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# Resource Management for Cognitive IoT Systems With RF Energy Harvesting in Smart Cities

**BANDER ALZAHRANI [1], (Member, IEEE), AND WALEED EJAZ [2], (Senior Member, IEEE)**
[1] Faculty of Computing and Information Technology, King Abdulaziz University, Jeddah, Saudi Arabia
[2] Department of Applied Science and Engineering, Thompson Rivers University, Kamloops, BC V2C 0C8, Canada

Corresponding author: Bander Alzahrani (baalzahrani@kau.edu.sa)

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**ABSTRACT** The number of Internet of Things (IoT) nodes is increasing in modern cities which demands spectrum and energy efficiency. Fifth-generation (5G) networks are considered as a key paradigm for the realization of future IoT applications. Particularly, cognitive radio and non-orthogonal multiple access are candidate technologies for 5G networks that can improve spectral efficiency and accommodate a large number of IoT devices. Furthermore, radio frequency (RF) energy harvesting can increase the energy efficiency of IoT networks. In this paper, we propose a resource management scheme for cognitive IoT network with RF energy harvesting in 5G networks. The objective is to maximize the throughput while assuring quality-of-service requirements in terms of data rate and minimum residual energy constraint on each IoT node. We use mixed integer linear programming and greedy approaches to solve the optimization problem. We then present the simulation results of the proposed scheme to exhibit the significant positive impact on the performance of the IoT network.

**INDEX TERMS** 5G networks, energy efficient, Internet of Things, smart cities, spectrum efficient.

## I. INTRODUCTION

The Internet of Things (IoT) is expected to play a major role in addressing the problems of growing population and urbanization. In IoT-enabled smart cities, common devices such as household machines, office devices, cars, and hospital equipment will be directly communicating with each other without human involvement [1], [2]. The objects will become intelligent enough to sense and process the information ubiquitously and in real time. The upcoming fifth generation (5G) networks are forecasted to play a major role in IoT systems. The second generation (2G) networks were meant for voice communications, third generation (3G) added data, and fourth generation (4G) was primarily focused on broadband Internet experiences. On the other hand, 5G is meant to communicate the objects with each other such that a large number of IoT nodes can exchange data with each other in real time [3]. These IoT nodes are expected to have the ability to share information, interact with real people, support intelligent business processes and even make smart decisions [4]. For example, the IoT-enabled transportation system in smart cities can overcome the problem of traffic congestion and reduce accidents; IoT-enabled distribution systems in supply chains can make better quality products at a reduced cost; smart grid solutions can help to optimize the electricity distribution and consumption. However, there are many challenges associated with the IoT-enabled solutions for smart cities. Particularly, we need spectral efficient solutions to accommodate a large number of IoT nodes.

IoT devices are expected to be interconnected through wireless communication technologies in smart cities, mainly 5G [3]. Therefore, it is indispensable to investigate IoT in 5G networks, which is expected to provide a massive connectivity along with high data rates. Due to a large number of users, wireless spectrum will be insufficient to cater the needs of all IoT devices. This can be mitigated by adopting intelligent frequency spectrum allocation schemes. Also, IoT applications should employ cognitive capabilities for effective spectrum utilization according to the available bandwidth and application needs. Therefore, cognitive radio (CR) technology needs to be adapted into IoT systems to increase the spectral efficiency and reliability [5], [6]. CR technology can efficiently address the spectrum underutilization problem, and also enhance the interoperability between various wireless communications systems. Incorporating CR technology in IoT systems can be a big step forward towards autonomous and self-reconfigurable IoT systems.

Energy management of IoT nodes is another key constraint in massive IoT deployments [7]. Aggregate energy consumption of low power devices in the networks may accumulate to become very large. Thus, we need to target extremely low power designs. Moreover, we intend to embed most of these devices in the environment managed remotely and operated perpetually without frequent battery replacements or bulky power cords. These requirements increase the interest in the concept of wireless power transfer techniques or harvesting energy from their surroundings. Energy harvesting from radio frequency (RF) signals is becoming quite popular these days [8]–[10]. Although the net energy gained from RF harvesting is very less as compared to other possible alternative sources such as renewable energy (solar/wind etc), its easy availability (inside/outside buildings, and throughout the day) makes it much attractive. In this paper, we enable IoT devices to harvest RF energy from ambient RF sources such as base stations.

Channel access techniques are extremely important in providing the user with a medium of communication in wireless networks. For instance, orthogonal frequency division multiple access (OFDMA) is used in 4G networks. However, every channel access technique has its own limitations, like in OFDMA where the number of users are restricted by the total number of resources and their scheduling. Recently, non-orthogonal multiple access (NOMA) has become a vital technology for 5G networks [11], [12]. It has numerous advantages as compared to previous techniques such as NOMA which supports multiple users on the same resource block in the same cell while harnessing channel gain differences of various users.

### A. CONTRIBUTIONS

In this work, we introduce a resource management scheme for cognitive IoT systems with RF energy harvesting. Following are the main contributions of this paper:

- We mathematically model a throughput maximization problem of IoT system in 5G networks. We adopt RF energy harvesting technology to enhance the energy efficiency of the network.
- The proposed model ensures the minimum required data rate and minimum residual energy constraints for each IoT node by using NOMA and RF energy harvesting technologies.
- We first convert the optimization problem from mixed integer non-linear programming (MINLP) to mixed integer linear programming (MILP) by using the rate function constant. We then solve the problem using MILP and greedy approaches.
- Finally, we analyze the performance of proposed framework to show the impact of incorporating NOMA and RF energy harvesting technologies in IoT systems.

### B. ORGANIZATION

The rest of the paper is organized as follows. Section II provides related work for RF energy harvesting in IoT, spectrum sharing in IoT, simultaneous wireless power transfer and spectrum sharing in IoT, and NOMA in IoT. The system model for the proposed resource management framework is provided in III. We present the proposed resource management framework for cognitive IoT systems in Section IV. The performance of proposed framework is evaluated in Section V. Finally, the paper is concluded in Section VI.

