Cognitive IoT Networks

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Abstract: The exponential growth of smart gadgets connected to the Internet as well as diverse applications has escalated the spectrum scarcity problem. Cognitive radio based spectrum sensing technique becomes a potential approach for detecting idle spectrum in licensed channels and gaining access to it on an as-needed basis. This improves the spectral efficiency in cognitive IoT networks. However, to support the cognitive radio features, the IoT sensor nodes demand a large amount of energy. In this research, we present a technique for improving detection performance and energy economy in cognitive IoT systems by combining spectrum sensing and energy harvesting. The IoT nodes are expected to be capable of spectrum detection and energy harvesting. We use a game theoretic technique to pick relevant IoT nodes for cooperative spectrum sensing based on their energy restrictions. Furthermore, we formulate an optimal channel assignment mechanism to improve opportunistic spectrum utilization. We develop a branch and bound based heuristic approach with low computing complexity to address the optimization problem. Various system parameters are used to evaluate the proposed system's performance. When compared to other current models, simulation results show that the proposed approach greatly improves energy efficiency and detection performance.

Keywords: Cognitive IoT networks, spectrum sensing, opportunistic spectrum utilization, energy harvesting, energy efficiency

1. Introduction

The Internet of Things (IoT) is a major paradigm change in fifth generation (5G) networks that enables enormous networking of smart objects via the Internet to support a wide range of applications and service demands [1]. The IoT system represents an intelligent infrastructure that interconnects physical objects, sensors, actuators, and embedded devices in order to create a fully automated and digital world. In recent times, IoT has found a wide range of applications such as, smart home, smart agriculture, e-health, smart cities, surveillance, automated transportation systems, etc [2]. The exponential growth of smart gadgets and huge interconnectedness of sensor networks with ubiquitous computing escalated the spectrum scarcity [3]. The existing fixed spectrum distribution technique, with its limited operating frequency bands, is clearly unsuitable to support the vast IoT deployments and gigantic data throughput requirements laid forth in 5G. As a result, to address the spectrum shortage issue, a dynamic spectrum sharing technique is necessary [4]. The cognitive radio (CR) technology has emerged as a viable method for gaining opportunistic access to licensed bands' idle spectrum [5].

In CR-enabled IoT systems, a massive number of cognitive sensor nodes are spatially dispersed to perform spectrum sensing and detect idle spectrum in the given environment. In the literature, various spectrum sensing techniques are proposed to effectively detect the status of the channel occupancy. Among these techniques, cooperative spectrum sensing (CSS) method gets more attention in recent times [6]. In CSS, the cognitive IoT nodes scan their local environment to get information about the statuses of licensed channels. The local readings are then forwarded to the central entity, which determines whether or not the channel is occupied by main users (PUs). However, there are many trade-offs in CSS such as, sensing time, energy consumption, and number of participating nodes in CSS [7].

Another key challenge in massive IoT deployments is the energy efficiency. Although the IoT nodes are low-power devices, they consume considerable energy as they frequently perform spectrum sensing [8]. In many IoT applications, most of the devices are battery operated. However, devices that only rely on batteries will no longer be in a self-sufficient and sustainable operation [9].

On the other hand, cognitive IoT nodes can harvest energy from ambient energy sources such as solar, thermal, vibrations, and RF signals [10]. In recent times, energy harvesting has become the most promising solution among emerging technologies to supply power for ultra-low power electronic sensors and IoT devices [11]. Indeed, the latest releases of the third generation partnership project (3GPP) allow IoT nodes to harvest energy from the environment [12]. Thus, incorporating RF energy harvesting in cognitive IoT networks can be considered as a pragmatic energy solution. Although the efficiency of harvesting energy from RF signals is low compared with other sources, it provides many advantages such as availability in any time (day and night), low cost, and ease of implementation [13].

TABLE I. List of Abbreviations

Abbreviation	Definition
5G	Fifth Generation
AWGN	Additive White Gaussian Noise
CR	Cognitive Radio
CSS	Cooperative Spectrum Sensing
CSSO	Cooperative Sensing and Scheduling Optimazation
DC	Direct Current
DCSS	Dynamic Colaborative Spectrum Sensing
$E^2JOSSEH$	Energy Efficient Joint Optimization of Spectrum Sensing and Energy Harvesting
ESA	Exhaustive Search Algorithm
IoT	Internet of Things
PBS	Primary Base Station
PS	Power Splitting
PU	Primary User
RCA	Random Channel Access
RF	Radio Frequency
RSS	Random Sensor Selection
SNR	Signal-to-Noise Ratio
SWIPT	Simultaneous Wireless Information and Power Transfer
TDMA	Time Division Multiple Access
TS	Time Switching
TTI	Transmission Time Interval

In RF energy harvesting system, the IoT network mainly consists of a transceiver antenna, RF energy harvester circuit, a rechargeable battery storage, and energy management unit. The transceiver antenna intercepts both information and energy from RF signals, which is called simultaneous wireless information and power transfer (SWIPT) technique. Recently, various types of receiver architectures have been proposed to implement SWIPT. Specifically, power splitting (PS) and time switching (TS) protocol architectures have gained more attention in the literature [14]. Incoming RF signals are divided into two halves by the PS protocol, one for energy harvesting and the other for information processing. To effectively decode multiple simultaneous transmissions and harvest energy at the same time, a successive interference cancellation (SIC) scheme is employed at the receiver node [15]. The harvester circuit converts the RF signal into DC electricity and directly supplies to the IoT node or accumulates it in the energy storage unit [16].

In energy-harvesting-enabled cognitive IoT networks, it is a great challenge to achieve both spectral efficiency and energy efficiency at the same time due to energy causality and collision constraints.The energy causality constraint is a trade-off between the energy harvested and the total energy consumed by IoT nodes for cognitive functions, while the collision constraint deals with avoiding interference between unlicensed users and PUs, which is directly related to the detection performance [17]. As a result, we model the interactions between the IoT gateway and nodes in this work based on game theory aiming at maximizing the detection performance and energy efficiency. The review of related works and the primary contributions of this paper are described in the following subsections.

