IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received February 18, 2019, accepted March 11, 2019, date of current version April 18, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2906863

Resource Efficient Allocation and RRH Placement for Backhaul of Moving Small Cells

ZAEEMA IFTIKHAR[1], SOBIA JANGSHER[2], HASSAAN KHALIQ QURESHI[1], (Senior Member, IEEE) AND MOAYAD ALOQAILY[3]

[1]School of Electrical Engineering and Computer Science (SEECS), National University of Sciences and Technology (NUST), Islamabad 44000, Pakistan
[2]Institute of Space Technology, Islamabad 44000, Pakistan
[3]Faculty of Engineering, Canadian University Dubai, Dubai, United Arab Emirates

Corresponding author: Zaeema Iftikhar (14mseeziftikhar@seecs.edu.pk)

ABSTRACT Mobile users suffer from deteriorating signal quality due to vehicle penetration losses. To solve this, small cells are deployed within the vehicles to improve the Quality of Service (QoS). These small cells called moving small cell access points (MSAPs), however, suffer from backhaul issues since they would have to send a huge amount of data to the core network. To solve the backhaul problem, cloud radio access network (CRAN) along with the millimeter wave (mmwave) can be a viable solution for moving vehicles. However, in order to realize its potential benefits, an effective remote radio head (RRH) deployment strategy and the resource-efficient allocation are needed. In this paper, we investigate the placement of RRH alongside a railway track; then, for the placed RRH, a joint time slot and power allocation problem are formulated with an objective of maximizing the resource efficiency (RE) of the MSAP backhaul network. An optimal Branch and Bound Algorithm (BnBA) is proposed for the constituted non-linear integer problem, and the effects of changing various model parameters are investigated. The simulation results show that our proposed algorithm deviates 52% of the sub-optimal result.

INDEX TERMS Energy efficiency, spectral efficiency, resource efficiency, moving small cells, mmwave, backhaul, fronthaul, CRAN, RRH.

I. INTRODUCTION

With the introduction of new devices in the market every year, the energy consumption of wireless communication network shows continuous growth. Due to this rapid deployment of smart devices and the growth of the Internet, users have become accustomed to experiencing a high speed connectivity independent of their location. Similarly, for mobile operators, excessive power consumption has become a critical concern exerting extra pressure on providing seamless communication in environments like high speed vehicles where new challenges have emerged because of high mobility [1]. Challenges different than traditional network exist in high speed vehicles. These include: frequent handover due to the high-speed movement among cells, handover failure due to Doppler frequency shift, low data rate due to fast fading, multipath loss and poor Quality-of-Service (QoS). Users suffer from deteriorating signal quality due to vehicular penetration losses causing a loss in QoS. Internet of Things (IoT) is used to make city planning smarter and in turn satisfies the high QoS standards of the users.

To improve the QoS for the users, small cells can be deployed within the vehicles, called Moving Small-cell Access Points (MSAPs) [2]. MSAPs can be deployed in moving vehicles to enhance user throughput, reduce overhead due to drop calls, signaling and to provide an extended coverage. Placed within the train, they are connected to the transceivers outside, this decreases the vehicular penetration losses and in turn provides the Mobile Station (MS) with a better received signal quality.

These MSAPs though, would have to send a huge amount of data to the core network; making offloading data difficult. Offloading network traffic focuses on two areas: mobile backhaul and the radio access network (RAN). For mobile operators, RAN is considered the most important asset in terms of providing uninterrupted, high data rate and high quality services to the subscribers. However, current wireless infrastructures are incapable of providing the

The associate editor coordinating the review of this manuscript and approving it for publication was Kostas Psannis.

necessary capacity, bandwidth and data rates needed by the High Speed Railway (HSR) users. This motivates the shift towards the 5th Generation (5G) paradigm, which compared to the 4G, provide 1000 times higher system capacity, 10 times higher Spectral Efficiency (SE) and much higher Energy Efficiency (EE).

One such promising architecture for 5G is to implement the Cloud-RAN (CRAN) [3]. CRAN when adopted can provide a reliable wireless network, on which the growth of IoT communication depends. CRAN allows for better performance, flexibility, and scalability; allowing 5G to provide connectivity for the large bulk of IoT devices imagined for smart cities. CRAN separates the baseband unit (BBU) from the Remote Radio Head unit (RRH), and moves it to the cloud [4]. CRAN facilitates the implementation of small-cell based networks with fantastic EE performances. Moreover, for a Heterogeneous-CRAN (H-CRAN) the SE performance gains are significant as the distance between the serving RRH and desired user are shortened. Although SE measures how efficiently a restricted frequency spectrum is utilized, it however, fails in accounting for how efficiently power is consumed. Therefore, green radio (GR) [5] (Emphasizing on both EE and SE) helps provide an effective solution. Unfortunately, SE and EE conflict at times i.e. increasing one decreases the other. Hence, EE and SE are balanced by incorporating another performance metric called Resource Efficiency (RE) [6].

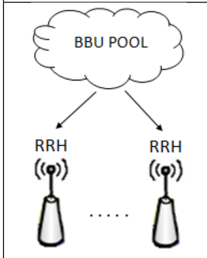
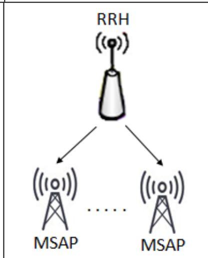
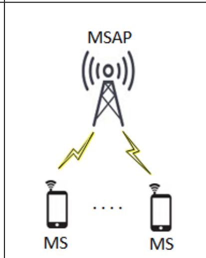
To connect the small cells at the edge to the core network millimeter-wave (mmWave) is considered. Already been standardized for short range services, if deployed either for fronthaul or backhaul, could provide incomparable data rates [7]. Moreover, using transceivers with MSAPs, we eliminate any obstruction between the MSAPs and RRH, making the link perfect for mmWave to be used (mmWaves require the link to be Line-of-sight (LOS)). However, to make sure that backhaul support is provided to the whole railway track, proper placement of the RRH is necessary, since the effectiveness of the MSAP network depends on the location and density of the RRH.