## II. RELATED WORK

Recently, a plethora of work has been done on energy harvesting, multi-band spectrum sharing and NOMA technique for IoT systems in 5G networks. Here, we present our literature review on these topics. We have observed that none of the existing work cover all three aspects at the same time.

### A. RF ENERGY HARVESTING FOR IoT

Takacs *et al.* [8] addressed the recent advances in the area of RF energy harvesting for IoT, particularly in structural health monitoring applications. Several rectenna (rectifier antenna) design topologies were presented and their performances in the various bands were discussed to prove the phenomenon of energy harvesting to monitor the condition of antenna panels of the satellites. A novel mechanism to optimize the placement and the number of energy transmitters in wireless sensor networks (WSNs) with wireless energy transfer was proposed in [9]. Similarly, Ejaz *et al.* [10] presented a mechanism to optimally locate the energy transmitters in software-defined WSNs with RF power transfer, and find optimal number of energy transmitters. Authors also presented a scheduling mechanism for energy transmitters for the given tasks of energy charging. The performance of the proposed scheme is proved by simulating fairness, energy charged, number of tasks, number of energy transmitters, and energy consumption. An effective energy harvesting-aware routing algorithm is developed by Nguyen *et al.* [13] to address the issues of energy efficiency, QoS, and network lifetime extension for IoT applications with the use of three energy harvesting techniques: solar-based, RF-based, and moving vehicle-based energy harvesting. Similarly, Michelusi and Levorato [14] developed a control framework for energy harvesting devices that are connected to a BS over a multiple access channel. The idea is to enable the nodes to make channel access decisions based on their own harvesting state, as well as of the other nodes in the network. Beng *et al.* [15] proposed a WSN farming animals health monitoring system using near field communication (NFC) to monitor the main parameters such as body temperature. Authors used RF energy captured by the remote wireless power transmitters to charge up the lithium battery of the WSN units attached to the animal. However, Takacs *et al.* [8], Ejaz *et al.* [9], [10], Nguyen *et al.* [13], Michelusi and Levorato [14], and Beng *et al.* [15] only focused on RF energy harvesting and did not address multi-band spectrum sharing and NOMA techniques for IoT systems.

### B. SPECTRUM SHARING FOR IoT

Rawat *et al.* [6] presented an approach to solve research challenges in the field of CR technology for M2M and IoT.

Authors reviewed CR techniques to address various problems of IoT including energy efficiency, scalability and heterogeneity etc. Energy efficient CR technology for the IoT is considered by Qureshi *et al.* [16]. Authors observed that the selection of reliable data channels for the IoT devices, and its integration with backup data channels, has reduced communication time among the secondary users, which plays a critical role, directly affecting the performance of the CR ad hoc networks in terms of energy consumption and throughput. A service prioritized scheduling scheme for IoT is presented in [17]. The authors proposed traffic modeler to support proposed scheme. The proposed model is the service-centric spectrum usage pattern of IoT nodes as a six-state continuous-time Markov chain. Authors showed that the QoS requires both real and non-real time services which are satisfied by the proposed scheme as compared to the mixed critical scheduling algorithm. Khan *et al.* [18] measured the spectrum usage behavior of three rotating radar systems that were fixed on ground at various different locations, in order to prove the appropriateness of the rotating radar spectrum for the IoT shared spectrum access. Etim and Lota [19] employed a power loss exponent that plays a vital role in various operating environments for IoT in the non-cooperative game cost function to evaluate the necessary transmission power in the CR network (CRN). Various secondary users will be able to transmit with less power using this approach, and save power consumption. Furthermore, Kim [20] worked on CR based IoT systems and designed a novel scheme for cooperative spectrum sensing and sharing based on the inspection game model. Based on simulations, the performance of system is improved while approximating the aspiration equilibrium status. The focus of [6] and [16]–[20] is on spectrum sharing for IoT and authors do not consider on energy harvesting and NOMA aspects.

### C. WIRELESS POWER TRANSFER AND SPECTRUM SHARING FOR IoT

Ercan *et al.* [21] proposed a spectrum and energy efficient IoT network for 5G systems. They showed that for the same amount of cellular traffic in the area, the IoT network utilization increases with the increase in the number of IoT devices. The broadcast nature of energy transfer results in a multi-user gain. A spectrum share model is proposed in [22] for IoT devices with capability of wireless power transfer. First, energy is harvested by secondary transmitters from the primary signal. The secondary transmitter then transmit information on primary signal without any harmful interference to primary users. The primary signal's transmit power and secondary transmitter's reflection coefficient is optimized to maximize the secondary system's capacity. Similarly, Tang *et al.* [23] proposed protocols for energy harvesting in cognitive networks. It is shown that the system performance (achievable rate of the secondary transmission) is improved by using proposed protocols.

Energy and channel management schemes are proposed in [24] for spectral and energy efficient CR sensor networks for IoT systems. The effectiveness of proposed schemes is evaluated in terms of functional nodes and residual energy of the network. Lyu *et al.* [25] proposed harvest-then-transmit and backscatter communication mode for the wireless power cognitive IoT systems to maximize throughput. Authors presented numerical results to show that the proposed scheme have higher throughput compared to traditional schemes. An analysis for the performance of the network considering wireless power and data transmission at the same time is conducted in [26]. The objective is to study the spectrum sharing in the CRN with a multi-antenna primary receiver using the antenna switching technique. The benefits of using secondary transmitter are proved and theoretical results are validated by the Monte Carlo simulations. Furthermore, Mou *et al.* [27] investigated secure communication for RF-powered CRNs. The secondry user harvest energy from primary user to transmit information in the presence of attacker. Although authors considered both wireless power transfer/RF energy harvesting in [21]–[27], however, none of them considered NOMA which is a key 5G candidate technology to improve spectrum efficiency.