A. Related Work

In order to increase both spectral and energy efficiency while considering opportunistic spectrum usage in licensed bands, several studies on cooperative spectrum sensing and energy harvesting in CR networks have been done.

In [18], the authors investigate dynamic spectrum sensing techniques to efficiently access the idle channels in licensed bands. To reduce the overhead, sensors with the best detection probability are chosen for CSS. Applying this sensor selection mechanism leads to only specific sensors to participate in CSS. Thus, these sensors encounter a fast battery drain and they no longer be alive in the network operation. In contrast with [18], we propose a game theoretic-based sensor selection mechanism to provide fairness among IoT sensor nodes that participate in CSS. A modified energy efficient sensor selection algorithm is introduced in [19]. The goal of this study is to increase energy efficiency by selecting nodes that consume the least amounts of energy to perform CSS. Furthermore, each IoT node has only a chance of accessing spectrum if it participates in CSS. In this algorithm, each IoT node with minimum energy consumption must always participate in CSS. Unlike [19], our proposed method considers energy constraints and lifetime limitations to select appropriate sensing nodes.

In [20], an energy efficient algorithm is developed to reduce total energy usage by separating the SUs into different subsets and activating only a certain subset with lowest cost function to listen the licensed signal periodically. In this paper, the authors considered a homogeneous CSS setting to balance SU energy usage, and all nodes are required to periodically sense the spectrum. With the increasing reporting error, the provision of reliable detection and spectrum sensing accuracy is not feasible to satisfy collision constraints. As an important difference with [20], in our algorithm, IoT sensor nodes are dynamically selected to participate in CSS based on their energy constraints to satisfy the minimum performance of detection with optimum detection and false alarm probabilities. A CoMAC-based CSS technique is developed in [21] to enhance energy efficiency in cognitive sensor networks. To enhance energy efficiency, this research investigated a simultaneous adjustment of sensing time, detection threshold, and sequence length. However, in addition to these parameters, joint optimization of sensing duration, optimal number of sensing nodes and power splitting parameter value of harvesting unit is necessary to improve the energy harvesting efficiency. Unlike [21], the power splitting parameter value is considered in our study.

To reduce the sensing time and power consumption of sensor nodes in cognitive IoT networks, an energy efficient dynamic spectrum sensing and power allocation technique is proposed in [22]. Similarly, a cost effective power control mechanism is proposed in [23] for industrial automation systems to improve the energy efficiency of cooperative spectrum utilization in CR and IoT networks. Authors of both [22] and [23] used adaptive power control mechanism to improve energy efficiency and maximize channel utilization while avoiding interference between PUs and SUs. Adaptive power control mechanism can be useful to effectively minimize interference, but this approach highly affects the RF energy harvesting gains. Hence, in contrast to this strategy, we propose the employment of SIC at each receiver node in order to boost the average harvested energy from strong interference signals without affecting the information decoding.

A novel resource allocation mechanism is provided in heterogeneous cognitive radio sensor networks to overcome the problems of spectrum underutilization, energy inefficiency, and spectrum sensing inaccuracy [24]. A hybrid energy efficient and energy harvesting cooperative spectrum sensing scheme is proposed in [25] to improve the detection performance of SUs considering the constrains in their sensing and reporting channel characteristics under heterogeneous conditions.

Most existing literature, on the other hand, assumes complete cooperation in spectrum sensing and ignores the intermittent behavior of ambient RF energy sources. Therefore, we propose an energy efficient joint optimization of spectrum sensing and energy harvesting (E^2JOSSEH) technique to enhance energy efficiency and opportunistic spectrum utilization in cognitive IoT networks.

B. Contributions

In our proposed technique, we adopt a game theoretic approach to model and analyze the interactions between the IoT gateway and IoT sensing nodes in cognitive IoT networks. The following are the major contributions of this study.

- We propose a new incentive-based game theory model, where the IoT gateway can allocate more channel to the cooperative nodes as a payoff for their participation in the CSS operation.
- Based on the proposed scheme, we apply a Stackelberg evolutionary game to compute optimum number of nodes that participate in CSS and a non-cooperative game for idle spectrum allocation. The IoT nodes act as followers to adjust their strategies in order to maximize the price rewarded by the IoT gateway and the IoT gateway act as a leader to improve its revenue.
- We build a fast and high-performance heuristic approach for solving the suggested optimization issue for optimal node selection using a branch and bound algorithm. For non-cooperative channel assignment game, the uniqueness and best response of the Nash equilibrium are analyzed.
- Finally, we verified the proposed system performance that significantly improves the detection accuracy and energy efficiency.

The rest of this paper is structured as follows: the proposed system model and mathematical formulations are described in Section II. Section III explains the proposed algorithms and analysis. In Section IV, we assess the proposed scheme's performance and compare it with other existing models. Finally, a concluding remark is drawn in Section V.

2. System Modeling

A. System Description

We consider a CR-based IoT network architecture with RF energy harvesting in heterogeneous 5G system as shown in Fig. 1. It is expected to enable a large number of cognitive IoT nodes, also known as secondary users (SUs), which will be spread randomly throughout the network coverage area [26]. Assuming that, the cognitive IoT nodes have both spectrum sensing and energy harvesting capability. Thus, the IoT nodes perform spectrum sensing to detect the idle spectrum in licensed bands and access it opportunistically. In the proposed system, there are two types of IoT devices called: IoT sensor nodes and IoT gateway. We assume that the IoT gateway is connected to a reliable power source and act as central entity to control the operation of IoT sensor nodes. The IoT gateway is responsible to collect sensory data, assign channel opportunities for data transmission/energy harvesting, and transfer energy to sensor nodes when the harvested energy is not sufficient. All IoT sensor nodes broadcast their battery and data buffer information to the IoT gateway at the start of the network's operation. Then, the IoT gateway synchronizes itself with the primary base station (PBS) using the beacon signal. The 5G radio access network with IoT communications will built on an enhanced, flexible OFDM-like air interface. As shown in Fig. 2, the proposed IoT network is considered to operate in time slots synchronously with the cellular network's transmission time interval (TTI) in 5G systems [27].