This paper presents a novel work on the deployment of a cellular network for a railway track in terms of EE and SE, taking into account resources like power and time slot allocation. We study the placement of RRH along the track of the train, to provide backhaul support to the users connected to the MSAPs.

The main contributions in the paper are as follows:

- We investigate the backhaul problem of MSAPs via proposing cloud radio access network (CRAN) along with the millimeter (mmWave) as a viable solution for moving vehicles.
- We investigate the RRH placement based on maximum coverage problem (MCP) with guaranteed QoS as the criterion. Considering cost of RRHs to maintain a stable connection, our problem tries to minimize the number of RRHs needed to cover the track.

TABLE 1. Different access technologies possible for different access links used.

BBU POOL to RRH	RRH to MSAP	MSAP to User
		
Possible Options Optical Fiber Microwave Copper Sub-6 GHz	**Possible Options** mmWave Microwave Sub-6 GHz Satellite	**Possible Options** Optical Fiber Copper Microwave Sub-6 GHz mmWave

- We formulate a RE maximization problem for the downlink transmission by jointly optimizing the power and time slots allocation for the placed RRHs.
- We propose an optimal Branch and Bound Algorithm (BnBA) to the RE problem which utilizes a local search algorithm, Iterative Resource Efficient Allocation Algorithm (IREAA).

The rest of the paper is organized as follows: Section II discusses the related work and justifies the choice of mmWave among other backhaul technologies, Section III provides the system model and notations used throughout the paper. In Section IV, we formulate a RE maximization problem as an optimization problem for a uniform placement of RRH. Section V presents the algorithm we develop for optimal allocation to optimize RE. In Section VI we investigate the conservatism of the solution as various model parameters are changed. Finally, we conclude our work in Section VII.

II. BACKGROUND AND RELATED WORK

A. BACKGROUND

We employ a heterogeneous mix of backhaul solutions [8]. Table 1 provides an insight regarding the feasibility and performance benefits of incorporating mmWave technology.

For BBU to RRH and MSAP to User, the cost and infeasibility of deployment of wired backhaul makes us shift to wireless options, which offers a cost-effective alternative [9]. Although Sub-6 GHz is cheaper than optical fiber; interference, traffic congestion and its low capacity does not allow its consideration as an access link in this case. Therefore, microwave (5-40 GHz) is considered as a cheaper fronthaul technology and more flexible option to deploy than optical fiber, at the expense, however, of low capacity.

The access link connecting the RRH to MSAP considers a wireless backhaul solution. The satellite option is costly and unrealistic to deploy in the existing cellular spectrum for a large scale backhaul [10]. If, however, the RRHs are placed along the train track with no obstruction between the MSAPs and RRH, the link becomes a LOS link and mmWaves are usable. MmWave frequencies in the 60 GHz and 70-80 GHz ranges are gaining prominence in mobile backhaul applications [11]. The links can be deployed faster and at a lower cost [12]. For shorter distances, sensitivity to blockages are ignored and has been shown that data rates of up to 10 Gbps can be achieved [13]. Therefore, making mmWave link a practical option as a backhaul link covering the last mile towards the MSAPs. To compensate for the path loss at these frequencies, highly directional antennas are assumed to be deployed.

B. RELATED WORK

We take inspiration for RRH placement from VANETs (Vehicular Ad hoc Networks); where roadside units (RSUs) improve the networks performance in terms of communication ranges, transmission delays and connectivity. An excessive work is done on deployment of RSUs [14]–[20], where they are placed along the road side, with the objective to find the optimal positions covering all the vehicles, while taking into consideration several constraints.

From VANETs perspective, RSU deployment is application dependent and does not aim at maximizing the data rate or providing a backhaul support. However, developments in HSR demand a high QoS communication link making us use MSAPs, and thus huge data needs to be sent back to the core. Although a lot of work has been done on HSR using MSAPs [21]–[24]; however, backhaul support has not been provided in HSR keeping in mind the placement of RRHs. We also present an architecture catering for the demands of 5G communication as mentioned in Section III, featuring CRAN with mmWave that can achieve better handoffs and higher data rate than a conventional network.

In [25], H-CRAN is proposed to achieve high SE and EE performances through the combination of cloud computing and HetNets. Prior work on H-CRANs resource allocation [26]–[29] are specific for EE/SE, not indicating the EE-SE tradeoff. Tang *et al.* [6] proposes a new paradigm for EE-SE tradeoff, namely the Resource Efficiency (RE) for OFDMA cellular network. In light of this and to the best of our knowledge, there is a lack of solutions for maximizing the RE performance in H-CRANs. Furthermore, the radio resource allocation to achieve an optimal RE performance in H-CRANs is still not investigated. As a solution, joint power allocation and time slot assignment subject to QoS constraints should be investigated that maximizes the RE of an H-CRAN.

III. SYSTEM MODEL

In this section, the proposed CRAN system model, the resources to be allocated and definition of resource efficiency are introduced. Based on the CRAN system model and defined RE, the number of RRHs to be placed are calculated and time slots are computed to optimize the RE in Section IV.

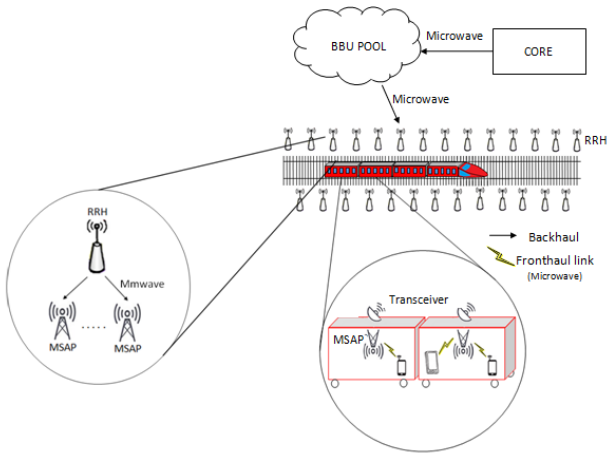


FIGURE 1. System model and backhaul access link used for RRH placement.

