# Spectrum and Energy Efficient Relay Station Placement in Cognitive Radio Networks

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***Abstract*—Cognitive radio technology enables secondary users (SUs) to opportunistically use the vacant licensed spectrum and significantly improves the utilization of spectrum resource. Traditional architectures for cognitive radio networks (CRNs), such as cognitive cellular networks and cognitive ad hoc networks, impose energy-consuming cognitive radios to SUs' devices for communication and cannot efficiently utilize the spectrum harvested from the primary users (PUs). To enhance the spectrum and energy efficiencies of CRNs, we have designed a new architecture, which is called the Cognitive Capacity Harvesting network (CCH). In CCH, a collection of relay stations (RSs) with cognitive capability are deployed to facilitate the accessing of SUs. In this way, the architecture not only removes the requirement of cognitive radios from SUs and reduces their energy consumption, but also increases frequency reuse and enhances spectrum efficiency. In view of the importance of the RSs on the improvement of spectrum and energy efficiencies, in this paper, we study the RS placement strategy in CCH. A cost minimization problem is mathematically formulated under the spectrum and energy efficiency constraints. Considering the NP-hardness of the problem, we design a framework of heuristic algorithms to compute the near-optimal solutions. Extensive simulations show that the proposed algorithms outperform the random placement strategy and the number of required RSs obtained by our algorithms is always within 2 times of that in the optimal solution.**

***Index Terms*—Relay station placement, cognitive radio, spectrum and energy efficient, design optimization**

## I. Introduction

In the past decade, the rapid growth of diversified mobile applications, such as mobile social networking, online gaming, live video meeting and so on, has led to significant increase in data traffic over wireless networks and the demand for spectrum resource. This trend will continue as the number of applications for 3D Internet grows. In parallel with that, tremendous under-utilized spectrum resource in both temporal and spatial domains has been observed, mainly due to the static spectrum allocation regulation of Federal Communications Commission (FCC). For example, the measurement study in [1] shows that the licensed spectrum under 3GHz is occupied by just an average of $5.2\%$ in time. Such circumstance motivates FCC to open up licensed spectrum and seek new spectrum sharing methods. As one of the most promising solutions, cognitive radio technology enables secondary users (SUs) to opportunistically access the vacant licensed spectrum, which could significantly improve the spectrum utilization.

Several network architectures have been proposed for the implementation of cognitive radio technology, which can be classified into three categories [2]–[5]: cognitive cellular networks, cognitive ad hoc networks and hybrid networks. In cognitive cellular networks, the SUs communicate with each other by connecting to the BSs via single-hop transmissions, which drastically limits frequency reuse as well as system capacity and increases the power consumption of SUs [6], [7]. In cognitive ad hoc networks, there is no centralized infrastructure and packets are always forwarded by multiple SUs to reach the destinations. The distributed nature of cognitive ad hoc networks inevitably leads to inefficient spectrum sharing among SUs due to transmission contention and interference, which may become even worse under unpredictable return of primary users (PUs). More importantly, all of these architectures rely on the premise that SUs have already carried advanced cognitive radios, which can switch across a wide range of spectrum (e.g., from 20MHz to 2.5GHz [8]) to sense the white spaces, select the unused spectrum bands and carry out communications accordingly without affecting the normal communications of PUs. Unfortunately, it is impossible to achieve such high cognitive capability in light-weight radios in practice currently. Even if certain desired features might be implemented in commonly used mobile devices in the future, enormous amount of time and efforts must be devoted to hardware design and signal processing, which will unavoidably add too much cost and complexity to the user side. The advanced radios may also significantly increase energy cost for its cognitive functionalities such as spectrum sensing and reconfiguration, which is also undesirable for the battery-powered devices of SUs.

Considering the aforementioned observations on the practicality of cognitive radio technology and the disadvantages of traditional CRN architectures, we have proposed a novel architecture for CRNs in [9], which is called the Cognitive Capacity Harvesting (CCH) network. Different from the tradi-

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tional architectures, we introduce an emerging entity, namely, secondary service provider (SSP), into the system, which collectively harvests spectrum resource on behalf of SUs from the primary networks and optimally allocates it to the SUs according to their service demands. A collection of relay stations (RSs) equipped with multiple cognitive radios are deployed by the SSP, which form the basic infrastructure of the CCH and provide communication services to all the SUs, either with cognitive capability or not. It has been shown that the CCH is able to address the issues we are concerned about existing CRN architectures and improve both spectrum and energy efficiencies (See Section III for more details). Therefore, we believe that the CCH is a competitive and promising candidate for the system paradigm of future CRNs.

Obviously, the achievement of such performance improvement in the CCH heavily depends on the placement strategy of RSs. On one hand, the deployment of RSs determines the energy cost for SUs to connect to the system. Intuitively, the more sparsely the RSs are deployed, the more energy the SUs will consume due to the increase of the communication distance. On the other hand, since spectrum availability at different geographical locations always varies drastically, the RS placement strategy also significantly affects the spectrum efficiency and system capacity. The RS placement problem has been extensively studied by many researchers in WiMAX networks and wireless sensor networks (WSNs) [10]–[24]. However, none of them investigate the problem from the perspective of spectrum and energy efficiencies. In addition, their works have not considered the uncertainty of channel availability, which is one of the most salient features of CRNs. To the best of our knowledge, how to find the optimal placement strategy of RSs in CRNs is still an open problem.

In this paper, we study the RS placement problem in CRNs, specifically in CCH, with joint consideration of both energy and spectrum efficiencies. The contribution of this work can be summarized as follows:

- Based on a new architecture we have proposed, we study the RS placement problem in CRNs. A cost minimization problem is mathematically formulated under the spectrum and energy efficiency constraints, which can be solved by Mixed-Integer Linear Programming (MILP) to obtain the optimal RS placement strategy.
- In view of the NP-hardness of the problem, we develop polynomial time heuristic algorithms to find near-optimal solutions.
- Simulation results show that the proposed algorithms achieve better performance than the random placement strategy and the number of RSs selected by our algorithms is always within 2 times of that from the optimal solution.

The rest of this paper is organized as follows. The related work is reviewed in Section II. In Section III, we describe the system architecture CCH in detail and discuss its attractive features. In Section IV, we introduce the network model and formally define the RS placement problem. Based on the spectrum and energy efficiency constraints, an optimization formulation is derived in Section V. In Section VI, we design a framework of heuristic algorithms to efficiently compute the near-optimal solutions. We conduct simulations and evaluate the performance of the heuristic algorithms in Section VII. Finally, we draw the concluding remarks in Section VIII.