Each frame structure with a duration of T is divided into three time slots known as sensing, reporting, and transmission/harvesting slots [27]. The following is a description of how the IoT nodes work in each time slot:

- The sensing slot (τ_s) in which the IoT nodes perform

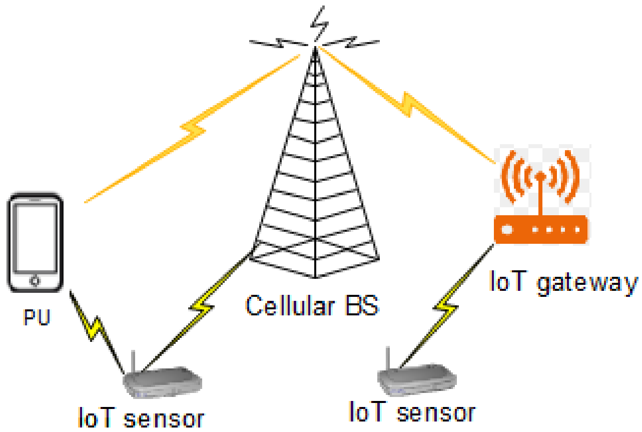

Figure 1. Proposed Network Architecture

spectrum sensing. In this slot, no IoT node can transmit data on the same channel as all sensed energy are considered as PU signal.

- The reporting slot (τ_r) in which each IoT node reports its local sensing results to the central entity. We assume that time division multiple access (TDMA) technique is used for reporting the local decisions of each IoT node to the central entity. The central entity decides whether the channel is busy or idle by applying a majority (n-out-of-N) rule.
- The transmission/harvesting slot (τ_u) in which IoT nodes can either transmit data or harvest energy. In this time slot, IoT nodes are classified into three groups based on their energy constraints and tasks to be performed: *i*) Group A nodes, a node with sufficient energy and ready to transmit data will be categorized into this group. Group A nodes are called potential nodes and compete to access the channel for data transmission. *ii*) IoT nodes that have at least one packet in the data queue and with insufficient energy for transmission can be categorized into Group B nodes. Group B nodes are also called non-potential sensors. *iii*) IoT nodes with empty packet in the data queue and have sufficient energy will be categorized into Group C nodes. Group C nodes will go to sleep mode until the next time frame.

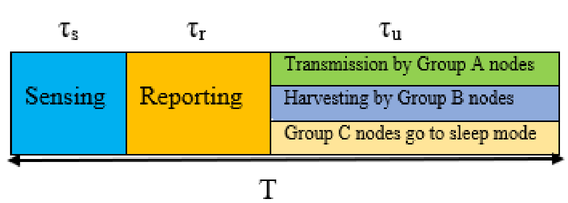

Figure 2. Cooperative spectrum detection and data transmission with energy harvesting frame structure

B. Cooperative Spectrum Sensing Model

All IoT sensor nodes communicate the status of their residual energy and SNR value to the IoT gateway at the start of each time frame. Then, the IoT gateway will sort the nodes in ascending order based on their residual energy and categorize them into two groups called potential sensors (Group A and Group C nodes) and non-potential sensors (Group B nodes). If the residual energy E_{res} is greater than the threshold value E_{th}, the node is categorized into potential sensors, otherwise it is non-potential sensors. This can be expressed by the binary function ϕ_n:

$$\phi_n = \begin{cases} 1, \; if \; E_{res} > E_{th} \\ 0, \; otherwise \end{cases} \tag{1}$$

Among the potential sensor nodes, an optimal number of nodes will be selected to participate in CSS. Detail explanation of IoT node selection is given in section **III-A**, Algorithm 1.

1) Local Spectrum Detection Mechanism

The selected nodes will then perform local spectrum sensing in order to detect the idle spectrum in licensed bands and send their local sensing decisions to the central entity. Various detection techniques are proposed to decide the presence or absence of PUs in the sensed channel [28]-[29]. In [28] an optimal matched filter detection scheme is developed. A matched filter is a linear detection model that filters the received signal by correlating with the original signal. It increases the SNR value. However, the matched filter needs prior information about PU signal and this makes it infeasible for sensor nodes with limited energy budget in IoT system. Another signal detection technique proposed for spectrum sensing in cognitive radio networks is feature detection. Feature detection is developed based on stationary noise and signal periodicity [30]. The feature detection technique can easily distinguish noise and signal, but, it has high computational complexity.

Energy detection scheme is extensively exploited in recent times since it is simple, compatible with any signal type, and independent of prior information about PU signal [29]. Thus, the energy detection technique is adopted for local spectrum detection mechanism. In energy detection, the received signal by IoT sensor node n can be represented by a binary hypothesis H_1 and H_0, where H_1 denotes that the channel is busy and H_0 states channel is idle. These two states can be expressed as:

$$\begin{aligned} H_1 &: y_n(i) = h_n(i)x(i) + w_n(i) \\ H_0 &: y_n(i) = w_n(i), i = 1, 2, ..., M \end{aligned} \tag{2}$$

where $y_n(t)$ is the received signal, $x(t)$ is the PU signal, $h_n(t)$ is the channel gain between PU and each IoT sensor node, M is number of samples, and $w_n(t)$ is the additive white Gaussian noise (AWGN) signal.