Figure 1 shows the system model with our proposed architecture and backhaul access links. A down-link Time Division Multiple Access (TDMA) based network, over K time slots denoted as $\mathcal{K} = \{1, 2, \ldots, K\}$ is considered. To cater for the poor QoS due to vehicular penetration losses, a set of J SAPs, $\mathcal{J} = \{1, 2, \ldots, J\}$ are installed inside the vehicle. For these MSAPs to send data back to the core we provide the backhaul support via placement of N RRH, $\mathcal{N} = \{1, 2, \ldots, Q\}$ (where $N \in \mathcal{N}$ and $N \leq Q$) alongside the train track of length Len. On the up-link, these RRHs are connected to the core via the BBU pool; we assume here, that one BBU pool is sufficient to cover the N RRHs. On the down-link, each RRH connects to M SAPs through a strong transceiver installed outside the vehicle, which in turn transmits to the user via MSAPs, eliminating the penetration losses. We thus eliminate any obstruction between the MSAPs and RRH, making the link perfect for mmWave to be used (as the practicability of mmWaves require the link to be Line-of-sight (LOS)). In this paper, we work on the RRH-MSAP link, where the choice of mmWave as backhaul is already discussed in Section II.

Let y_j^k be a binary variable indicating whether or not time slot k is assigned to the j^{th} MSAP by an RRH. Then a matrix variable is constructed i.e $\mathbf{Y}= \left[y_j^k\right]_{J\times K}$ denoting time slot to MSAP allocation by an RRH. Let I be an indicator variable, which, for a given MSAP j, indicates whether the total data rate sent over K time slots for the j^{th} MSAP is greater than the threshold rate:

$$I_j = \begin{cases} 1, & \text{if } \sum_{k=1}^{K} y_j^k.\rho_j^k \geq R_{th}\ \forall j \\ 0, & \text{otherwise.} \end{cases}$$

where ρ_j^k is achievable data rate for a TDMA system of MSAP j on time slot k and R_{th} is the threshold data rate.

The total time T, for which the train is on the track is divided into C time instances ($T = C \times \Delta t$) by incorporating the mobility of the train. (Where $C = (N.M) + J - 1$ is generalized by considering the RRHs connecting to the incoming MSAPs as the train moves along the track). The duration of a time instance is $\Delta t = \frac{(LU-\epsilon)}{v}$ after which MSAP j moves to the location of $j^{th}+1$ MSAP (ϵ represents a small distance between train units and LU, the length of the train unit). A matrix variable of size C is constructed as $X = [X_c]_{1\times C}$. X identifies all possible combinations in which J MSAPs can connect to N RRH over the complete track for time T. Out of these C ways in which MSAPs and RRHs connect, $X_c = \left[X_{nj}(t)\right]_{N\times J}$represents a potential connectivity, i.e.

$$X_{nj}(t) = \begin{cases} 1, & \text{if RRH n connects to MSAP j at a time instant t} \\ 0, & \text{otherwise.} \end{cases}$$

The achievable data rate for a TDMA system of MSAP j on time slot k from RRH n is given by:

$$\rho_{n,j}^{k} = \tau_k log(1 + SINR_{n,j}^{k}), \tag{1}$$

where τ_k is equal sized duration of the time slots and

$$SINR_{n,j}^{k} = \frac{P_{nj}^{k}.\left|h_{nj}^{k}\right|^2}{N_o + I_j^k}. \tag{2}$$

where P_{nj}^k, h_{nj}^k and N_o are the transmit power of n^{th} RRH to j^{th} MSAP, norm of channel gain for the j^{th} MSAP and noise density respectively. And the interference received on the k^{th} time slot on MSAP j from i^{th} RRH is $I_j^k = \sum_{\substack{i\in N \\ i\neq n}} P_{ij}^k \left|h_{ij}^k\right|^2$.

We define a binary time slot assignment indicator:

$$z_{n,j}^{k} = \begin{cases} 1, & \text{if RRH n assigns k}^{\text{th}} \text{ time slot to MSAP j,} \\ 0, & \text{otherwise.} \end{cases}$$

For our resources that are to be allocated, we construct two $N \times J \times K$ matrix variables, $Z = \left[z_{n,j}^k\right]_{N\times J\times K}$ and $P = \left[P_{n,j}^k\right]_{N\times J\times K}$ as the feasible time slot assignment and power allocation for RRH, respectively. Therefore, the overall throughput of the system is expressed as:

$$R(Z,P) = \sum_{n\in\mathcal{N}}\sum_{j\in\mathcal{J}}\sum_{k\in\mathcal{K}} z_{n,j}^k \rho_{n,j}^k. \tag{3}$$

According to [30], the total power consumption of H-CRAN is given by:

$$P_T = \sum_{n\in\mathcal{N}}\sum_{j\in\mathcal{J}}\sum_{k\in\mathcal{K}} z_{n,j}^k P_{n,j}^k, \tag{4}$$

And the overall power budget at the RRH is:

$$P_{tot} = P_{max}. \tag{5}$$

Spectrum Efficiency (SE) is a measure of how efficiently the frequency resources are utilized regardless of the power consumption. SE is defined as the total (average) number of delivered bits per unit bandwidth.

$$\lambda_{SE} = \frac{R(\mathbf{Z},\mathbf{P})}{W} = \frac{\sum_{n\in\mathcal{N}}\sum_{j\in\mathcal{J}}\sum_{k\in\mathcal{K}} z_{n,j}^k \rho_{i,j}^k}{W} \tag{6}$$

To maximize the SE, system uses as much power possible therefore reducing the efficient use of resources in terms of power.