## II. Related Work

### A. CRN Architecture

In literature, three types of architectures for CRNs have been proposed: cognitive cellular networks (infrastructure-based CRNs) [2], [3], [5], cognitive ad hoc networks [2]–[4] and hybrid networks [3]. There exists a central entity in cognitive cellular networks, such as a base station (BS) or an access point (AP). SUs are equipped with cognitive radios and directly connect to the BS/AP for communicating with each other or accessing other communication systems. In cognitive ad hoc networks, there is no infrastructure. Each SU transmits and relays packets to other SUs through ad hoc connections over unoccupied licensed spectrum. The hybrid architecture is an integration of cognitive cellular networks and cognitive ad hoc networks, which enables wireless communications between different BSs/APs. In hybrid networks, a SU can either communicate with BSs/APs directly or employ other SUs as multi-hop forwarders.

### B. Relay Station Placement

The RS placement problem in traditional wireless networks, such as WSNs and WiMAX networks, has been extensively studied by many researchers. In WSNs, it has been investigated from three general perspectives, namely, the routing structure, the connectivity requirement and the location constraint. Based on the routing structure, existing work can be classified into single-tiered and two-tiered [10]–[12]. In single-tiered RS placement, sensor nodes (SNs) may also relay packets for other nodes. But in two-tiered relay node placement, the data generated at each SN could only be transmitted to RSs or BSs for further forwarding. According to different connectivity requirements, previous studies can be classified into connected and survivable [11], [13]–[15], in which the RS placement must ensure the connectivity and biconnectivity between SNs and BSs, respectively. Most of the prior research [11]–[18] concentrates on the unconstrained RS placement problem, in the sense that RSs can be deployed anywhere. Recently, Misra et al. [19] and Yang et al. [20] address the problem under the location constraint, i.e., the RSs could only be placed at a set of candidate locations.

In WiMAX networks, the deployment of RSs could significantly extend coverage and increase system capacity. In [21], Lin et al. investigate the RS placement problem in a novel dual-relay architecture of WiMAX networks, where each subscriber station (SS) is connected to a BS via two RSs through decode-and-forward scheme. Yu et al. [22] introduce a clustering based approach to determine the locations of BSs and RSs in WiMAX networks. The entire network is divided into multiple distinct clusters. In each individual cluster, the problem is optimally solved with an integer linear programming formulation. Considering the channel capacity constraint and different user data rate requirements, Zhang et al. [23] study the distance-aware RS placement problem in WiMAX mesh networks and present two approximation algorithms to strategically deploy RSs in order to provide sufficient data

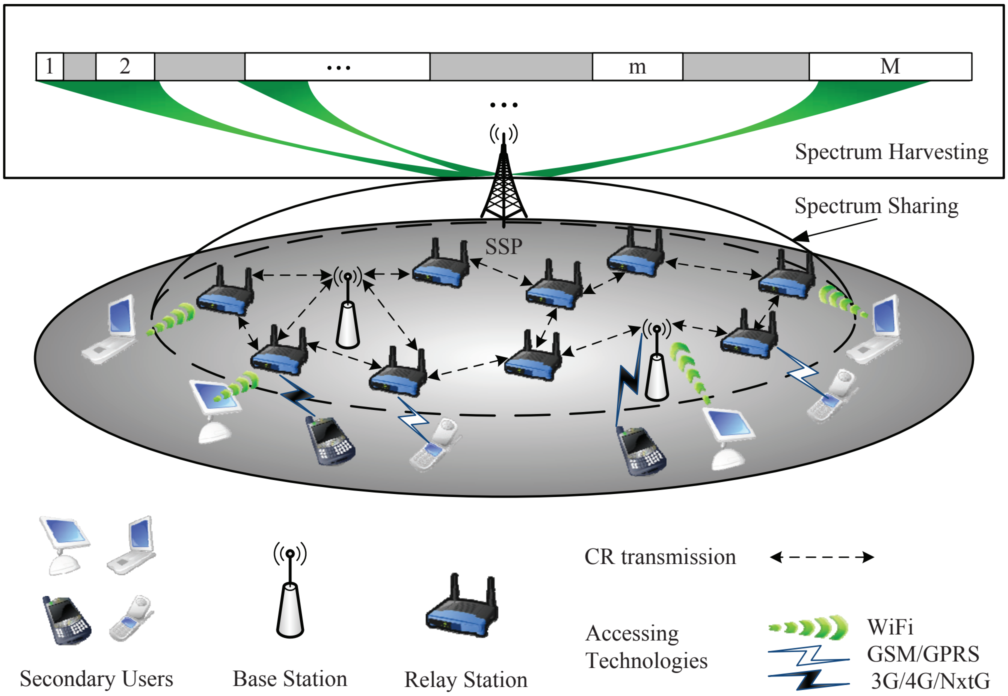



Fig. 1. System architecture.

rate for each SS as well as ensure the connectivity between BSs and RSs. The RS placement problem for cooperative communications in WiMAX networks is addressed by Yang et al. [24].

## III. System Architecture

In [9], we have introduced a novel flexible architecture for CRNs, which is called the Cognitive Capacity Harvesting network (CCH). Here, we further extend the architecture with consideration of base stations (BSs). As shown in Fig. 1, the CCH consists of four types of entities: an SSP, base stations, relay stations (RSs) and SUs. The SSP is an independent wireless service provider with its own spectrum, referred to as the SSP's basic bands. It also harvests additional spectrum resource from other primary networks to enhance its services for SUs. The BSs are interconnected with high-speed wired links, and the SUs can communicate with the BSs in order to further connect to Internet or other data networks. A collection of RSs are deployed by the SSP to facilitate the accessing of SUs. Both the BSs and RSs are equipped with multiple cognitive radios, which can tune to any basic band or harvested band for communications. The SUs can be any device using any accessing technology (e.g., laptops or desktop computers using Wi-Fi, cell phones using GSM/GPRS, smart phones using 3G/4G/NxtG, etc.). There is no specific requirement on cognitive capability imposed on them. If the SUs have cognitive capability, they can communicate with the BSs and RSs over both basic bands and harvested bands. For a SU that does not carry any cognitive radio, the BSs or RSs can switch to the basic band which the SU normally uses to provide communication services. Some basic bands can be reserved to establish the common control channels, through which control signaling and other important information are exchanged.