From (2), the energy statistic of y_n used for signal detection is given by:

$$E_n = \frac{1}{M}\sum_{i=1}^{M} y_n^2(i) \tag{3}$$

The energy detector decides the presence or absence of PU by comparing the received signal energy with a predefined detection threshold value ϵ_s. Then, it declares the presence of PU if the received signal energy is greater than the threshold value, otherwise it decides PU is absent. The energy detection performance can be evaluated with the probability of detection P_d and the probability of false alarm P_f [31]. The probability of detection refers to the likelihood that the spectrum is truly occupied by PUs, whereas the probability of false alarm refers to the likelihood that the spectrum is occupied by PUs in error.

From (3), for a large number of M, E_s becomes a Gaussian distribution function. Thus, the two probabilities are defined as follows:

$$P_d = Q\left((\epsilon_s - \gamma_s - 1)\sqrt{\frac{M}{\gamma_s + 1}}\right) \tag{4}$$

and

$$P_f = Q\left((\epsilon_s - 1)\sqrt{M}\right) \tag{5}$$

where ϵ_s is detection threshold value to make a local spectrum decision, γ_s is the average SNR received at the detector and $Q(.)$ is the normalized Gaussian distribution function.

2) Global Spectrum Detection Mechanism

During the reporting time of τ_r, each IoT node communicates its local decision to the IoT gateway at the end of the local spectrum sensing procedure over a binary symmetric channel [32]. The IoT gateway determines whether the spectrum is busy or idle by applying the appropriate data fusion rule (n-out-of-N). Based on (2)-(5), the global probability of detection P_D and the global probability of false alarm P_F at the central entity can be obtained as follows:

$$P_D = \sum_{n=1}^{N} \binom{N}{n} (1 - P_d)^{N-n} \tag{6}$$

and

$$P_F = \sum_{n=1}^{N} \binom{N}{n} \left(1 - P_f\right)^{N-n} \tag{7}$$

where P_d and P_f are the local probability of detection and false alarm as defined in (4) and (5), respectively.

C. Throughput and Energy Utility Model

Once the IoT gateway has complete information about total channel occupancy, it may assign available channels to IoT nodes to transmit data in the most efficient manner possible. Then, the achievable data rate of n^{th} IoT node can be calculated as

$$r_n = Blog_2\left(1 + \frac{h_c P_s}{N_0 + \sum_{i=n+1}^{N} P_i}\right) \tag{8}$$

where B is the system bandwidth, P_s denotes the transmission power, h_c is the average channel gain, N_0 is the noise power, and P_i denotes the interfering power from i^{th} node. If the absence probability of PU is denoted by P_{H0}, then the total data rate of the secondary network in a given channel is given by

$$R_{c,n}^t = r_n(1 - P_F)P_{H0} \tag{9}$$

where P_F and r_n are defined in (7) and (8), respectively.

In EH-enabled IoT systems, before executing cognitive activities, the IoT gateway must check the remaining energy in each IoT node. The energy consumption of IoT nodes, as shown in Fig. 2, accounts for all energy expenditures for spectrum sensing, reporting local choices to the central entity, and data transmission, according to the traditional energy model [33]. Then, the residual energy of each IoT node at the beginning of the next time frame is given as

$$E_{res}(t+1) = E_{res}(t) + E_h(t) - E_s(t) - E_r(t) - E_{tx}(t) \tag{10}$$

where $E_{res}(t)$ is the energy that was left over at the start of the time period, $E_s(t)$ is the consumed energy for spectrum sensing during the time τ_s, $E_r(t)$ is the consumed energy for reporting during the time τ_r, $E_{tx}(t)$ is the energy consumed for data transmission during τ_u, and $E_h(t)$ is the amount of energy harvested. The harvested energy at a receiver node n from RF sources can be modeled as

$$E_h(t) = \eta\tau_u \sum_{s=1}^{S} p_s |h_{s,n}|^2 \tag{11}$$

where η denotes the harvester unit's energy conversion efficiency, p_s stands for energy source's transmission power, and $h_{s,n}$ represents the channel gain between the RF source and the receiver node.

3. Proposed Algorithm Framework

In this section, we propose an energy-efficient joint optimization of spectrum sensing and energy harvesting (E^2JOSSEH) technique to improve detection performance and energy efficiency in cognitive IoT networks. The flow chart of the solution for the proposed E^2JOSSEH technique is shown in Fig. 3.

In the following subsections, the proposed E^2JOSSEH algorithm will be modified and split into two sub-algorithms called leader-follower and non-cooperative games to analyze optimal node selection and channel assignment mechanism, respectively.