### D. NOMA (NON-ORTHOGONAL MULTIPLE ACCESS)

Ding *et al.* [11] compared the effect of user pairing on the performance of two systems that were based on NOMA. 1) F-NOMA (with fixed power allocation), 2) CR-NOMA (inspired by CR). Liang *et al.* [28] studied the user pairing in a downlink NOMA network, where the power was allocated to the pairwise users by the base station. Authors solved the power allocation and user pairing problem in the CR-NOMA systems by using the matching theory. Application of NOMA to multi-cast CRNs is investigated in [29], where the authors presented a dynamic cooperative NOMA scheme. Authors proved significant improvements using proposed scheme as compared to non-cooperative NOMA. Ding *et al.* [30] proposed a MIMO-NOMA scheme for IoT systems, where QoS requirements for one user are satisfied while serving other users opportunistically using NOMA. The performance of the proposed scheme is demonstrated by analytical and numerical results. A massive NOMA technique is presented in [31] as a promising solution to support a large number of IoT devices in cellular networks. Zhang *et al.* [32] introduced multiple antenna techniques in the existing CR based NOMA, by specifying a certain number of primary users, and then optimized the energy efficiency such that QoS requirements are met for each primary user. For this, authors proposed an algorithm based on the sequential convex approximation. A power-domain uplink NOMA is proposed in [33] for narrow band (NB)-IoT systems. Simulation results are presented to demonstrate that the proposed NOMA technique is able to increase the number of successfully connected nodes in NB-IoT systems compared to orthogonal multiple access. Ding *et al.* [11], [30], Liang *et al.* [28], Lv *et al.* [29], Shirvanimoghaddam *et al.* [31], Zhang *et al.* [32], and Mostafa *et al.* [33] considered NOMA for IoT and

**TABLE 1.** Summary of existing literature on RF energy harvesting for IoT, spectrum sharing for IoT, wireless power transfer and spectrum sharing for IoT, and NOMA.

| Ref. | Year | E[a] | S[b] | N[c] | Remarks |
|---|---|---|---|---|---|
| [8] | 2017 | ✓ | | | Recent advances in RF energy harvesting for IoT are addressed with focus on structural health monitoring applications. |
| [9] | 2015 | ✓ | | | The placement and the number of energy transmitters are optimized in WSNs with wireless energy transfer |
| [10] | 2016 | ✓ | | | A mechanism is proposed to optimally locate the energy transmitters in software-defined WSNs with RF power transfer. |
| [13] | 2017 | ✓ | | | An effective energy harvesting-aware routing algorithm is developed to address the issues of energy efficiency, QoS, and network lifetime extension for IoT applications. |
| [14] | 2017 | ✓ | | | A control framework is developed for energy harvesting devices that are connected to a BS over a multiple access channel. |
| [15] | 2016 | ✓ | | | RF energy harvesting is used to charge WSN units for livestock health monitoring system. |
| [6] | 2016 | | ✓ | | A review of CR techniques is presented to solve research challenges for IoT and M2M communication including energy efficiency, scalability, and heterogeneity. |
| [16] | 2017 | | ✓ | | The selection of reliable channels for IoT devices and its integration with backup channels is studied to improve the performance of CR ad hoc networks. |
| [17] | 2015 | | ✓ | | A traffic modeler is proposed to support service prioritized scheduling scheme for IoT. |
| [18] | 2017 | | ✓ | | The spectrum usage behavior of three rotating radar system is measured to validate the usefulness of rotating radar spectrum for the IoT shared spectrum access. |
| [19] | 2016 | | ✓ | | A power loss exponent is employed in IoT operating environment in the non-cooperative game cost function to reduce transmit power of secondary users in CRN. |
| [20] | 2017 | | ✓ | | A cooperative spectrum sensing and sharing scheme is proposed based on inspection game model to improve performance of CR based IoT systems. |
| [21] | 2017 | ✓ | ✓ | | A spectrum and energy efficient IoT network for 5G systems is proposed to show multi-user gain because of the broadcast nature of energy transfer. |
| [22] | 2017 | ✓ | ✓ | | A spectrum sharing model named as riding on the primary (RoP) is proposed to maximize the ergodic capacity of the secondary system. |
| [23] | 2017 | ✓ | ✓ | | A time-switching relaying (TSR) and power-splitting relaying (PSR) based energy harvesting is proposed for cognitive wireless acoustic sensor networks. |
| [24] | 2018 | ✓ | ✓ | | Energy and channel management schemes are proposed for spectral and energy efficient CR sensor networks for IoT systems. |
| [25] | 2018 | ✓ | ✓ | | Harvest-then-transmit and backscatter communication mode are proposed for the wireless powered cognitive IoT systems to maximize throughput. |
| [26] | 2016 | ✓ | ✓ | | The performance analysis of a network is conducted considering wireless power and data transmission at the same time with an objective to study the spectrum sharing. |
| [27] | 2016 | ✓ | ✓ | | Secure communication for RF-powered CRNs using harvested energy from primary transmitter is investigated. |
| [11] | 2016 | | ✓ | ✓ | The effect of user pairing is compared on the performance of F-NOMA and CR-NOMA. |
| [28] | 2017 | | ✓ | ✓ | The user pairing in a downlink NOMA network and power allocation are proposed in the CR-NOMA systems. |
| [29] | 2017 | | ✓ | ✓ | Application of NOMA to multi-cast CRNs is investigated. |
| [30] | 2016 | | ✓ | ✓ | A MIMO-NOMA scheme for IoT systems is proposed where QoS requirements for one user are satisfied while serving other users opportunistically using NOMA. |
| [31] | 2017 | | | ✓ | A massive NOMA technique is studied to support a large number of IoT devices in 5G networks. |
| [32] | 2016 | | ✓ | ✓ | Multiple antenna techniques are introduced in the existing CR based NOMA. |
| [33] | 2017 | | | ✓ | A power-domain uplink NOMA is proposed for narrow band (NB)-IoT systems to increase the number of connected nodes. |
| Our | 2018 | ✓ | ✓ | ✓ | We consider spectrum sharing in IoT with RF energy harvesting in 5G networks (NOMA). |

[a](E)nergy harvesting or wireless power transfer.
[b](S)pectrum sharing.
[c](N)on-orthogonal multiple access.

CR based NOMA. However, RF energy harvesting was not considered to improve energy efficiency.