The CCH enjoys a number of attractive features for CRN implementation and can address the concerns we have mentioned in Section I on traditional CRN architectures. First, the CCH preserves the advantages of both cognitive cellular networks and cognitive ad hoc networks. In CCH, multi-hop transmissions via RSs drastically shorten the transmission distance, increase spectral reuse and reduce energy consumption of SUs for accessing the network [7]. On the other hand, the existence of the centralized SSP facilitates collective resource sharing among SUs based on their service demands and maximizes spectrum efficiency. Second, SUs in CCH can receive communication services without the premise that they must have cognitive capability. Therefore, the CCH successfully exploits cognitive radio technology while minimizing the changes in the mobile devices of SUs, which shifts the design complexity to the system side from the user side. In addition, the removal of high-cost cognitive radios from the SUs' devices could further reduce their energy consumption and enhance energy efficiency. Finally, BSs and RSs may collect statistics for temporal and spatial spectrum availability as well as the service demands from different SUs and submit them to the SSP over the common control channels, which can be used to design more efficient strategies to allocate and utilize the harvested spectrum resource. In this way, the CCH could handle the randomness of both the spectrum availability due to the unpredictable return of PUs and the time-varying service demands of SUs more efficiently.

From the above description and analysis, we can see that the deployment of the RSs directly determines the system performance of the CCH in terms of both spectrum and

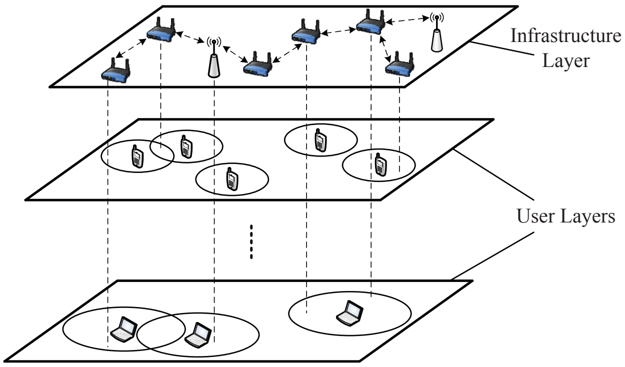



Fig. 2. Multi-layer network model for the CCH network.

energy efficiencies, which is one of the most critical issues for the CCH. In the rest of the paper, we will systematically investigate the RS placement strategy in CCH. In practice, there may be some physical constraints on the placement of the RSs. For example, two RSs must be a certain distance away from each other to reduce the interference, or there exist some forbidden regions where the RSs cannot be deployed. Therefore, we assume that the RSs can only be placed at a set of candidate locations. In next section, we will introduce the network model and formally define the RS placement problem.

## IV. Network Model and Problem Definition

### A. Network Model

Consider a typical CCH network with an SSP, BSs, RSs and SUs. We make a conservative assumption that all the SUs do not have cognitive capability. Thus, they cannot use the harvested licensed spectrum but only the basic bands owned by the SSP for communications. For the ease of presentation, we abstract the CCH network into a multi-layer network model as illustrated in Fig. 2. The most upper layer is called the infrastructure layer, which consists of all the BSs and RSs deployed in CCH and provides communication services for the SUs. In the rest of the paper, BSs and RSs are also collectively referred to as infrastructure nodes. The other layers are called user layers, each of which contains the SUs with the same accessing technology. Considering the mobility of SUs, we do not make any assumption on their distribution at each user layer. In other words, we assume that the SUs with different accessing technologies may appear everywhere within the area covered by the CCH.

Since all the SUs at one user layer exploit the same accessing technology, they have the same transmission power levels. Consider the following power propagation model [25]:

$$P_r = \gamma \cdot d^{-\alpha} \cdot P_t, \tag{1}$$

where $P_t$ and $P_r$ denote the transmission power at sender and the received power at receiver, respectively. $\gamma$ is an antenna related constant, $\alpha$ is the path loss factor and $d$ is the distance between sender and receiver. For a SU at user layer $u$, we assume that it could successfully connect to an infrastructure node only if the power received at the infrastructure node exceeds the sensitivity $\tau_u$, which varies over different user layers. Let $P_u$ denote the maximum transmission power of the SUs at user layer $u$. Then, when they are able to communicate with the infrastructure nodes, the distance between them must satisfy $d \leq (\gamma P_u/\tau_u)^{1/\alpha}$, which comes from $\gamma \cdot d^{-\alpha} \cdot P_u \geq \tau_u$. We define $r_u = (\gamma P_u/\tau_u)^{1/\alpha}$ as the communication range of the SUs at user layer $u$. Similarly, we also define the communication range of the infrastructure nodes when they communicate with each other, which is denoted as $R$.

In CRNs, SUs are allowed to use licensed bands when these bands are not occupied by PUs, but they must evacuate immediately when PUs return. Therefore, the availability of the harvested licensed channels for SUs is affected by the unpredictable activity of PUs, which is highly uncertain. Based on the statistical characteristics of spectrum bands obtained from observations and experiments in [26]–[28], we model the spectrum vacancy of different licensed bands as a series of random variables. Specifically, denote $W_{ij}^m$ the unoccupied bandwidth of licensed band $m$ over link $(i, j)$, where $W_{ij}^m$ is a random variable with a certain distribution. In order to model the availability of basic bands and harvested bands in a unified manner, we consider the available bandwidth of a basic band as a special random variable which is equal to its bandwidth with probability 1. Let $\mathcal{M}$ denote the set of all the spectrum bands that can be used in the system, including the basic bands and the harvested bands. Then, according to Shannon-Hartley theorem, when infrastructure node $i$ transmits data to infrastructure node $j$, the capacity of link $(i, j)$ can be calculated as

$$c_{ij} = \rho_{ij} \sum_{m \in \mathcal{M}} W_{ij}^m \log_2\left(1 + \frac{\gamma \cdot d_{ij}^{-\alpha} \cdot Q}{\eta}\right), \tag{2}$$

where $d_{ij}$ is the distance between nodes $i$ and $j$, $Q$ is the transmission power of infrastructure nodes and $\eta$ is the ambient Gaussian noise power at node $j$. $\rho_{ij}$ is a binary variable. We have $\rho_{ij} = 1$, if $d_{ij} \leq R$; otherwise, $\rho_{ij} = 0$. We assume that all the links between infrastructure nodes are symmetric, i.e., $c_{ij} = c_{ji}$. Note that when $\rho_{ij} = 1$, $c_{ij}$ is not a constant number but a random variable due to the uncertainty of available bandwidth $W_{ij}^m$.

Given the BSs and RSs deployed in the CCH, the infrastructure layer can also be represented by an undirected graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, which is referred to as the relay communication graph. Here, each vertex $v \in \mathcal{V}$ corresponds to an infrastructure node, and there is an undirected link $(i, j) \in \mathcal{E}$ if $d_{ij} \leq R$.

### B. Problem Definition

***Definition 1:*** **[Relay Station Placement Problem (RSPP)]** Let $\mathcal{B}$ denote the set of BSs and $\mathcal{C}$ denote the set of candidate locations where RSs can be deployed, respectively. Let $\mathcal{A}$ stand for the area intended to be covered by the CCH. Let $\mathcal{U}$ be the set of all the user layers in the corresponding multi-layer network model. Then, a subset $\mathcal{R} \subseteq \mathcal{C}$ is called a feasible Relay Station Placement (RSP) if both of the following constraints are satisfied:

- **Energy Efficiency Constraint:** For each user layer $u \in \mathcal{U}$, the SUs at any location within area $\mathcal{A}$ can connect to at least one infrastructure node with the maximum transmission power $P_u$.