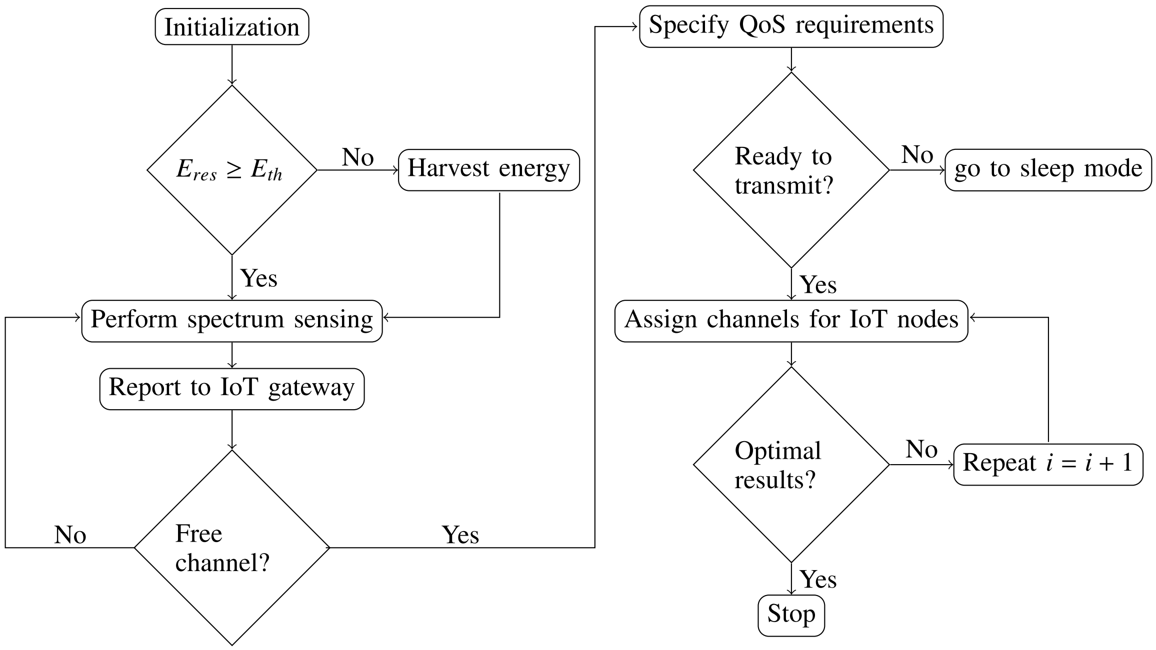

Figure 3. Flow chart of the proposed framework

A. Optimal node selection for CSS

In EH-enabled IoT systems, selfish nodes may opt to be free-riders and listen to the central entity's sensing data. As a result of the selfish behavior of nodes, no one engages in cooperation spectrum sensing, resulting in an extremely low likelihood of detection. If all nodes participate in sensing at random, however, a high chance of detection is attained at the cost of less remaining time for data transmission and energy harvesting. Therefore, we propose an incentive-based game approach to model the cooperation between the IoT gateway and sensing nodes.

In our proposed model, the IoT gateway can play the leading role in the game by providing incentives for cooperative nodes. This interaction between the IoT gateway and the nodes can be formulated as a Stackelberg game model. We define the game as follows.

- Players: IoT gateway (leader) and multiple IoT sensor nodes (followers)
- Strategies: Set of strategies s, which can be selected by the players to maximize their utility.
- Utility: The payoff received by the players. It is used to quantify the level of satisfaction.

The main objective of the IoT gateway is to increase its revenue and reduce the price paid to the cooperating nodes in order to enhance the performance spectrum detection. This is directly related to the participating nodes' overall throughput. Hence, the revenue of the IoT gateway can be represented by the average achievable throughput, while, it can forward power to nodes through beamforming as an incentive for their cooperation in spectrum sensing. Therefore, the utility function of the IoT gateway can be defined as

$$U_{GW} = w\bar{R} - I \tag{12}$$

where w denotes the weighting factor of benefit per unit of average data rate, $\bar{R}$ is the average achievable throughput, and I is the total incentive that the IoT gateway will distribute to all participating nodes. The total incentive can be defined as

$$I = \sum_{i=1}^{L} e_i x_i \tag{13}$$

where e_i represents arrived energy per unit time at the receiver of each node, $\mathbf{e}$=$[e_1, e_2, e_3, ..., e_L]$, x_i denotes the price per unit energy paid by sensing nodes, $\mathbf{x}$=$[x_1, x_2, x_3, ..., x_L]$, and L represents the maximum energy storage capacity. Similarly, each node tries to maximize the incentives received from the IoT gateway and minimize the energy cost for spectrum sensing. We define the energy cost for spectrum sensing as a quadratic function as follows.

$$c_i = a_i x_i^2 \tag{14}$$

where a_i is coefficient of energy cost. Then, the utility function of cooperative node n can be defined as follows.

$$U_n = e_i x_i - c_i \tag{15}$$

where e_i, x_i, and c_i are defined in (13) and (14), respectively.

In general, the IoT gateway provides incentives to encourage the cooperating nodes in order to maximize its utility, whereas each IoT node maximize its utility by optimizing the incentives received from the gateway and energy cost for spectrum sensing. The optimization problem for IoT gateway to maximize its utility function can be formulated as

$$\begin{array}{ll} \max\limits_{\mathbf{s},\mathbf{x}} & U_{GW}(\mathbf{s},\ \mathbf{e},\ \mathbf{x}) \\ \text{s.t.} & c_1 : x_i \geq 0 \\ & c_2 : \sum_{i=1}^{N} x_i s_i \leq L \\ & c_3 : s_i \in \{0, 1\} \end{array} \tag{16}$$

where c_1 denotes the price provided by the IoT gateway must be greater than or equal to zero. c_2 ensures that the total energy allocated as an incentive should not be exceed its energy storage capacity. c_3 represents all strategy variables to be a binary variable. The optimization problem for IoT sensor nodes to maximize its utility function can be formulated as

$$\begin{array}{ll} \max\limits_{e_i} & U_n(e_i, x_i) \\ \text{s.t.} & c_1 : 0 \leq e_i \leq P_{max} \end{array} \tag{17}$$

where c_1 denotes the value of the energy arrival rate should be between zero and the maximum power transmitted by the base station.

We might use the exhaustive search method to tackle the optimization problems in (16) and (17). However, this method is computationally expensive and complex for large number of IoT sensor nodes [34]. Therefore, we design a high performance heuristic algorithm to find the optimal number of nodes that participate in the CSS, as described in Algorithm 1. The computational complexity of the proposed model is $O(N \log N)$ which is extremely low compared to exhaustive search algorithm with computational complexity of $O(N^N)$.