Energy Efficiency (EE) is also an important performance metric that indicates the data throughput in relation to the energy consumed. EE for a down-link transmission is defined as the total delivered bits per unit energy. Here, energy consumption comprises of circuit energy consumption in active mode and transmission energy consumption.

$$\lambda_{EE} = \frac{R(\mathbf{Z},\mathbf{P})}{P_T} = \frac{\sum_{n\in\mathcal{N}}\sum_{j\in\mathcal{J}}\sum_{k\in\mathcal{K}} z_{n,j}^k \rho_{n,j}^k}{P_T} \tag{7}$$

Like SE, optimizing EE reduces the efficient use of resources in terms of bandwidth, as it will use as much bandwidth as possible. Thus, increasing EE would require an increase in the bandwidth, that adversely affects the SE.

As indicated, using either an energy-efficient or a spectral-efficient only design has its drawbacks regarding inefficient use of resources. Thus, to optimize both EE and SE, we would have to introduce a multi-objective optimization. Instead, a new metric called resource efficiency defined below is used that is a combination of both EE and SE [6].

Definition 1 (Resource Efficiency): A performance metric that provides a tradeoff between EE and SE.

$$\lambda_{RE} = \frac{R(\mathbf{Z},\mathbf{P})}{P_T}\left(1 + \beta\frac{\eta_P}{\eta_W}\right) \tag{8}$$

where β is a weighted factor to control the balance of EE and SE and η_P and η_W represent power utilization and bandwidth utilization respectively, given by:

$$\eta_P = \frac{P_T}{P_{tot}}, \tag{9}$$

$$\eta_W = \frac{W}{W_{tot}}. \tag{10}$$

RE results from combining the above equations as proved in [6] and gives us a tradeoff in the relationship of EE and SE.

$$\lambda_{RE} = \lambda_{EE} + \acute{\beta}\lambda_{SE} \tag{11}$$

where $\acute{\beta} = \beta\left(\frac{W_{tot}}{P_{tot}}\right)$. β is the weight between SE and EE, such that RE optimizes EE when $\beta = 0$ but optimizes SE when $\beta = \infty$.

IV. PROBLEM FORMULATION

In this section, the problem formulation of RRH placement and joint time slot and power allocation is discussed. Instead of solving a problem as one, we have decomposed it, where each part depends on its counterpart. The problem is divided into:

1) **Maximum coverage problem (MCP) for one RRH:** Finds the minimum number of RRH ($N \in \mathcal{Q}$) that is to be placed alongside the track.
2) **Placement based on MCP:** These N RRH are then uniformly placed alongside the track.
3) **RE maximization for the placed RRH:** For these uniformly placed RRH, we jointly optimize the time-slot to MSAP allocation and power on each RRH, maximizing the RE for the whole MSAP network.
4) **Optimizing over the complete time period (Section:V):** Lastly, using mobility information, we find how MSAPs change their connectivity with RRHs over the whole time period.

Our problem is to place a minimum number of RRH along the track to provide backhaul support to small cells inside the vehicle. Then for this placement strategy, joint power and time slot allocation is done such that resource efficiency of the system is maximized. In the following subsections we will chronologically investigate each part mentioned:

A. MAXIMUM COVERAGE PROBLEM OF ONE RRH

We calculate the maximum number of MSAPs j= $1, 2, ..M(M \ll J)$, that can be connected to a single RRH so as to satisfy that the QoS rate requirement is guaranteed. Then, using this (M) together with already known information, as for example the total number of MSAPs, we can find an approximate minimum number of RRHs ($N \in \mathcal{Q}$) that can cover the entire track. These RRHs are then placed along the track such that our requirement for maximum RE is satisfied.

We call this problem maximum coverage problem (MCP), and is formulated as:

$$\max_{Y} \sum_{j=1}^{J} I_j \tag{12}$$

$$s.t: \sum_{j=1}^{J} y_j^k \leq 1 \quad \forall k = 1, 2, \ldots K \tag{13}$$

$$\sum_{k=1}^{K} y_j^k \leq K \quad \forall j = 1, 2, \ldots J \tag{14}$$

$$y_j^k \in [0, 1] \tag{15}$$

The objective (12) is to find **Y** (which will give us the number of MSAPs connected to the RRH), that maximizes $I_j = 1, 2..J$. Constraint (13) ensures that each time slot is not assigned to more than one MSAPs for data transmission; i.e. one time slot is dedicated to either one MSAP or none. Constraint (14) makes sure that total number of time slots utilized by each MSAP does not exceed the total number of slots (K). Constraint (15) indicates that variable y can only take integer values (0 or 1), making the optimization problem a Non-Linear Integer Problem (NLIP). The algorithm used to solve MCP are discussed in Section V.

Using the total number of MSAPS, J, the length of the track, *Len*, and the M MSAPs which connect to one RRH, we can now find the total number of RRHs required to cover the complete track, i.e. ($N = \frac{Len}{Lm}$).

B. PLACEMENT BASED ON MCP

The identification of where along the track, the RRHs are to be deployed is important as it will provide a backhaul support to the MSAPs, while an optimal placement strategy will be maximizing the resource efficiency. Now that N number of RRHs to be placed are calculated using MCP and linear relations, we place them uniformly along the track.