- **Spectrum Efficiency Constraint:** The relay communication graph $\mathcal{G}$ induced by $\mathcal{B} \cup \mathcal{R}$ is connected by the links with capacity no less than $\pi$.

The size of a feasible RSP is $|\mathcal{R}|$. The Relay Station Placement Problem (RSPP) seeks the feasible RSP with the minimum size.

In practice, the density of SUs is also an important factor to the deployment of the RSs. However, due to the mobility of the SUs, the density at different areas might change over time and is difficult to obtain. In addition, even if we have the knowledge about the density of SUs, their service demands is still dynamic and it is hard to characterize its effect on the RS placement. Therefore, we will not take the density of SUs into consideration. The solutions we derive in this paper ensure that the SUs at any location within the area covered by the CCH can connect to the network, which is the basic requirement for communication systems.

## V. Optimal Relay Station Placement

In this section, we mathematically express the spectrum efficiency and energy efficiency constraints and formulate RSPP into a cost minimization problem, which can be solved by Mixed-Integer Linear Programming (MILP) to obtain the optimal solution.

### A. Objective Function

Let $\omega_i$ be a binary variable associated with each candidate location $i$ in $\mathcal{C}$. We denote

$$\omega_i = \begin{cases} 1 & \text{if a RS is deployed at candidate location } i, \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

According to ***Definition** 1*, our objective is to minimize $\sum_{i \in \mathcal{C}} \omega_i$ under the energy efficiency and spectrum efficiency constraints.

### B. Energy Efficiency Constraint

Based on the definition of communication range, every infrastructure node is associated with a region for each user layer $u$, within which the SUs can communicate with it. The region is defined as the communication region of the infrastructure node for user layer $u$. We define a subarea $s$ as a collection of spots in $\mathcal{A}$ that are within the same set of communication regions. Then, for each user layer $u \in \mathcal{U}$, area $\mathcal{A}$ can be divided into a set of subareas, which is denoted as $\mathcal{S}_u$. The subareas at the same user layer $u$ satisfy $\bigcup_{s \in \mathcal{S}_u} s = \mathcal{A}$ and $s_n \cap s_v = \emptyset, \forall s_n, s_v \in S_u, s_n \neq s_v$. Fig. 3 shows a simple example of subarea division on different user layers. Let $\mathcal{S}$ stand for the set of all the subareas at different user layers, i.e., $\mathcal{S} = \bigcup_{u \in \mathcal{U}} \mathcal{S}_u$. Then, the energy efficiency constraint in ***Definition** 1* is equivalent to the constraint that the SUs within all the subareas in $\mathcal{S}$ can communicate with at least one infrastructure node. Next, we mathematically formulate this constraint.

Let $\theta_{si}$ be another binary variable which indicates the accessing status of the SUs in subarea $s$ to infrastructure node $i$. If the SUs in $s$ can communicate with infrastructure node $i$, $\theta_{si} = 1$; otherwise, $\theta_{si} = 0$. That is

$$\theta_{si} = \begin{cases} 1 & \text{if } d_{si} \leq r_u, \\ 0 & \text{otherwise,} \end{cases} \tag{4}$$

where $d_{si}$ can be calculated as the distance between an arbitrary SU in subarea $s$ and infrastructure node $i$.

According to the energy efficiency constraint, the SUs in each subarea $s \in \mathcal{S}$ must be ensured to connect to at least one infrastructure node. Thus, we have

$$1 - \prod_{i \in \mathcal{C}} (1 - \omega_i \cdot \theta_{si}) \cdot \prod_{j \in \mathcal{B}} (1 - \theta_{sj}) > 0. \tag{5}$$

Given $\theta_{si}$ and $\theta_{sj}$, (5) is a nonlinear constraint of the variable $\omega_i$. Note that it is equivalent to

$$\prod_{i \in \mathcal{C}} (1 - \theta_{si})^{\omega_i} \cdot \prod_{j \in \mathcal{B}} (1 - \theta_{sj}) < 1. \tag{6}$$

By taking logarithms on both sides of (6), we are able to transform (5) into the following linear constraint:

$$\sum_{i \in \mathcal{C}} \omega_i \cdot \log(1 - \theta_{si}) + \sum_{j \in \mathcal{B}} \log(1 - \theta_{sj}) < 0. \tag{7}$$

### C. Spectrum Efficiency Constraint

The spectrum efficiency constraint can be formulated based on the multi-commodity flow problem [29]. We first construct a directed graph $\mathcal{H} = (\mathcal{N}, \mathcal{L})$, where each node in $\mathcal{N}$ corresponds to a BS or a candidate location for RSs, i.e., $\mathcal{N} = \mathcal{B} \cup \mathcal{C}$, and there is a pair of directed links in $\mathcal{L}$ between any two nodes. Each link $(i, j) \in \mathcal{L}$ is associated with link capacity $c_{ij}$. In order to simplify the constraint formulation, we also introduce a virtual sink node $t$ into the graph $\mathcal{H}$, which is connected to all the BSs. Then, We obtain a new graph $\mathcal{H}^+ = (\mathcal{N}^+, \mathcal{L}^+)$, where $\mathcal{N}^+ = \mathcal{N} \cup \{t\}$ and $\mathcal{L}^+ = \mathcal{L} \cup \{(j, t) | j \in \mathcal{B}\}$. We set $c_{jt} = +\infty$ for all the links $(j, t) \in \mathcal{L}^+$. Then, the spectrum efficiency constraint will be satisfied if and only if the flow starting from each RS with traffic load $\pi$ can be routed to the sink node $t$ along a path. In the rest of this subsection, the flow with source node $k$ is simply called flow $k$. Next, we will mathematically formulate the constraints.