B. Optimal Channel Assignment Mechanism

In this subsection, we model the channel assignment for cognitive IoT nodes as a strategic form non-cooperative game. The channel assignment problem of a non-cooperative game can be defined as

$$G = \{N, \{S_n\}_{n \in N}, \{U_n\}_{n \in N}\} \tag{18}$$

where N is the set of players (i.e,, cognitive IoT nodes), S_n is the set of strategies (i.e., channel assignment) for node n to choose the available idle channels, and U_n is the utility function. In this game, the utility function of each node n can be formulated as

$$U_n(C_n, C_{-n}) = \frac{\sum_{c=1}^{C} R_{c,n}^t}{E_c} \tag{19}$$

Algorithm 1 Algorithm for optimal node selection to perform CSS

Initialize()
Repeat
The IoT gateway announce the incentive I
for $n = 1 to N$ **do**
  Compute U_n
  if $U_n > 0$ **then**
    Node n will accept to cooperate, send the vector $V_n = \{E_{res}, \gamma_n, d_n\}$ to the IoT gateway
  end if
end for
The IoT gateway sort the set of vector values $\{E_{res}, \gamma_n, d_n\}$ in descending order
for $j = 1 to N_c$ **do**
  Compute U_{GW}
  if $U_{GW} > U_{GW}^*$ **then**
    $U_c = U_c + 1$
    Update $I_c = \{i_1, ..., i_n\}$
    Update the iteration number $i = i + 1$
  else if then
    Break
  end if
end for
Return (I_c^*, N^*), variables with * are optimal values

where C_n and C_{-n} are the available idle channel profiles relative to strategy S_n and S_{-n}, respectively. E_c is the energy consumed in the link. In a non-cooperative game, nodes can select any channel assignment strategy with competition among other players. For each node n, its strategy set is the available idle channel profiles, which is given by

$$C_n = \{C_n | C_n > c, \sum_{n=1}^{N} C_n = C\} \tag{20}$$

where C is the total available idle channel of the system. Based on the idle channel profiles in (20), the utility function of each node n can be rewritten as

$$\begin{aligned} U_n(C_n, C_{-n}) &= \frac{\sum_{c=1}^{C} R_{c,n}^t}{E_c} \\ &= \sum_{n \in N} \frac{\psi_n C_n}{\sum_{m \in N} \mu_m C_m} \end{aligned} \tag{21}$$

where $\psi_n = \mu_n N_c$, μ_n denotes the population state, and N_c is the number of nodes in group c choosing strategy C_n. According to the utility function in (21), the optimization problem to maximize the overall energy efficiency of the network can be formulated as follows.

$$\begin{array}{ll} \max\limits_{\mu_n, c} & U_n = \sum_{n=1}^{N} \sum_{c=1}^{C} \frac{\psi_n C_n}{\sum_{m \in N} \mu_m C_m} \\ \text{s.t.} & c_1 : R_{c,n} \geq R_{min} \\ & c_2 : \sum \mu_n = 1 \end{array} \tag{22}$$

where c_1 guarantees the minimum data rate requirement for selected nodes to access the idle channel. c_2 ensures that only one channel is assigned for each node. Each IoT node makes a decision iteratively to select a strategy that maximizes energy efficiency. At some point of the game, players may select an optimal strategy, where no players can further change their strategies to increase its utility function. This stable operating point is a Nash equilibrium point. In the proposed non-cooperative game, there always exists at least one channel assignment that converges to a Nash equilibrium. The best response of the n^{th} node decision of profile C_n^* is unique, while the decisions of other nodes profile C_{-n} remains constant.The best response for Nash equilibrium of the proposed game can be given as

$$C_n^* = max\{c, \sqrt{\frac{N_c \lambda_n(C_{-n})}{\mu_n}} - \frac{\lambda_n(C_{-n})}{\mu_n}\} \quad (23)$$

where λ_n denotes the influence factor from other nodes. Based on these findings, we devised an algorithm to assign channels to IoT nodes in the most efficient way possible, as presented in Algorithm 2.

Algorithm 2 Algorithm for optimal channel assignment scheme

```
Initialize()
while Available idle channel is greater than zero do
    Calculate utility of channel using (21)
    Channel=Channel+1
    Compute max c_n (U_n(c_n)) to select the best channel
    for each node n to be scheduled for a channel c do
        if R_{c,n} > R_min then
            if node n hasn't been scheduled any channel yet then
                Assign channels for data transmission
                Update the best response C_n(t) using (23)
            end if
        end if
    end for
end while
Return (C_n^*, U_n^*), variables with * are optimal values
```

4. Simulation Results and Performance Analysis

In this section, we evaluate the performance of the proposed E^{2}JOSSEH technique and compare it with other algorithms with respect to different parameters. For simulations, we consider cognitive IoT nodes are randomly distributed in a square region with length of $400m$ to access the idle spectrum in licensed bands. All channels between each node and the IoT gateway is modeled as AWGN channel.

The snap shot of the network model considered for this simulation is depicted in Fig. 4. Details of the simulation parameters are listed in Table II. The simulation results in this section provide insights into the performance of the proposed algorithm compared with other techniques over different metrics. The proposed E^{2}JOSSEH algorithm is compared with the following algorithms:

- Random sensor selection (RSS) algorithm [35]: In RSS algorithm, sensors are randomly selected to participate in CSS with equal probability. RSS algorithm has a minimum complexity for computing a solution, however, it has the maximum energy consumption.
- Dynamic collaborative spectrum sensing (DCSS) algorithm [22] : In this algorithm, sensor nodes form clusters and collaboratively sense the availability of licensed channels to reduce the energy consumption. Each sensor node broadcasts messages periodically to the neighboring nodes to collaborate. This method is poor at low SNR.
- Cooperative sensing and scheduling optimization (CSSO) technique [7]: In this scheme multiple sensor nodes can cooperate to reduce the channel sensing time.
- Exhaustive search algorithm (ESA) [34]: This algorithm considers each search point inside the search zone and so returns the best possible match; nonetheless, it necessitates a significant amount of computing time.
- Random channel access (RCA) scheme [36]: In this approach, IoT nodes are scheduled for a random channel in different time slots and transmit data with all their available energy.