C. RE MAXIMIZATION FOR THE PLACED RRH

For these uniformly placed RRH, our objective (16) is to maximize the resource efficiency (*definition*1) of the whole network, to find optimal time slot allocated to each MSAP, Z; Power and MSAP to RRH connections at a time stamp (X) which is later used to map the trains connectivity with RRHs over the complete time period via incorporating mobility. The objective function that maximizes our resource efficiency is formed for a complete time period as follows:

$$\max_{Z,X,P} \sum_{n \in \mathcal{N}} \sum_{j \in \mathcal{J}} X_{n,j}(t) \left(\frac{\sum_{k \in \mathcal{K}} z_{n,j}^k \rho_{n,j}^k}{P_T} \left(1 + \beta \frac{\eta_P}{\eta_W}\right) \right) \tag{16}$$

$$s.t: \sum_{j \in \mathcal{J}} X_{n,j}(t) \leq M \quad \forall n \in \mathcal{N} \tag{17}$$

$$\sum_{n \in \mathcal{N}} X_{n,j}(t) \leq 1 \quad \forall j \in \mathcal{J} \tag{18}$$

$$\sum_{j \in \mathcal{J}} z_{n,j}^k \leq 1 \quad \forall k \in \mathcal{K};\ \forall n \in \mathcal{N} \tag{19}$$

$$\sum_{k \in \mathcal{K}} \rho_{n,j}^k . z_{n,j}^k \geq R_{th} \quad \forall j = 1, 2, \ldots M;\ \forall n \in \mathcal{N} \tag{20}$$

$$\sum_{k \in \mathcal{K}} \sum_{j=1}^{M} P_{n,j}^k \leq P_{max} \quad \forall \mathcal{N} \tag{21}$$

$$X_{n,j}(t), z_{n,j}^k \in [0, 1] \tag{22}$$

Constraint (17) indicates that the maximum number of MSAPs connected to an RRH cannot exceed M. Constraint (18) refers to the fact that each MSAP can be connected to only one RRH at a time instant. Constraint (19) shows that one time slot cannot be assigned to more than one MSAP by an RRH. Constraint (20) indicates that the rate at which an RRH transmits to M MSAPs on all K time slots must be greater than the threshold. Constraint (21) indicates that the power of all MSAPs connected to an RRH should be less than the total maximum transmit power, and Constraint (22) refers to variable X and Z taking only integer values (0 or 1), making the optimization problem an non-linear integer problem (NLIP).

Algorithm 1 REAP Algorithm

1: Calculate N number of RRH to be placed using MCP
2: Place N number of RRH along the track uniformly
3: With uniform RRH placement, the RE problem (16) can be solved for one time instant via:
   (a) Optimal method (BnBA);
   (b) Iterative Resource Efficient Allocation Algorithm (IREAA).
4: Optimize over complete time period.

V. RESOURCE EFFICIENT ALLOCATION AND PLACEMENT (REAP) ALGORITHM

In this section, we discuss algorithms which can be used to solve our posed joint time slot and power allocation in RRH placement, and RE maximization problem. Resource Efficient Allocation and Placement (REAP) algorithm in Algorithm 1 is an overall framework algorithm showing a comprehensive plan on how our decomposed problem as indicated in Section IV is solved.

In Step 1, MCP is solved using a Distance Discarding based MSAPs Connection (DDMC) algorithm. DDMC attempts to find a near optimal solution by applying a threshold on the number of MSAPs that can be connected to an RRH, thus reducing the implementation complexity. We find the number of MSAPs connected to an RRH via DDMC, and in turn find the number of RRH required to be placed along the track. These RRH are then placed uniformly in Step 2. Step 3 solves the RE maximization problem for one time instant using optimal and IREAA method and Step 4 plots the result of one time instant from Step 3 over the complete time period. REAP algorithm steps are discussed in detail in the following subsections.

A. MCP FOR ONE RRH

DDMC-MCP, takes into account that an RRH cannot transmit to MSAPs out of its transmission range Tr. The algorithm aims to reduce the total number of combinations of y_j^k found through exhaustive search (Optimal method) over all J MSAPs. It does so by setting a threshold distance, Tr_{th}, which is chosen in a way that the MSAPs farthest from the RRH are excluded, keeping the closest ones for manipulations. Tr_{th} is relaxed and kept greater than Tr, ($Tr_{th} = 2 \times Tr$), to cater for the maximum number of possible MSAPs to be connected. Instead of finding a solution over J MSAPs, it finds it over $j \in 1, 2, ..th$ where MSAPs $j \in th+1, .., J-1, J+1$ are bound to be out of the range of an RRH.

Let B_j be the distance of an RRH to the j^{th} MSAP, and let $\mathcal{B} = \{1, 2, \ldots, B\}$ be a set of B random distances where each $b \in [1m, 2km]$ and B is the same as the total number of MSAPs (B=J). DDMC, excludes those MSAPs which lie beyond the considered threshold ($B_j > Trth$); i.e. if the distance of MSAP j is greater than the threshold set, its not in the range of the RRH, and is excluded.

B. RE MAXIMIZATION FOR THE PLACED RRH

For the uniformly placed RRH, rather than solving the continuous RE problem (16), we strategically solve it for one time instant and later map it over the complete time period. We use two methods to solve (16). First we use an optimal method to find an optimum solution for this NP hard problem. And then use an Iterative Resource Efficient Allocation Algorithm (IREAA) to cater for the complexity factor of the exhaustive methods.

1) BRANCH AND BOUND ALGORITHM (BnBA)

Algorithm 2 shows the BnB algorithm adopted to find the optimal solution for this NP hard problem, where the solution space is branched till an optimal solution is found.

Algorithm 2 BnBA

1: **Initialization:**
2: Let the initial lower bound of Problem 1 be $LB = -\infty$
3: Find the relaxed solution using solver BONMIN, $\hat{\phi}_1$
4: The objective function of $\hat{\phi}_1$ is the upper bound UB_1
5: **Main Iteration:**
6: Select the Problem p having the maximum upper bound UB_p value among all problems in the list
7: Update upper bound by $UB = UB_p$
8: Find ϕ_p, the feasible solution via the local search algorithm (IREAA) by initializing with the solution to $\hat{\phi}_1$.
9: Let the objective value of ϕ_p be LB_p
10: **if** $LB_p > LB$
   Set $LB = LB_1$
   if $UB \leq (1-\epsilon)LB$
   Stop
   else
   Remove all other problems $\hat{p}'$ with $UB_p' \leq (1-\epsilon)LB$
   end if
   end if
11: Partition the value set of variable z into two sets based on its value in $\hat{\phi}_1$ and label them p1, p2 and remove problem p from the problem set.
12: Obtain UB_2 and UB_3 via relaxation
13: If $UB_{p1} \leq (1-\epsilon)LB$ add Problem p1 in the problem list
14: If $UB_{p2} \leq (1-\epsilon)LB$ add Problem p2 in the problem list
15: **if** the problem list is empty:
   STOP
   else
   Go to step 5.
   end if