In summary given in Table 1, existing literature has considered RF energy harvesting for IoT, spectrum sharing for IoT,

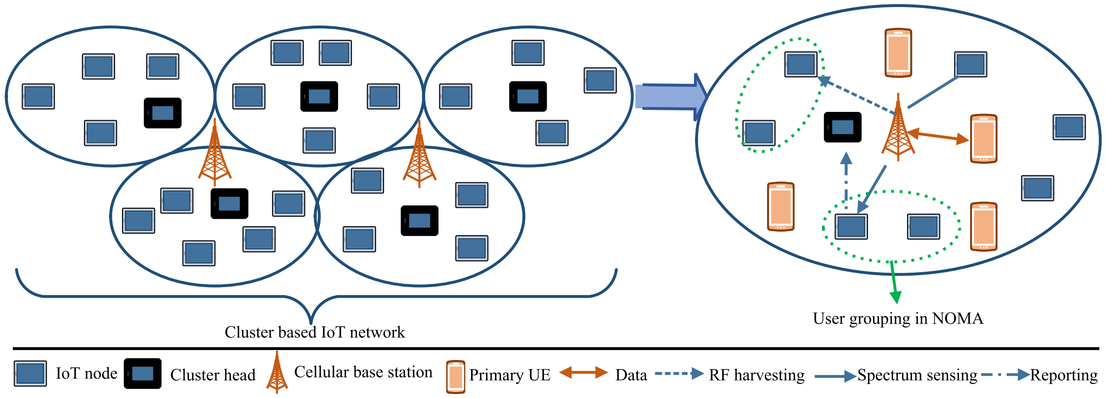


**FIGURE 1.** Architecture of cluster based IoT network.

simultaneous wireless power transfer and spectrum sharing in IoT, and NOMA as a potential candidate of 5G networks. However, spectrum sharing in IoT with RF energy harvesting in 5G networks (NOMA) is not well investigated. In this paper, we propose a resource management scheme for cognitive IoT systems in 5G networks.

## III. SYSTEM MODEL

We consider a 5G heterogeneous network with RF energy harvesting in smart cities. The architecture can have multiple primary networks with the different number of available channels. We assume that each primary network is comprised of multiple clusters, where each cluster consists of $N$ IoT devices and $C$ channels in each cluster. The architecture of cluster-based IoT network is demonstrated in Fig. 1. We assume that the number of IoT devices is greater than the number of channels, i.e., $N > C$. We also assume that every IoT node is associated with only one wireless interface, i.e., nodes can either transmit data or harvest energy. We consider cluster heads in each cluster as energy-rich nodes. The cluster head in each cluster can act as a central entity/fusion center for spectrum sensing and resource allocation. For illustration purposes, we consider only one cluster in this paper. The users in the primary network are the licensed users to utilize channels, while IoT devices can use the channels opportunistically. The primary users can transmit data over the channels in time slot manner with frame duration $T$. The duration of frame in 4G (long-term evolution (LTE)) network is 1ms [21], however, it is expected to be dynamic in 5G systems [3].

The frame structure of the cluster based IoT network with RF energy harvesting is shown in Fig. 2. We assume that each frame is divided into three slots, i.e., sensing slot, scheduling slot, and user slot. At the beginning of sensing slot, each IoT node will check its residual energy and perform spectrum sensing for multiple channels if its residual energy ($E_{R,n}$) is

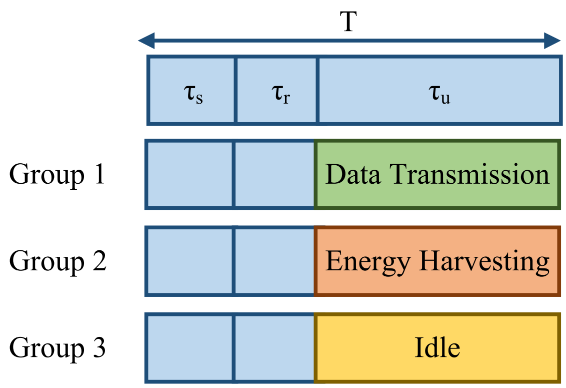


**FIGURE 2.** Frame structure of the cluster based IoT network with RF energy harvesting.

greater than a certain threshold $\theta_s$. This can be written as:

$$\phi_{nc} = \begin{cases} 1, & E_{R,n} \geq \theta_s \\ 0, & \text{otherwise}, \end{cases} \tag{1}$$

where $\phi_{nc}$ will be 1 if *n-th* IoT node is performing spectrum sensing and 0 if it is harvesting energy or in idle mode. The duration of sensing slot is $\tau_s$ and depends on several factors such as signal to noise ratio (SNR) of the channel, sensing method, computation power of the device, the number of channels to be sensed, etc. We consider energy detection scheme for spectrum sensing and multi-band approach for cooperative spectrum sensing [34].

The IoT devices will forward their sensing outcome to the central entity for cooperative spectrum sensing. The central entity will then make a global decision by fusing the outcome from multiple IoT devices about the channel state, i.e., busy or available. In this way, the central entity will have occupancy information of all $C$ channels. The central entity will then assign appropriate channels to IoT nodes for data transmission or energy harvesting. Reporting and scheduling will be done in scheduling slot for duration $\tau_r$. Let $\tau_u$ be the user slot duration, which is given by $\tau_u = T - \tau_s - \tau_r$. IoT devices can be scheduled for data transmission or energy harvesting in this duration depending on their residual energy ($E_{R,n}$) and requirements. Thus, the IoT devices will be divided into three groups as shown in Fig. 2.

### A. ENERGY HARVESTING MODEL

Let $g_{n,c}$ be the channel gain of *n-th* IoT node to the *c-th* channel. The gain consists of several parameters including path loss and antenna factor. Let $P_C$ be the transmit power of base station on channel *c*. As mentioned above, IoT devices can harvest energy during $\tau_u$ Then, energy harvested by *n-th* IoT node can be written as:

$$E_n^H = \omega g_{n,c} P_C \tau_u, \tag{2}$$

where $\omega$ is the harvesting efficiency. The harvesting circuit will convert the received RF energy into DC electricity for storage in the IoT node. There are several possible losses during this process. Thus, the harvesting efficiency mainly depends on the quality of harvesting circuit.