Let $f_{ij}^k$ denote the amount of traffic from flow $k$ that is transmitted over link $(i, j)$, where $(i, j) \in \mathcal{L}^+$. There will be a flow originating from candidate location $i$ with traffic load $\pi$ if it is selected to place a RS, which can be expressed as:

$$\sum_{j:(i,j) \in \mathcal{L}^+} f_{ij}^i = \omega_i \cdot \pi, \tag{8}$$

$$\sum_{j:(j,i) \in \mathcal{L}^+} f_{ji}^i = 0. \tag{9}$$

If node $i$ is an intermediate node for flow $k$, i.e., $i \neq k$, the total amount of traffic transmitted into $i$ that is attributed to flow $k$ should be exactly equal to that transmitted out of $i$. That is

$$\sum_{j:(j,i) \in \mathcal{L}^+} f_{ji}^k - \sum_{j:(i,j) \in \mathcal{L}^+} f_{ij}^k = 0. \tag{10}$$

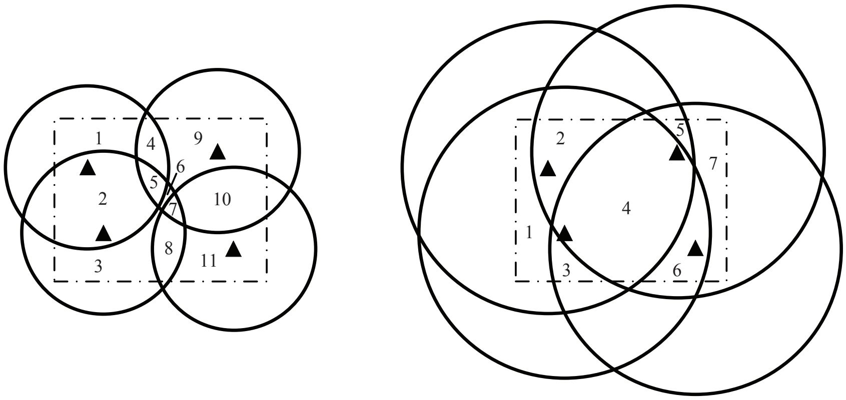



Fig. 3. A simple example of subarea division at different user layers.

The sink node $t$ is the common destination of all the flows, which can be described by the following constraints:

$$\sum_{j:(j,t)\in\mathcal{L}^+} f^i_{jt} = \omega_i \cdot \pi, \tag{11}$$

$$\sum_{j:(t,j)\in\mathcal{L}^+} f^i_{tj} = 0. \tag{12}$$

Let $\delta^k_{ij}$ be a binary variable denoting whether the flow $k$ is routed over link $(i, j)$, i.e.,

$$\delta^k_{ij} = \begin{cases} 1 & \text{if flow } k \text{ is routed over link } (i,j), \\ 0 & \text{otherwise.} \end{cases}$$

To enforce the single-path restriction on routing of each flow from a RS, $\delta^k_{ij}$ should satisfy the following constraint for any RS $i \in \mathcal{C}$:

$$\sum_{j:(i,j)\in\mathcal{L}^+} \delta^k_{ij} \leq 1. \tag{13}$$

In addition, if flow $k$ is transmitted over link $(i, j)$, the traffic load must be feasibly supported by the link, i.e.,

$$f^k_{ij} \leq c_{ij} \cdot \delta^k_{ij}. \tag{14}$$

Also note that if there exists nonzero amount of traffic from arbitrary flow $k$ transmitted through candidate location $i$, it must be selected to deploy a RS to relay such traffic toward the sink node $t$. Thus, we have

$$\sum_{j:(j,i)\in\mathcal{L}^+} f^k_{ji} \leq \omega_i \cdot \pi. \tag{15}$$

### D. Optimal Relay Station Placement

Integrating the objective function with all the constraints above, RSPP can be formulated as follows:

$$\textbf{Min} \quad \sum_{i\in\mathcal{C}} \omega_i$$

$$\begin{aligned}
\textbf{S.t.} \quad & \sum_{i\in\mathcal{C}} \omega_i \cdot \log(1-\theta_{si}) + \sum_{j\in\mathcal{B}} \log(1-\theta_{sj}) < 0 \\
& \hfill (\forall s \in \mathcal{S}) \\
& \sum_{j:(i,j)\in\mathcal{L}^+} f^i_{ij} = \omega_i \cdot \pi \qquad (\forall i \in \mathcal{C}) \\
& \sum_{j:(j,i)\in\mathcal{L}^+} f^i_{ji} = 0 \qquad (\forall i \in \mathcal{C}) \\
& \sum_{j:(j,i)\in\mathcal{L}^+} f^k_{ji} - \sum_{j:(i,j)\in\mathcal{L}^+} f^k_{ij} = 0 \\
& \hfill (\forall k \in \mathcal{C}, \forall i \in \mathcal{B}\cup\mathcal{C}, i \neq k) \\
& \sum_{j:(j,t)\in\mathcal{L}^+} f^i_{jt} = \omega_i \cdot \pi \qquad (\forall i \in \mathcal{C}) \\
& \sum_{j:(t,j)\in\mathcal{L}^+} f^i_{tj} = 0 \qquad (\forall i \in \mathcal{C}) \\
& f^k_{ij} \leq \delta^k_{ij} \cdot \rho_{ij} \sum_{m\in\mathcal{M}} W^m_{ij} \log_2(1 + \frac{\gamma \cdot d^{-\alpha}_{ij} \cdot Q}{\eta}) \\
& \hfill (\forall (i,j) \in \mathcal{L}^+, \forall k \in \mathcal{C}) \\
& \sum_{j:(i,j)\in\mathcal{L}^+} \delta^k_{ij} = 1 \qquad (\forall i,k \in \mathcal{C}) \\
& \sum_{j:(j,i)\in\mathcal{L}^+} f^k_{ji} \leq \omega_i \cdot \pi \qquad (\forall i,k \in \mathcal{C}) \\
& \omega_i \in \{0,1\} \qquad (\forall i \in \mathcal{C}) \\
& \delta^k_{ij} \in \{0,1\} \qquad (\forall i,j \in \mathcal{B}\cup\mathcal{C}, k \in \mathcal{C}) \\
& f^k_{ij} \geq 0 \qquad (\forall (i,j) \in \mathcal{L}^+, \forall k \in \mathcal{C})
\end{aligned}$$

where $\omega_i$, $\delta^k_{ij}$ and $f^k_{ij}$ are optimization variables, and $\theta_{si}$, $d_{ij}$ and $\pi$ are constants. Note that the available bandwidth $W^m_{ij}$ is not a constant but a random variable here as illustrated in Section IV-A, which makes (14) a stochastic constraint. One way to address it is to use the first order statistics $E(W^m_{ij})$ instead of $W^m_{ij}$, which is intuitive and easy to calculate. However, this method suffers from the robust problem [30]. Based on stochastic programming, we reformulate it as a chance constraint as follows:

$$\mathbf{Pr}\Big[f_{ij}^k \le \delta_{ij}^k \cdot \rho_{ij} \sum_{m\in\mathcal{M}} W_{ij}^m \log_2(1+\frac{\gamma\cdot d_{ij}^{-\alpha}\cdot Q}{\eta})\Big] \ge \beta. \tag{16}$$

where $\beta \in [0,1]$ indicates the confidence level for stochastic constraint (14) to be satisfied. Therefore, the solutions under the new constraint ensure that all the infrastructure nodes are connected by the links with capacity no less than $\pi$ with confidence $\beta$. Note that (16) can be rewritten as

$$f_{ij}^k \le \delta_{ij}^k \cdot \rho_{ij} \cdot \log_2(1+\frac{\gamma\cdot d_{ij}^{-\alpha}\cdot Q}{\eta}) \cdot F_{W_{ij}}^{-1}(1-\beta), \tag{17}$$

where $W_{ij} = \sum_{m\in\mathcal{M}} W_{ij}^m$ and $F_X(x)$ is the cumulative distribution function (CDF) of random variable $X$. Therefore, given the distribution of random variables $W_{ij}^m$, (14) is a linear constraint of $f_{ij}^k$ and $\delta_{ij}^k$.