TABLE II. Simulation Parameters

Parameter	Symbol	Value
Maximum transmit power of base station	P_{max}	20W
Minimum system battery level	E_b	5mJ
Energy consumption of sensing for $1ms$	E_s	$40mJ$
Energy harvesting efficiency	η	0.5
Minimum required data rate	R_i^{min}	125kbps
Frame duration	T	10ms
Sensing duration	τ_s	1ms
Retorting duration	τ_r	1ms
Utility duration	τ_u	8ms
Target probability of detection	P_D	95%
Absence probability of PU	P_{H0}	90%

First, we evaluate the detection performance of the proposed technique for different values of SNR as shown in Fig. 5. It is observed that the detection performance of the proposed technique is better than other techniques. For example, with SNR value of $4dB$, the E^{2}JOSSEH algorithm shows $7.61\%, 16.84\%$ and 31.3% higher detection performance than DCSS, CSSO, and RSS techniques, respectively. Also, probability of detection exponentially increased as SNR increased, which indicates that less interference and better protection for channels occupied by PUs.

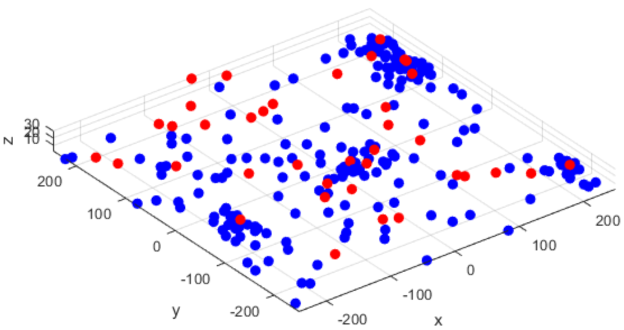

Figure 4. Snap shot of the IoT nodes distributions: the cluster IoT users and the PPP users are indicated by blue and red dots, respectively

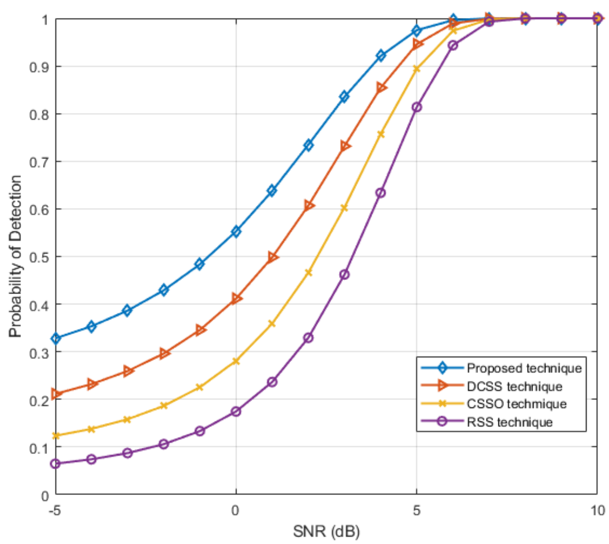

Figure 5. Probability of detection versus SNR(dB)

The detection probability versus the probability of false alarm is represented in Fig. 6. It is clearly observed that the proposed E^{2}JOSSEH technique relatively displays higher detection performance compared with other techniques. The E^{2}JOSSEH algorithm has almost achieved the theoretical limit values of probability of false alarm rate and detection probability. This proves that spectrum detection accuracy is improved with appropriate selection of IoT sensor nodes to participate in CSS. As the number of IoT nodes participating in CSS grows, the detection reliability improves considerably, allowing access to the idle spectrum without interfering with PUs. It's worth mentioning that adopting the energy harvesting technique increased the number of nodes participating in CSS. Therefore, it is evident that the proposed technique can play a vital role to accurately detect the available spectrum and efficiently utilize the idle channels in licensed bands.

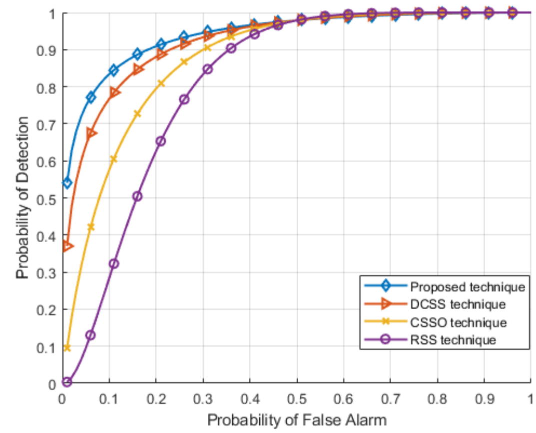

Figure 6. Probability of detection versus probability of false alarm

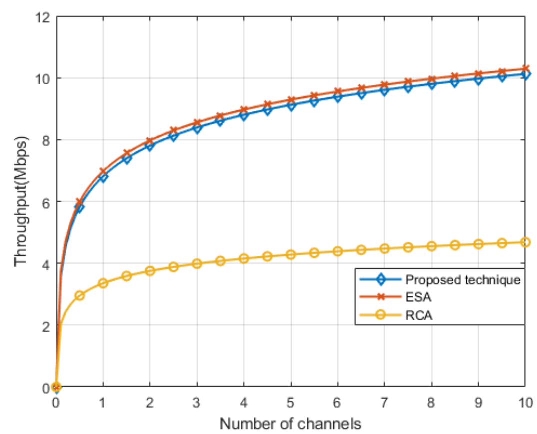

Figure 7. Throughput versus Number of channels

Fig.7 illustrates the performance of average data throughput versus the number of channels assigned for SUs. It is observed that RCA has minimum throughput and doesn't improve with number of channels increase. This is due to the channels are randomly assigned for all active IoT nodes and probability of collision becomes higher. On other hand, as the number of channels assigned for IoT nodes increases, the proposed E^{2}JOSSEH technique and ESA provide better throughput. However, E^{2}JOSSEH still performs better than ESA approach. For example, if 8 channels are assigned, the proposed E^{2}JOSSEH technique achieves a throughput about 46.04% higher than the RCA scheme. This shows that the proposed optimal channel assignment mechanism significantly improves the system throughput. Fig. 8 illustrates the average harvested energy from RF sources across different number of IoT nodes. It compares the E^{2}JOSSEH technique with greedy and random approaches. It is clear from the simulation result that the proposed technique provides significant energy harvesting gains. For example, with 50 IoT nodes, the E^{2}JOSSEH technique harvests 35.48% and 8.67% higher energy compared with random and greedy approaches, respectively.