### B. ENERGY CONSUMPTION MODEL

Each IoT node consumes energy while performing different tasks shown in Fig. 2. Thus, energy consumption will be different in transmission mode, energy harvesting mode, and idle mode. Let $P_{S,n}$ be the power consumed in the sensing process by *n-th* IoT node. Then, the total energy consumption for sensing process will be $P_{S,n} \times \tau_s$. Energy will also be consumed during its communication with the central entity and scheduling process. The IoT node needs power $P_{R,n}$ for communication with the central entity, then the energy consumed by the IoT node during this slot will be $P_{R,n} \times \tau_r$. Moreover, the device's processor and hardware circuit will also consume power for duration $\tau_u$ when it is in active mode (i.e., transmission mode). The total energy consumed by *n-th* IoT device during transmission phase (Group 1) can be given as:

$$E_n^{C,T} = (P_{S,n} \times \tau_s) + (P_{R,n} \times \tau_r) + ((P_{RF} + P_{HC} + P_{tr}) \times \tau_u), \tag{3}$$

where $P_{RF}$, $P_{HC}$, and $P_{tr}$ are the power consumed by RF module, hardware circuit, and transmission of data respectively.

In the case, when the residual energy of IoT node is less than $\theta_s$, the IoT node will be in harvesting mode (group 2). The RF to DC circuit will also consume power to store energy in the IoT node, let the power consumption for this process be $P_{rd}$. Further, the energy consumption includes power consumed in reception and power consumed by RF module. This can be written as:

$$E_n^{C,H} = (P_{R,n} \times \tau_r) + ((P_{RF} + P_{rc} + P_{rd}) \times \tau_u), \tag{4}$$

where the power consumed in reception is $P_{rc}$.

### C. DATA RATE

Since the number of IoT nodes is more than the number of channels. We are using NOMA to accommodate IoT nodes in the network. It is assumed that the IoT nodes are sorted with respect to their gain, where $g_{1,c} > g_{2,c} > g_{3,c} \cdots > g_{n,c}$. The data rate of *n-th* IoT node on *c-th* channel can be represented as:

$$R_{n,c} = \tau_u \log_2 \left(1 + \frac{P_{tr} g_{n,c}}{N_0 + \sum_{i=n+1}^{N}, P_i g_{i,c}}\right), \tag{5}$$

where $N_0$ is the noise.

A descriptive list of the symbols is provided in Table 2.

**TABLE 2.** Definition of the variables used in the model.

| Symbol | Description |
|---|---|
| $N$ | Number of IoT nodes |
| $C$ | Number of channels in one cluster |
| $T$ | Frame duration |
| $E_{R,n}$ | Residual energy |
| $\phi_{nc}$ | Binary variable will be 1 if *n-th* IoT node is performing spectrum sensing and 0 if it is harvesting energy or in idle mode |
| $\tau_s$ | Sensing slot duration |
| $\tau_r$ | Scheduling slot duration |
| $\tau_u$ | User slot duration |
| $g_{n,c}$ | Channel gain of *n-th* IoT node to the *c-th* channel |
| $P_C$ | Transmit power of base station on channel $c$ |
| $E_n^H$ | Energy harvested by *n-th* IoT node |
| $\omega$ | Harvesting efficiency |
| $P_{S,n}$ | Power consumed during sensing process by *n-th* node |
| $P_{R,n}$ | Power consumed by *n-th* node during communication with the central entity |
| $E_n^{C,T}$ | Total energy consumed by *n-th* IoT device during transmission phase (Group 1) |
| $P_RF$ | Power consumed by RF module |
| $P_HC$ | Power consumed by hardware circuit |
| $P_{tr}$ | Power consumed by the transmitter of node n |
| $P_{rd}$ | Power consumed by RF to DC circuit |
| $P_{rc}$ | Power consumed in reception |
| $R_{n,c}$ | Data rate of *n-th* IoT node on *c-th* channel |

## IV. RESOURCE MANAGEMENT FRAMEWORK FOR COGNITIVE IoT SYSTEMS

At the beginning of network operation, each IoT device will check its residual energy and decide to participate in cooperative multi-band spectrum sensing process or not. The cluster head/fusion center then assigns some channels to sense by the IoT devices, which have sufficient energy to perform multiband spectrum sensing. On the other hand, the IoT devices with low residual energy will do nothing until the end of sensing slot. The cluster head then combines the sensing outcome from IoT devices and applies majority rule to decide presence or absence of primary user on each channel. It is assumed that the cluster head will manage all IoT devices and collects the information about primary network channels. This paper focuses on channel assignment and network selection, therefore, do not propose a novel multi-band spectrum

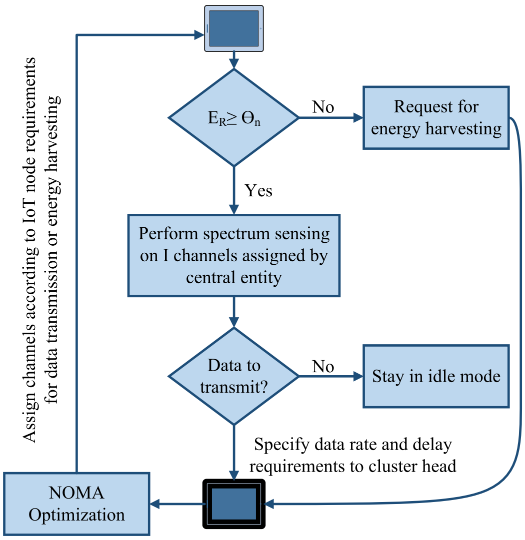


**FIGURE 3. Proposed framework for cluster based IoT network with RF energy harvesting.**

sensing scheme. We adopt the centralized multiband spectrum sensing scheme proposed in [5]. When the IoT node has sufficient energy and data to transmit then it will specify its minimum data rate requirement to the central entity during scheduling slot. Now that the central entity has information about the occupancy of all $C$ channels, it can schedule IoT devices optimally based on their requirements. The proposed framework is shown in Fig. 3. We consider IoT nodes to be capable of performing both spectrum sensing as well as energy harvesting. The assumption is valid as IoT node is considered as node which can conned many sensor nodes (small devices) with it [5].