Replacing (14) with (16), we reformulate RSPP into the following Mixed-Integer Linear Programming (MILP):

$$\begin{aligned}
\mathbf{Min}\quad & \sum_{i\in\mathcal{C}} \omega_i \\
\mathbf{S.t.}\quad & \sum_{i\in\mathcal{C}} \omega_i \cdot \log(1-\theta_{si}) + \sum_{j\in\mathcal{B}} \log(1-\theta_{sj}) < 0 && (\forall s\in\mathcal{S}) \\
& \sum_{j:(i,j)\in\mathcal{L}^+} f_{ij}^i = \omega_i\cdot\pi && (\forall i\in\mathcal{C}) \\
& \sum_{j:(j,i)\in\mathcal{L}^+} f_{ji}^i = 0 && (\forall i\in\mathcal{C}) \\
& \sum_{j:(j,i)\in\mathcal{L}^+} f_{ji}^k - \sum_{j:(i,j)\in\mathcal{L}^+} f_{ij}^k = 0 && (\forall k\in\mathcal{C}, \forall i\in\mathcal{B}\cup\mathcal{C}, i\ne k) \\
& \sum_{j:(j,t)\in\mathcal{L}^+} f_{jt}^i = \omega_i\cdot\pi && (\forall i\in\mathcal{C}) \\
& \sum_{j:(t,j)\in\mathcal{L}^+} f_{tj}^i = 0 && (\forall i\in\mathcal{C}) \\
& \mathbf{Pr}\Big[f_{ij}^k \le \delta_{ij}^k\cdot\rho_{ij}\sum_{m\in\mathcal{M}} W_{ij}^m \log_2(1+\frac{\gamma\cdot d_{ij}^{-\alpha}\cdot Q}{\eta})\Big] \\
& \ge \beta && (\forall (i,j)\in\mathcal{L}^+, \forall k\in\mathcal{C}) \\
& \sum_{j:(i,j)\in\mathcal{L}^+} \delta_{ij}^k = 1 && (\forall i,k\in\mathcal{C}) \\
& \sum_{j:(j,i)\in\mathcal{L}^+} f_{ji}^k \le \omega_i\cdot\pi && (\forall i,k\in\mathcal{C}) \\
& \omega_i \in \{0,1\} && (\forall i\in\mathcal{C}) \\
& \delta_{ij}^k \in \{0,1\} && (\forall i,j\in\mathcal{B}\cup\mathcal{C}, k\in\mathcal{C}) \\
& f_{ij}^k \ge 0 && (\forall (i,j)\in\mathcal{L}^+, \forall k\in\mathcal{C})
\end{aligned}$$

## VI. HEURISTIC ALGORITHMS

### A. Computational Complexity

When $|\mathcal{U}| = 1$ and $\pi = 0$, RSPP reduces to the connected sensor coverage problem in [31], which was proved to be NP-hard. Therefore, RSPP is also NP-hard. Given the hardness of the problem, it is impossible to find a polynomial time optimal solution unless P = NP [32]. In this section, we develop efficient heuristic algorithms for RSPP to find the near-optimal solutions.

---

**Algorithm 1:** Heuristic Algorithms for RSPP

---

**Input** : The set $\mathcal{B}$ of BSs, the set $\mathcal{S}$ of subareas and the set $\mathcal{C}$ of candidate locations for RSs. An approximation algorithm $\mathbb{A}$ for the set cover problem and an approximation algorithm $\mathbb{B}$ for the Steiner tree problem.

**Output**: A RSP $\mathcal{R} \subseteq \mathcal{C}$.

`/* Step #1: Satisfy Energy Efficiency Constraint */`

1 Remove all the subareas that can access to the BSs in $\mathcal{B}$ from $\mathcal{S}$;

2 Apply algorithm $\mathbb{A}$ to obtain a set cover $\mathcal{R}_{\mathbb{A}}$ of $\mathcal{S}$;

`/* Step #2: Satisfy Spectrum Efficiency Constraint */`

3 Construct the relay communication graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$;

4 Assign weight to the edges in $\mathcal{E}$. For an edge $(i,j)$ in $\mathcal{E}$, if $\mathbf{Pr}(c_{ij} \ge \pi) \ge \beta$, we have
$$w(i,j) = |(\mathcal{C}\backslash\mathcal{R}_{\mathbb{A}}) \cap \{i,j\}|;$$
otherwise, we have $w(i,j) = +\infty$.

5 Apply algorithm $\mathbb{B}$ to compute a low weight Steiner tree which spans the nodes in $\mathcal{B}\cup\mathcal{R}_{\mathbb{A}}$ in $\mathcal{G}$. Denote the set of Steiner nodes as $\mathcal{R}_{\mathbb{B}}$.

6 Return $\mathcal{R} = \mathcal{R}_{\mathbb{A}} \cup \mathcal{R}_{\mathbb{B}}$.

---

### B. A Framework of Heuristic Algorithms

Based on the energy efficiency and spectrum efficiency constraints in the MILP formulation attained in Section V-D, we decompose RSPP into two sub-problems and address them one by one. First, we study the sub-problem under the energy efficiency constraint, i.e., choose the minimum set of RSs from the set $\mathcal{C}$ so that the SUs within each subarea in $\mathcal{S}$ can connect to at least one infrastructure node. Given the value of $\delta_{si}$ for every subarea $s$ and infrastructure node $i$, it is actually a set cover problem [33], which has been well studied in the literature. We employ an algorithm $\mathbb{A}$ for the set cover problem to solve this sub-problem and the solution is denoted as $\mathcal{R}_{\mathbb{A}}$. Then, we move to the infrastructure layer and select the minimum number of RSs to connect the RSs in $\mathcal{R}_{\mathbb{A}}$ with the BSs under the spectrum efficiency constraint. This sub-problem can be considered as a Steiner tree problem [34]. Thus, we apply an existing algorithm $\mathbb{B}$ for the Steiner tree problem to solve it and the result is denoted as $\mathcal{R}_{\mathbb{B}}$. The framework of heuristic algorithms for RSPP is the combination of the two algorithms $\mathbb{A}$ and $\mathbb{B}$, and the final solution is the union of $\mathcal{R}_{\mathbb{A}}$ and $\mathcal{R}_{\mathbb{B}}$. The detailed procedures are illustrated in Alg. 1.