The upper bound of the objective function is found by relaxation of the RE problem. The relaxed problem is solved via BONMIN binary search under the assumption that $I_j^k << N_o$. Using the relaxed solution as the starting point, BnBA employs IREAA, a local search algorithm (discussed in the next subsection) to find a feasible solution to the original problem. This feasible solution provides the lower bound to the objective function. If the attained upper and lower bounds are within a tolerance of $(\epsilon - 1)$ with each other, the current feasible solution is the optimal. To narrow down the solution, in step 9, the variable z found is further partitioned into two sets and BnB is applied to these sub problems until $(\epsilon - 1)$ tolerance is reached within the upper and lower bounds.

BnBA aims to provide an exact solution, however, at the cost of complexity. Therefore, we propose an IREAA which addresses this problem and attempts to find a near optimal solution.

2) LOCAL SEARCH ALGORITHM: IREAA

In this section, we propose a local search algorithm to find the lower bound for BnBA: Iterative Resource Efficient Allocation Algorithm (IREAA) as shown in Algorithm 3 is proposed. IREAA iteratively updates power and time slot allocation after satisfying the constraints(19) to (21).

We initialize the algorithm in step 1 using X and Z found from the optimal algorithm with uniform power allocation over all time slots. Step 2 calculates F_{RE}, our objective function from equation: (17) that is maximizing the RE and is also the stopping criteria. In Step 3 data rate from the n^{th} RRH sent to the j^{th} MSAP on the k^{th} time slot is calculated and then Step 4 checks for the QoS constraint (20) by comparing the data rate of each MSAP with the threshold value. If the calculated data rate of a user is greater than the threshold value then the power is decreased by a constant small size δ and vice versa.

With the power calculated in Step 6 we again check for our QoS constraint (20), if it still is not satisfied we inverse our MSAP time slot allocation vector such that (19) remains intact. Step 10 takes account of the maximum power constraint (21) that ensures that the sum of the power of all MSAPs connected to the RRH should be less than the maximum power of the RRH. To ensure that the sum of power of the connected MSAPs does not exceed the maximum transmit power P_{max} of the corresponding RRH we calculate the additional power needed by the RRH and reduce the power transmitted from each MSAP equally by Δ.

For the stopping criteria, we compute F_{RE} for the next iteration in Step 9 using the results of Steps 4 and 7 and then in Step 12 compare it with the previous values of F_{RE}. If the calculated value of F_{RE} is less than previous three consecutive values, we have maximized our objective and terminate our algorithm. The optimal power and time slot allocation values are the desired power and time slot allocation that maximizes the RE.

Algorithm 3 IREAA

1: Initialization:
  iter = 0;
  $X^t_{n,j}$ using the result from Algo:1
  $P^k_{nj}(iter) = \left[\frac{P_{max}}{K}\right]$
  $z^k_{nj}(iter)$
2: Calculate objective function $F_{RE}(iter)$ using eq:16
3: **for** each RRH n transmitting to MSAP j on the k^{th} time slot **do**
4:   Find data rate $\rho^k_{n,j}$ using eq:1
  if $\rho^k_{n,j}.z^k_{n,j}(iter) \geq R_{th}$ **then**
  $P^k_{nj}(iter+1) = P^k_{nj}(iter) - \delta$
  else
  $P^k_{nj}(iter+1) = P^k_{nj}(iter) + \delta$
  end if
5: **end for**
6: **for** each RRH n transmitting to MSAP j on the k^{th} time slot **do**
7:   Find data rate $\rho^k_{n,j}$ using eq:1 and $P^k_{nj}(iter+1)$ calculated in step:4
  if $\rho^k_{n,j}.z^k_{n,j}(iter) \geq R_{th}$ **then**
  $z^k_{nj}(iter+1) = z^k_{nj}(iter)$
  else
  $z^k_{nj}(iter+1) = \overline{z^k_{nj}}(iter)$ s.t $\sum_{j\in\mathcal{J}} z^k_{n,j} \leq 1$ is met
  end if
8: **end for**
9: Find $F_{RE}(iter+1)$ using the results of Steps 4 and 7
10: **if** $\sum_{k\in\mathcal{K}} \sum_{j=1}^{M} P^k_{n,j}(iter+1) \leq P_{max}$
  Proceed to step: 11
  else
  $\Delta = P_{max} - P^k_{n,j}(iter+1)$
  $P^k_{n,j}(iter+1) = P^k_{n,j}(iter+1) - \Delta$
  end if
11: **if** $F_{RE}(iter) > F_{RE}(iter+1)$
  $z^k_{nj} = z^k_{nj}(iter)$ and $P^k_{nj} = P^k_{nj}(iter)$
  else
  $z^k_{nj} = z^k_{nj}(iter+1)$ and $P^k_{nj} = P^k_{nj}(iter+1)$
  end if
12: **if** $F_{RE}(iter+1) \leq F_{RE}(iter-3), F_{RE}(iter-2),$
  $F_{RE}(iter-1)$
  STOP
  else
  Go to Step: 2
  end if
13: iter=iter+1

C. OPTIMIZING OVER THE COMPLETE TIME PERIOD WITH RESPECT TO VELOCITY

We now have for a time instant, the connectivity between the RRHs and MSAPs, $X(t)$; using this information and mobility we further find the positions of the MSAPs to RRH for any time instant over a time period $X(t+\Delta t)$.

Assuming that foremost on the track, the trains last unit (i.e. J^{th} MSAP) moves towards the first RRH; then in accordance to this, at the next time instance the MSAPs and RRH connection w.r.t time instant t, changes as follows:

$$X_{n,j}(t+\Delta t) = X_{n,j+1}(t).$$

With a condition that if: $\sum_{j=1}^{J} X_{n,j}(t) = M \ \forall i$ **&** $X_{n,J}(t) = 1$; then: $X_{n+1,J}(t) = 1$ and $X_{n,J}(t) = 0$.