The objective is to assign channels such that the system throughput is maximized. It is important to note that harvesting and data transmission can not occur on the $c$-$th$ channel for the same IoT node. We define a binary indicator function $b_{n,c}$, which is 1 when the $n$-$th$ IoT node is using the $c$-$th$ channel and 0 otherwise. This can be represented as:

$$b_{n,c} = \begin{cases} 1, & \text{if } n\text{-}th \text{ user is using } c\text{-}th \text{ channel} \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

Each IoT node can be scheduled for data transmission or energy harvesting. A binary indicator $\psi_n$ defines the scheduling of $n$-$th$ IoT node, where $\psi_n = 1$ when $n$-$th$ IoT node is scheduled for data transmission and $\psi_n = 0$ when $n$-$th$ IoT node is scheduled for energy harvesting. This can be written as:

$$\psi n = \begin{cases} 1, & \text{if } n\text{-}th \text{ IoT node transmit data} \\ 0, & \text{if } n\text{-}th \text{ IoT node harvest energy.} \end{cases} \tag{7}$$

Our objective is to increase the system throughput while optimizing $b_{n,c}$ and $\psi_n$ for all $n$ and $c$. The optimization problem for this framework can be written as:

$$\begin{aligned} &\max_{b,\psi} : \sum_{n=1}^{N}\sum_{c=1}^{C} R_{n,c} b_{n,c}, \\ &\text{Subject to } C1 : R_{n,c} \geq \psi_c R_c^{min} b_{n,c}, \quad \forall\, n \text{ and } c \\ &\qquad C2 : E_{R,n} \geq \theta_s, \quad \forall\, n, \\ &\qquad C3 : \sum_{n=1}^{N} b_{n,c} \leq 1, \quad \forall\, c, \\ &\qquad C4 : b_{n,c} \leq \psi_n, \quad \forall\, n \text{ and } c, \\ &\qquad C5 : \psi_n \in \{0,1\}, \quad b_{n,c} \in \{0,1\}, \ \forall\, n \text{ and } c, \end{aligned} \tag{8}$$

where C1 ensures the minimum data rate requirement of each IoT node selected for channel $c$, C2 guarantees that the residual energy of each IoT node will be greater than threshold $\theta_s$, C3 makes sure that one IoT device can only use one channel, and C4 will make sure that $b_{n,c}$ should be zero if the $n$-$th$ IoT node is not selected for data transmission. C5 represents the binary variables to restrict $\psi_n$ and $b_{n,c}$. The optimization problem formulated in (8) is a MINLP. In general, this type of optimization problems is NP-hard.

### A. SOLUTION

The objective function in (8) involves $R_{n,c}$ parameter which is calculated using a log function. This gives us a non-linear equation if we use the complete log function in the objective function, and hence we have a non-linear optimization problem. In order to solve the optimization problem in (8), we can either use MINLP or convert it into a linear problem to be solved using linear approaches. In this paper, we opted for the latter option. We separately calculated values of the rate for all the values of $n$ and $c$, and populated a matrix $R_{n,c}$ which then consists of only constant values. Now we can use $R_{n,c}$ in our objective function equation as it becomes a linear problem. We have used the following two linear approaches to optimally assign the channels to the users in order to maximize network throughput.

#### 1) MIXED INTEGER LINEAR PROGRAMMING

We used MILP approach to solve the reformulated problem of (8). We used a solver from the optimization toolbox provided by MATLAB to solve our MILP optimization problem. Here we take into consideration all of the constraints as mentioned above in the system model. We initialize the vectors $f(x)$, $lb$, and $ub$, matrices $A$ and corresponding vector $b$, and a set of indices intcon. Since we do not have any equality constraint in our system model, we do not use $Aeq$ and $Beq$. After initializing, we run the MILP solver to solve our problem for vector $x$.

$$\begin{aligned} &\max_{x} : f^T x, \\ &\text{Subject to } x(intcon) areintegers, \\ &\qquad A.x \leq b, \\ &\qquad lb \leq x \leq ub, \end{aligned} \tag{9}$$

where $f(x)$ is the coefficient matrix of the objective function, lb and ub are lower and upper bounds, respectively. Since this is an assignment problem, we are solving it by MILP. Thus, we can only have binary values for $x$ which mean $lb = 0$ and $ub = 1$. Matrix $A$ and corresponding vector $b$ are the left hand side coefficients of our inequality constraints and right hand side, respectively. This solver involves the following main steps:

- Preprocessing of the data to check if the number of variables or the number of constraints can be reduced.
- Solve an initial relaxed (non-integer) problem using linear programming (dual-simplex method). Our objective functions and constraints remain the same, but any integer constraints are removed.
- Apply heuristics to find feasible points. Intermediate settings are used in order to optimize the runtime of the algorithm.
- Apply branch and bound algorithm to find a sub-optimal solution. This solves linear programming relaxations with restricted ranges of feasible values of the integer variables and generates a sequence of updated bounds on the optimal objective function value. Here we use the best-first or global-first method as branching rule.
- The bud nodes continue to generate further nodes as we analyze and discard the ones that do not improve the value of the objective function until we reach incumbent solution such that the absolute gap tolerance is 1e-5.

The steps involved in the MILP approach are given in Algorithm 1.

**Algorithm 1** Algorithm for MILP Approach

**Input:** Total number of users ($N$), total number of channels ($C$), residual energy threshold ($E_r$), an array ($Wn$), i.e., which channels are in harvesting and which ones are in transmitting mode, and minimum rate ($R_C^{min}$)
Set throughput variable to zero, i.e., initial overall throughput of the network
**Output:** $b_{n,c}$ and $\psi_n$
**while** incumbent solution is reached **do**
  Populate $R_{n,c}$ matrix using (5) (assigning rates for each user-channel)
  Initialize a column vector $f$ of constants (by reshaping $R_{n,c}$ matrix)
  Initialize a column vector $x$ of variables (same as the number of elements of $R_{n,c}$)
  Initialize a matrix $A$ of all constraints and their corresponding vector $b$ (this will incorporate the minimum rate, residual energy threshold, and whether the node is in transmitting or harvesting mode)
  Initialize lower bound $lb$ on the variables, i.e., 0
  Initialize upper bound $ub$ on the variables, i.e., 1
  Solve mixed integer linear problem by using $f$,$A$,$b$,$lb$, $ub$ to get $x$ vector
  Reshape the vector $x$ to convert it into matrix form to see which channel has been assigned to which users
  Multiply each element of $x$ with corresponding element of $R_{n,c}$ and add all values to get the *throughput* of the network
**end while**
Take average of all throughput values obtained at each iteration
**return** Throughput value for the network with particular number of users and channels
**repeat**
For different number of users while keeping fixed number of channels
**repeat**
For different number of channels while keeping fixed number of users