***Theorem 1:*** The worst case running time of Alg. 1 is $\mathcal{O}(T_{\mathbb{A}}+T_{\mathbb{B}}+|\mathcal{B}\cup\mathcal{C}|^2)$, where $T_{\mathbb{A}}$ and $T_{\mathbb{B}}$ are the time complexity of the approximation algorithms $\mathbb{A}$ and $\mathbb{B}$, respectively. The number of RSs in the feasible solution computed by Alg. 1 is at most $a+3.5b$ times of the optimal solution to RSPP, where $a$ and $b$ are the approximation ratios of $\mathbb{A}$ and $\mathbb{B}$, respectively.

*Proof:* The proof has been given in [20] Theorem 3.1, which is omitted here. ■

***Theorem*** *1* indicates that Alg. 1 will achieve different performance with different choices of algorithms $\mathbb{A}$ and $\mathbb{B}$. For example, if we use the PTAS in [35] as algorithms $\mathbb{A}$ and the $(1+\frac{\ln 3}{2})$-approximation algorithm in [36] as algorithm $\mathbb{B}$, the feasible solution obtained by Alg. 1 is within $6.43+\epsilon$ times of the optimum for RSPP.

## VII. Numerical Results

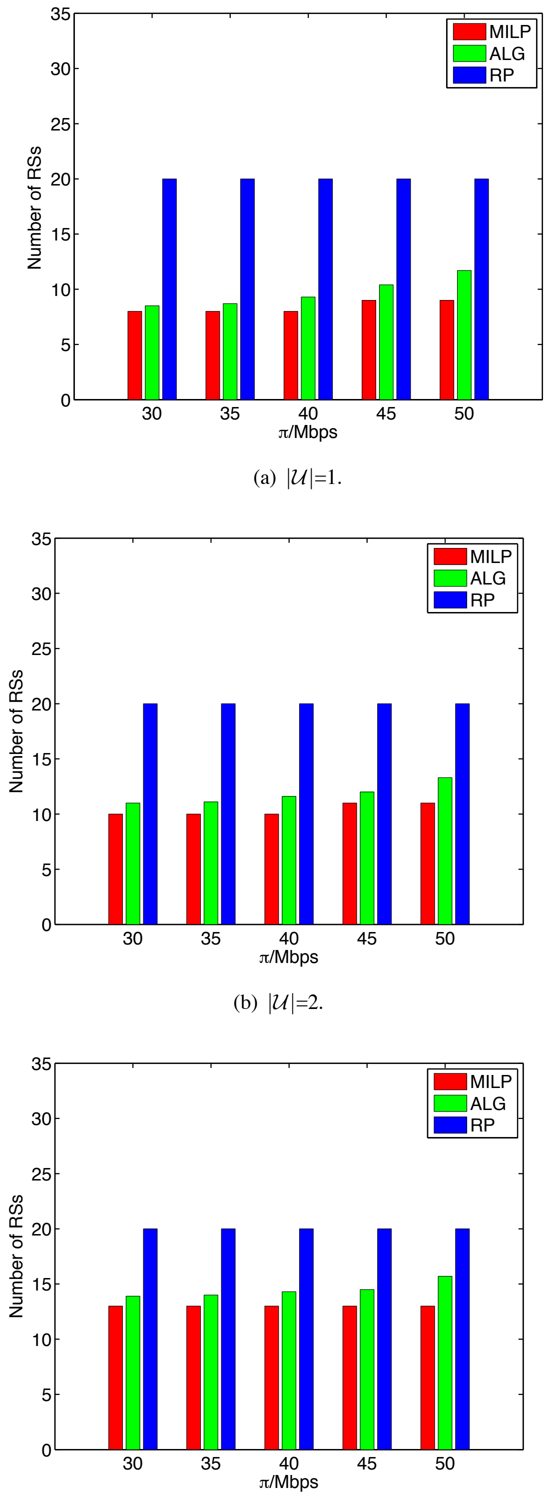
### A. Simulation Setup

Consider a CCH network that covers a square area. One BS is deployed at the center of the area. The candidate locations of RSs are randomly distributed within the area. Assume that the CCH provides communication services for up to three types of SUs, i.e., $|\mathcal{U}|=1,2$ or 3. For the communication ranges, we set $R=500m$, $r_1=300m$, $r_2=250m$ and $r_3=200m$. Considering the AWGN channel, we assume the noise power $\eta=10^{-9}W$ at all infrastructure nodes. Moreover, suppose the path loss factor $\alpha=4$, the antenna parameter $\gamma=2.5$ and transmission power $Q=10W$. We assume that there are 3 basic bands and 5 licensed bands that can be used by the BSs and RSs, and thus $|\mathcal{M}|=8$. For illustrative purpose, all the bands are assumed to have identical bandwidth, which is equal to 10MHz. Based on the observed data and the statistical analysis in [28], we assume that the ratio of the available bandwidth to the entire bandwidth of a licensed band follows the truncated exponential distribution within $[0,1]$, i.e., $h_Y(y,\lambda)=\frac{\frac{1}{\lambda}e^{-\frac{y}{\lambda}}}{1-e^{-\frac{1}{\lambda}}}$, where $\lambda\in(0,3]$. During the simulations, we set $\beta=0.7$.

All the simulations are conducted on a laptop with 2.8GHz Intel Core 2 Duo CPU and 3GB memory. Note that there may exist no feasible solutions for some test cases where the energy and spectrum efficiency constraints cannot be satisfied. We will only focus on the cases with feasible solutions and take the average value of 10 test cases as results.

### B. Algorithm Selection

In the simulations, we choose the $H_n$-approximation algorithm in [33] as $\mathbb{A}$ where $H_n=\sum_{i=1}^{n}\frac{1}{n}$, and the 2-approximation algorithm in [37] as $\mathbb{B}$ with consideration of running times. The experiment results show that the number of RSs attained by Alg. 1 is always within 2 times of the optimum for all of the test cases. This implementation of Alg. 1 is denoted as ALG. For the purpose of comparison, we also consider the scheme of random placement (RP), which randomly selects one RS from the remaining candidates in $\mathcal{C}$ each time and adds it into $\mathcal{R}$ until both the energy efficiency and spectrum efficiency constraints are satisfied. The optimal solution to each simulation instance is calculated as well by solving the MILP formulation, which serves as a benchmark to evaluate the performance of ALG and RP.