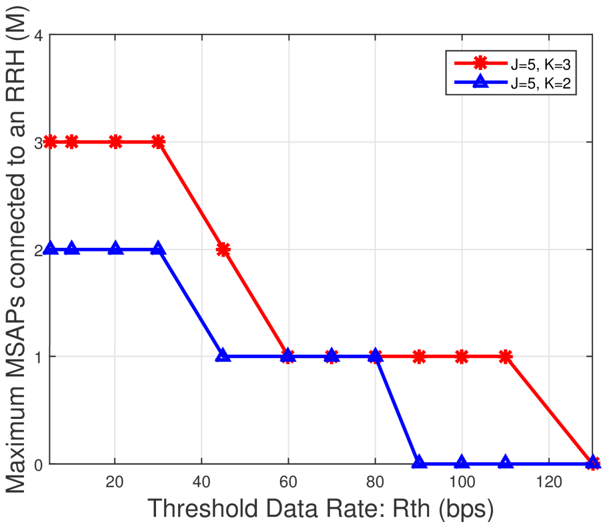


FIGURE 2. Impact of Rth on the number of total number of MSAPs connected to an RRH.

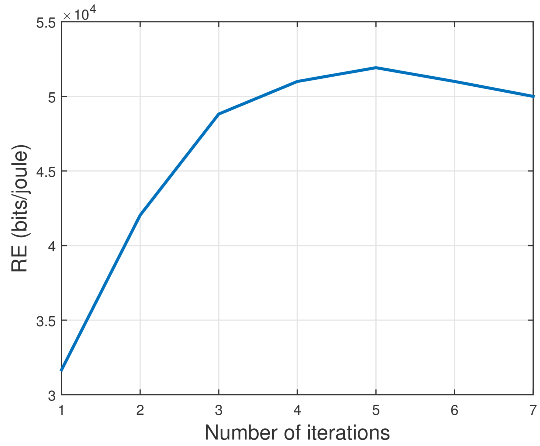
VI. PERFORMANCE EVALUATION

In this section, performance of our REAP algorithm is evaluated with simulations.

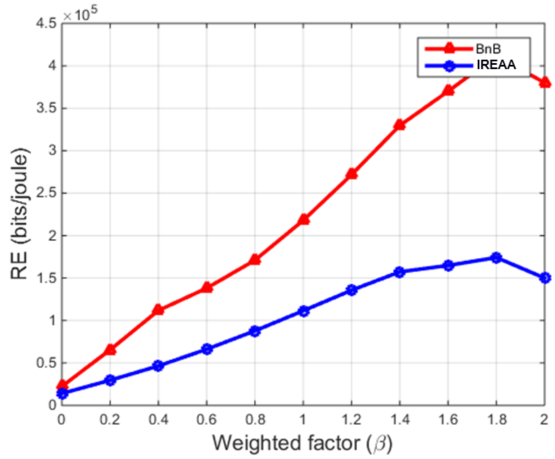
We first solve MCP and investigate the effect of changing the data rate threshold. For this experiment we consider J=5 and two values of K (K=2, K=3). As the threshold (Rth) is increased, a decrease in the maximum number of MSAPs (M) connected to an RRH is observed in Fig 2. This is due to the fact that an increase in Rth, signifies a tighter bound on the QoS; making it more likely that the total data rate sent on the k^{th} time slots for the j^{th} MSAP is less than the threshold rate. Thus, MSAP j is not connected to the RRH. It is also noted that although the total number of MSAPs were 5, the maximum connected MSAPs did not exceed the total number of time slots as a result of Constraint 14.

Next, we simulate our RE maximization problem using BnBA and IREAA. Fig 3 shows the results obtained for RE in *bits/joule* with respect to different parameters.

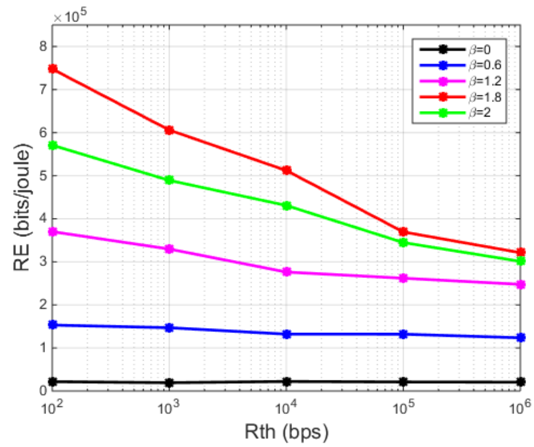
- Fig 3a shows the behavior of the IREAA as the number of iterations increase with $\beta = 0.6$. As the number of iterations increase, the algorithm stops to give the maximum RE reached. We see here, that our algorithm reaches a local maximum at iteration number 5 and thus algorithm stops at the next iteration.
- Fig 3b explains the impact of weighted factor β to corresponding RE. The results show that RE increases till $\beta = 1.8$ and then starts to decrease for higher values of β. This relationship between RE and β provides us with the optimal value of β that maximizes the RE. When β is in the range of 0 to 0.8, the value of RE increases and starts decreasing after the optimal value of β. From Fig 3c we also compare the performance of BnBA against the sub-optimal IREAA. We evaluated overall $\beta's$, the average percentage deviation of the sub-optimal algorithm compared to the optimum branch and bound over and found out that IREAA deviates 52% from the optimal algorithm.
- Fig 3c shows for IREAA, the relationship of changing rate threshold with the resource efficiency for different



(a)



(b)



(c)

FIGURE 3. BnBA and IREAA simulation for RE with different parameters. (a) Converging behavior of the proposed IREAA, (b) Impact of weighted factor β on RE, (c) Threshold data rate vs Resource efficiency for BnBA.

values of β. We see that as the data rate threshold is increased, the resource efficiency decreases as the QoS constraint 14 becomes difficult to satisfy. As indicated earlier in Fig 3b we again see that for $\beta = 1.8$ the RE is maximum.