### 2) GREEDY APPROACH

In the case of greedy approach, we assign to the user, the first available channel that satisfies the minimum QoS requirement. The following steps are involved:

- For each user that is in transmitting mode, we check all the available channels in sequence.
- If no channel has been previously assigned to that user and the channel's throughput satisfies the minimum threshold, we assign that channel to the user.
- We re-iterate these steps until all the transmitting nodes have been assigned their channels and then calculate the total throughput of the network.

The detailed steps for the greedy approach that solve the optimization problem are given in Algorithm 2.

The time complexity of both MILP and greedy approaches is analyzed for fair comparison. The MILP approach is essentially based on the Branch and Bound method in our solution. The performance of the branch-and-bound algorithm depends on the branching rule for choosing which node to branch further. We have used global first rule. We observe that the time complexity is $O(b^m)$, where $b$ is the maximum branching factor of the search tree and $m$ is the maximum depth of the state space. For the greedy approach, the time complexity is $O(n^2)$. It is fairly easy to compute as each node has to iterate through the channel using nested for loop.

## V. SIMULATION RESULTS

We simulate the proposed framework for resource management for IoT in 5G networks to evaluate its performance. We consider a cluster based IoT system in a cognitive 5G network with RF energy harvesting. For simulations, we consider $N = 1$ to 200 IoT nodes and $C = 1$ to 20 channels in each cluster. The probability of PU activity is taken as 0.5, i.e., 50% of the channels are available for data transmission.Further we consider frame duration $T = 1$ms, sensing slot duration $\tau_s = 1$ms, user slot duration $\tau_u = 8$ms, transmit power of base station $P_C = 46$dBm, the energy consumption of sensing for 1ms is 40 $\mu$J [35]. We evaluated the performance of proposed scheme using MINLP approach and proposed heuristic greedy based approach.

**Algorithm 2** Algorithm for Greedy Approach

**Input:** Total number of users ($N$), total number of channels ($C$), residual energy threshold ($E_r$), an array ($Wn$), i.e., which channels are in harvesting and which ones are in transmitting mode, and minimum rate ($R_C^{min}$)
Set throughput variable to zero, i.e., initial overall throughput of the network
**Output:** $b_{n,c}$ and $\psi_n$
**while** 1000 iterations **do**
  Populate $R_{n,c}$ matrix using equation 5 (assigning rates for each user-channel)
  **for** each channel $i$ that is to be assigned to a user **do**
    **for** each node $j$ that is to be assigned a channel **do**
      **if** $R_{i,j}$ value is at-least equal to the minimum rate requirement **then**
        **if** the user $j$ hasn't been assigned any channel previously **then**
          **if** the node $j$ is in transmitting mode **then**
            assign the channel i to the user j
            Set $B_{i,j}$ to 1
            add $R_{i,j}$ to the variable *throughput*
          **end if**
        **end if**
      **end if**
    **end for**
  **end for**
**end while**
take average of all *throughput* values obtained at each iteration
**return** the *throughput* value for the network with particular number of users and channels
**repeat**
For different number of users while keeping fixed number of channels
**repeat**
For different number of channels while keeping fixed number of users

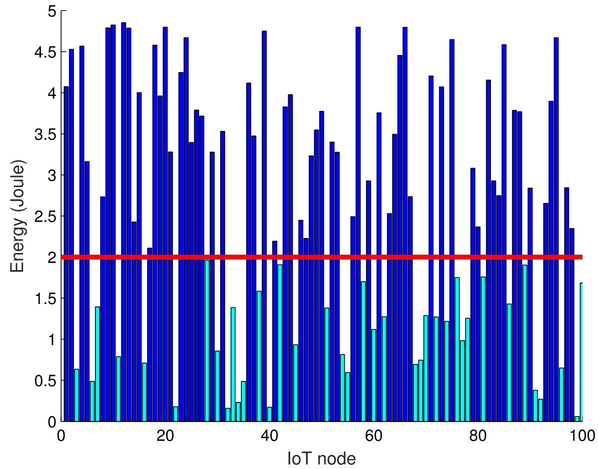


**FIGURE 4.** Residual energy of different IoT nodes.

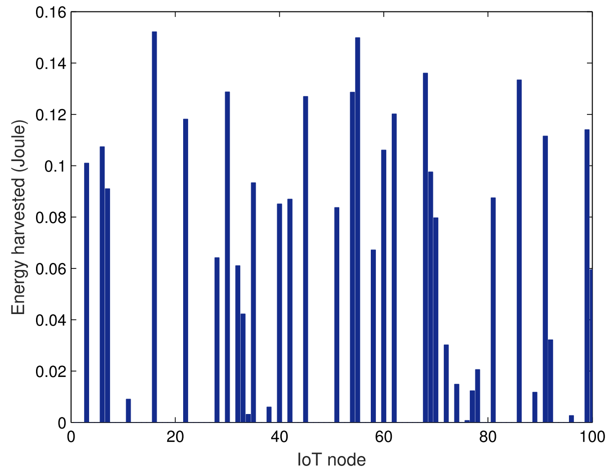


**FIGURE 5.** Energy harvested by different IoT nodes that are below the threshold of the minimum requirement.

Fig. 4 shows the residual energy for different IoT nodes. The horizontal line in the middle indicates the minimum required residual energy for data transmission. The IoT nodes that have energy level less than the minimum requirement, do not have sufficient energy for transmission. Therefore, these nodes request for energy harvesting prior to data transmission. Once the nodes have sufficient energy, channels can be assigned for data transmission. On the contrary, the IoT nodes that have energy level higher than the minimum requirement can participate in multi-band spectrum sensing process and then transmit data.