(a) $|\mathcal{U}|$=1.

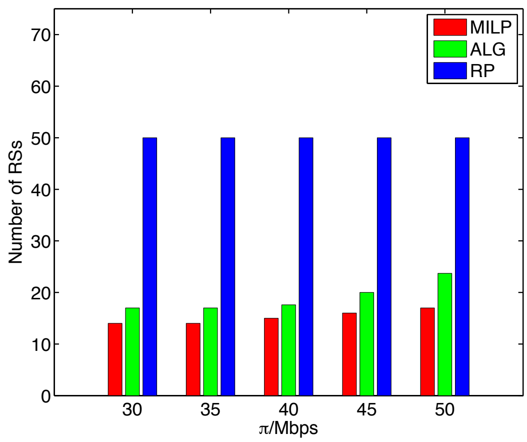
(b) $|\mathcal{U}|$=2.

(c) $|\mathcal{U}|$=3.

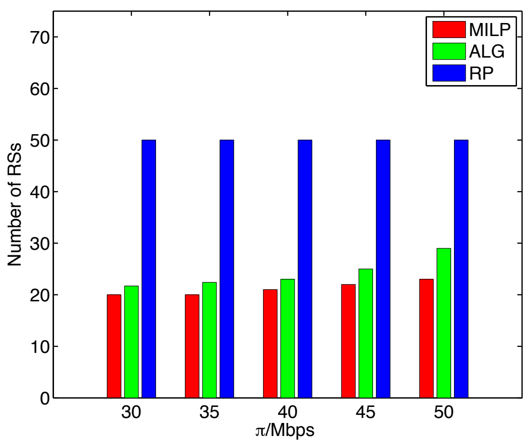
Fig. 4. The number of RSs selected by ALG, RP and MILP when the area is $600\times 600m^2$ and $|\mathcal{C}|=20$.

### C. Results and Analysis

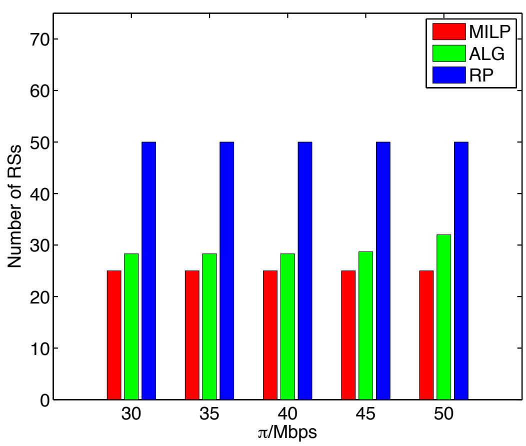
Fig. 4 shows the experiment results under different number of user layers when the area is $600\times 600m^2$ and $|\mathcal{C}|=20$. It is illustrated that the average number of RSs attained by RP is




(a) $|\mathcal{U}|$=1.




(b) $|\mathcal{U}|$=2.




(c) $|\mathcal{U}|$=3.

Fig. 5. The number of RSs selected by ALG, RP and MILP when the area is $1000 \times 1000m^2$ and $|\mathcal{C}| = 50$.

about 20. The reason is that in general, RP has to deploy more RSs to meet the energy efficiency constraint compared with ALG and MILP, due to its nature of random placing. But as the number of RSs selected increases, it becomes more difficult to satisfy the connectivity requirement of the infrastructure layer. Thus, RP will always output all the candidate locations in $\mathcal{C}$

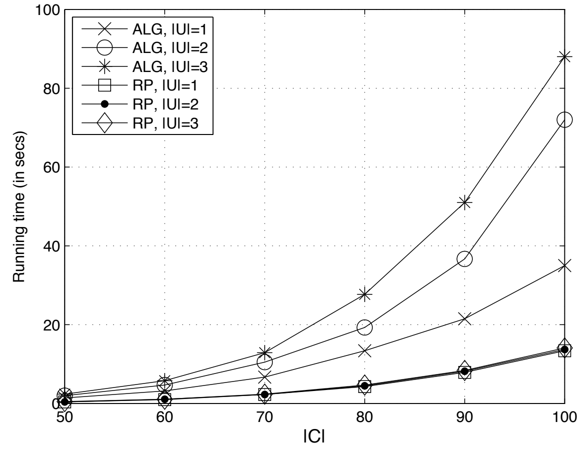



Fig. 6. Running times of ALG and RP.

as the final solution, which has the worst performance. As the link capacity threshold $\pi$ and the number of user layers $|\mathcal{U}|$ increase, the number of RSs obtained from ALG increases since more RSs need to be deployed to ensure the connectivity of the infrastructure layer and the accessing capability of SUs, respectively. But the result is still much smaller than that of RP, and it is within 2 times of the optimal solution by MILP. For example, when $|\mathcal{U}| = 2$ and $\pi = 40$Mbps, the average number of RSs deployed with MILP, ALG and RP is 10, 11.6 and 20, respectively.

Fig. 5 illustrates the performance comparison of different RS placement schemes when the area is $1000 \times 1000m^2$ and $|\mathcal{C}| = 50$, from which we can draw the similar conclusions: RP has the maximum number of RSs. ALG performs much better than RP and the number of RSs needed with ALG is smaller than 2 times of the optimum from MILP. For instance, when $|\mathcal{U}| = 1$ and $\pi = 35$Mbps, the average number of RSs attained by ALG and RP is 1.2 times and 3 times of the optimal solution, respectively.

In Fig 6, we compare the running times of ALG and RP under different number of candidate locations of RSs and user layers. It is shown that the running times of ALG and RP increase as $|C|$ and $|\mathcal{U}|$ increase, since there are more subareas to be dealt with. Though the running time of ALG is larger than that of RP, it is still very small and acceptable even when the problem scale is quite large.

## VIII. Conclusion

In this paper, we study the spectrum and energy efficient relay station placement problem (RSPP) for CRNs. We mathematically formulate a cost minimization problem to compute the optimal RS placement strategy with the consideration of uncertain channel availability. In view of the NP-hardness of the problem, we also develop a framework of heuristic algorithms to efficiently find the near-optimal solutions within polynomial time. We compare the performance of the heuristic algorithms with the random placement strategy and the optimal solution through extensive simulations. The results show that our heuristic algorithms outperform the random placement scheme and the number of RSs obtained by our algorithms is always within 2 times of that from the optimal solution.

As the future work, we will extend our framework to the case where the links between infrastructure nodes are not symmetric and also take the density and service demands of the SUs into consideration.

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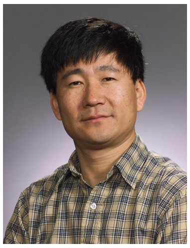

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