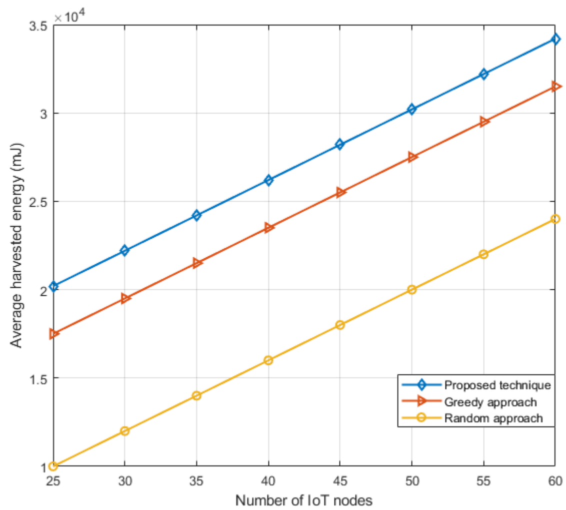

Figure 8. Average Harvested Energy versus Number of IoT nodes

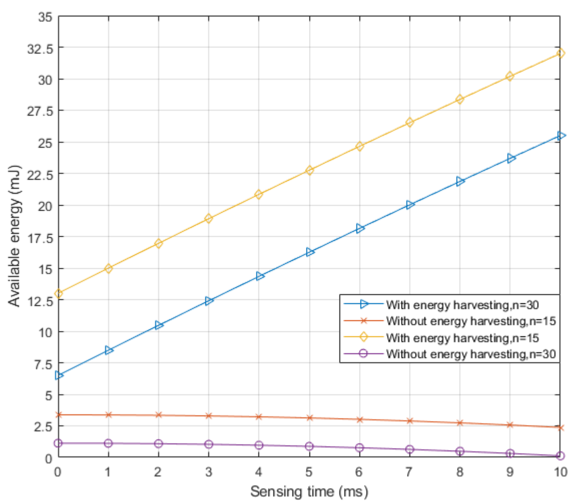

Figure 9. Available energy per node versus sensing time

Fig. 9 compares the available energy per node of the conventional and proposed cooperative spectrum sensing without energy harvesting and with energy harvesting for different sensing time. It is observed that the available energy per node is decreased with the increase of sensing time in the conventional model. However, in the proposed technique, the available energy per node increases with sensing time. This shows that the harvested RF energy compensates the energy consumed for cooperative spectrum sensing. In Fig. 9, it is also observed that the available energy per node is decreased with the increase of IoT sensor nodes. For example, at sensing time ($\tau = 9ms$) when the IoT node n increased from 15 to 30, the available energy per node decreased from $30mJ$ to around $23.5mJ$ for the proposed technique and it almost goes from $2.5mJ$ to $0J$ in conventional model.

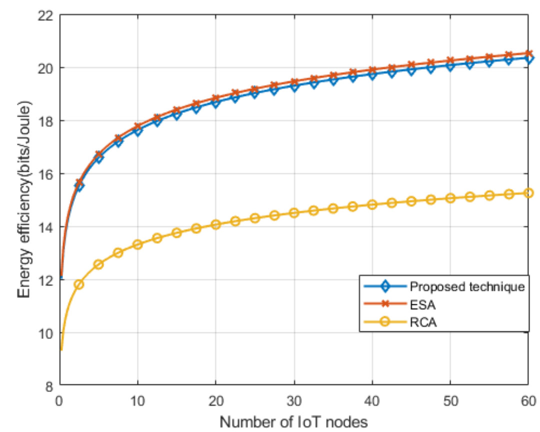

Figure 10. Energy efficiency versus number of IoT nodes

In Fig. 10, we demonstrate the average energy efficiency versus the number IoT sensing nodes. The figure shows that the energy efficiency of the proposed technique is higher than other techniques as the number of IoT nodes increase. For example, with 50 IoT nodes, the proposed technique shows 26.88% better energy efficiency as compared to the RCA scheme. This can be realized that energy harvesting technique provides sufficient energy for sensing nodes. Thus, it is evident that energy harvesting techniques play vital role to deploy energy efficient green technologies in future telecommunication networks.

5. Conclusion

The exponential growth of smart gadgets connected to the Internet as well as diverse applications and broad service demands has escalated the spectrum scarcity in 5G networks. Dynamic spectrum sensing becomes a promising solution to detect the idle spectrum channels in licensed bands and access it opportunistically. However, to improve the detection performance, sensors require significant energy consumption. In this paper, we propose a dynamic cooperative spectrum sensing technique with energy harvesting for cognitive IoT systems in 5G networks. We formulate a joint optimization of harvesting and spectrum sensing algorithm to improve the energy efficiency and idle channel utilization. We solved the optimization problem by using a branch and bound heuristic algorithm in order to maximize the energy efficiency while guaranteeing the minimum data rate requirement and detection performance. The performance of the proposed technique is evaluated, analyzed and compared with existing models. Simulation results show that the proposed algorithm performs better than other existing models in terms of detection probability, data throughput, and energy efficiency. For example, the detection performance and energy efficiency is improved by 31.3% and 26.88%, respectively as compared to the random approach. Therefore, this is evident that incorporating RF energy harvesting plays an important role to improve the overall performance of rechargeable cognitive IoT systems in 5G networks. As a future work, we will investigate additional QoS requirements for heterogeneous IoT nodes and exploiting interference for energy harvesting.

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