Fig. 5 shows the energy harvested by the IoT nodes that are below the threshold of the minimum requirement. The amount of energy harvested depends on the distance of IoT node from energy transmitter as well as on the efficiency of harvesting circuit. Therefore, it is evident that the energy harvested by each IoT node is different. Once the nodes have sufficient energy, they will be ready for multi-band spectrum sensing and data transmission. The nodes that were meeting the minimum energy requirement criteria are contributing in multi-band spectrum sensing and transmitting data. In other words, these nodes are not harvesting energy and thus these nodes are not shown in the result.

Fig. 6 shows throughput versus number of IoT nodes for simplex method, greedy approach, and random approach. It is illustrated that simplex method and the greedy method performed better as compared to the random approach. On the other hand, simplex method explained in section IV-A, performed even better than the greedy approach method. This is because of the proposed framework, which maximizes the throughput of IoT nodes by assigning optimal channels. This shows the significance of the proposed resource allocation scheme to maximize the throughput of IoT systems.

The performance of throughput versus the number of channels is shown in Fig. 7 for simplex method, greedy approach, and random approach. The throughput performance with the

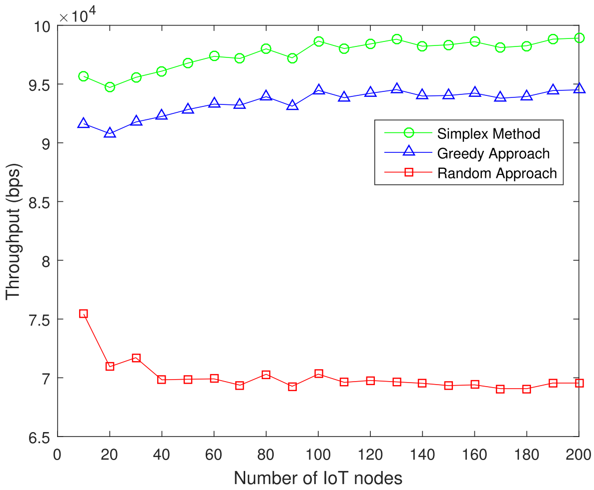


**FIGURE 6.** **Throughput versus number of IoT nodes for the cluster based IoT network with RF energy harvesting.**

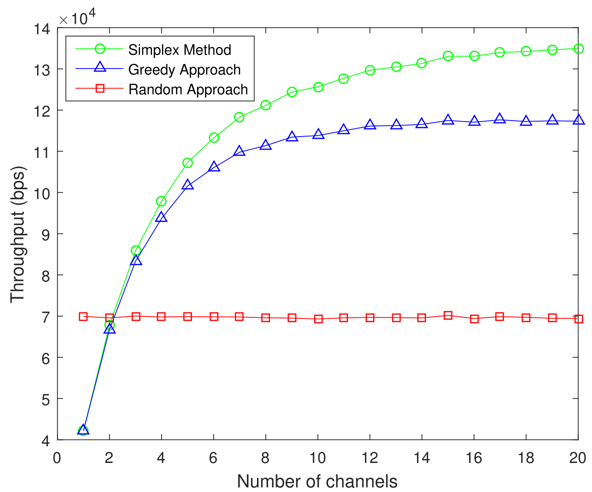


**FIGURE 7.** **Throughput versus number of channels for the cluster based IoT network with RF energy harvesting.**

random approach does not improve with the increase in the number of channels. This is because the channels are assigned randomly. On the contrary, in the other two approaches, throughput improves drastically with the increase in the number of channels. Initially, the result of the analysis of the simplex method and the greedy approach was the same. However, as the number of channel increases, the simplex method provides better throughput as compared to the greedy approach. This shows the optimal assignment of channels in the case of simplex method.

## VI. CONCLUSION

The continuous growth of sophisticated IoT applications requires spectrum and energy efficient solutions. NOMA is considered as a potential solution to enhance spectral efficiency in 5G networks. The paper introduced a resource management framework for cognitive IoT network with RF energy harvesting in 5G networks. We formulated an optimization problem with the objective of maximizing system throughput while satisfying constraints on the QoS requirements and residual energy. We then solved the formulated problem with the simplex method and heuristic algorithm to find an appropriate solution. We evaluated the performance of the proposed framework for resource management in terms of system throughput and harvested energy. The simulation results showed the performance of the proposed heuristic greedy algorithm is near to the simplex method. The proposed framework is an important step towards future research work in the area of resource management based on NOMA for IoT in 5G networks.

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**BANDER ALZAHRANI** received the B.Sc. degree in computer science from King Abdulaziz University, Saudi Arabia, in 2006, and the M.Sc. degree in computer security and the Ph.D. degree in computer science from the University of Essex, U.K., in 2010 and 2015, respectively. He is currently an Assistant Professor with King Abdulaziz University. He has authored over 25 research papers in international journals and conferences. His research interests include secure routing, authentication protocols, ICN/SDN, and IoT.

**WALEED EJAZ** (S'12–M'14–SM'16) received the B.Sc. degree in computer engineering from the University of Engineering and Technology, Taxila, Pakistan, in 2006, the M.Sc. degree in computer engineering from the National University of Sciences and Technology, Islamabad, Pakistan, in 2008, and the Ph.D. degree in information and communication engineering from Sejong University, South Korea, in 2014. He completed certificate courses on teaching and learning in Higher Education from The Chang School, Ryerson University, Canada. Since 2014, he has held academic and research positions with Carleton University, Canada; Ryerson University; and Queen's University, Canada. He is currently an Assistant Professor with Thompson Rivers University, Kamloops, BC, Canada. His current research interests include Internet of Things, energy harvesting, fifth-generation cellular networks, and mobile cloud computing. He is a registered Professional Engineer in ON, Canada. His professional activities include an Associate Editor of *IEEE Communications Magazine*, the IEEE CANADIAN JOURNAL OF ELECTRICAL AND COMPUTER ENGINEERING, and the IEEE ACCESS. In addition, he is handling several special issues in prestigious journals as well as in organizing committees of several major IEEE conferences and workshops.