TABLE 2. Run time complexity comparison.

REAP Algorithm sub-part	Method used	Computational Time(s)
MCP	Optimal	30.226
	DDMC	0.049
RE maximization	BnBA	55.05
	IREAA	0.05

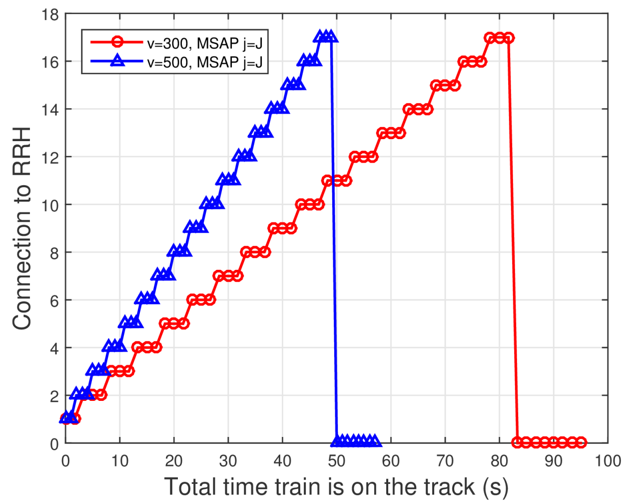
Table 2 compares how the different methods we used in the REAP Algorithm perform in terms of time; and compared optimal and suboptimal algorithms of MCP and RE maximization. In order to check the complexity of MCP, we simulated them with 3 time slots, transmitting data to 5 MSAPs (J=5, K=3). It is observed that the computational time has significantly decreased by approximately 99% when using DDMC-MCP rather than an optimal exhaustive method.

This is because, in DDMC-MCP, we had initially discarded possible MSAPs that lie outside an RRH's range. And so, instead of a total of 5 MSAPs, only 2 MSAPs lie within the RRH range and thus instead of $2^{(JK)}$ combinations (over which an exhaustive MCP would search), it searches over $2^{((th)K)}$ (where $th < M < J$) combinations in order to maximize the objective function, thus decreasing the computational time. To check the complexity of the algorithms used for RE maximization, we simulated both for N = 2; J = 2; K = 2. It is observed that the computational time significantly decreases by 99.9%, if only a local search algorithm IREAA is used. Although BnB gives an optimum solution, but in terms of time and resources used IREAA surpasses it.

Next, we provide the computational complexity analysis of IREAA and BnBA in terms of big O notation. For IREAA, it is seen that in steps 3 and 6, data rate from the N RRH send to M MSAP on K time slot is calculated thus the complexity of both is $O(NMK)$. The remaining steps in IREAA have a complexity in terms of constants and can therefore be ignored. Let n be the total number of iterations required for IREAA computation, overall complexity of IREAA therefore becomes $O(n(NMK)^2)$. On the other hand, for BnBA we find the complexity of upper bound (relaxed solution) and lower bound as well. Upper bound is solved via BONMIN which uses binary search that has a complexity of $O(log(x))$; where x is the number of iterations it takes to find the upper bound. BnBA finds the upper bound thrice so the complexity becomes $O(3logn)$. As lower bound is found using local search algorithm IREAA, its complexity is $O(n(NMK)^2)$. Let w be the total number of iterations required for BnBA to find the optimal solution, the overall complexity therefore becomes $O(w(3\ log$âĄą$(x)+(n(NMK)^2))$. Consequently, it can be deduced that IREAA can achieve higher efficiency in terms of complexity as compared to BnBA.

To check the feasibility of RRH placement in terms of cost, we calculate that for 1km, only 2 RRH are required.

(a)



(b)

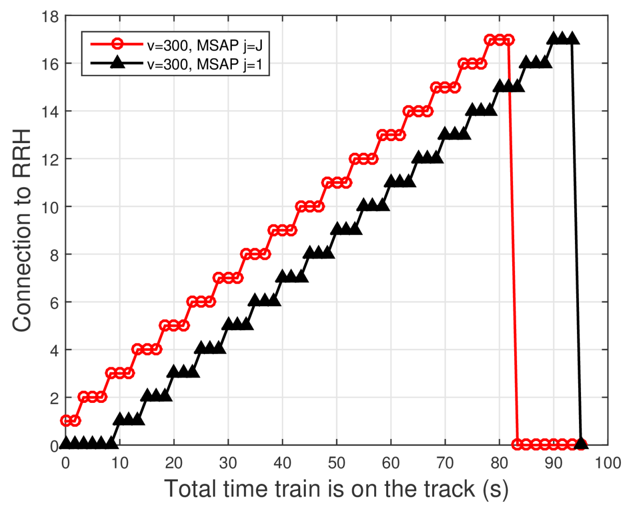


FIGURE 4. Plots of MSAP connectivity to RRHs along the track over time. (a) Tracking MSAP j=J on track with speed $v = 300ms^{-1}$, $500ms^{-1}$. (b) Tracking MSAP j=1 and j=J on track with speed $v = 300ms^{-1}$.

Lastly, we present a scenario (for N=17, M=3, J=8, Len=10km, Lm=600m) for optimization over the complete track. Fig 4 records an MSAP's journey over the track as it connects to N RRHs along the way for a total time period (Where the markers on the graph indicate the C time instances). We first see the effect of varying the speed for an MSAP connecting to RRHs over the track. Secondly, we investigate how a specific MSAP position in a train, i.e. MSAP on the first train unit (j=J) and MSAP on the last train unit (j=1), effects the connectivity to an RRH over the trains total journey on the track. The scenario is explained as follows:

- Fig 4a shows the effect of speed. We compare the first MSAP (j=J) connectivity over time with two different speeds. For both speeds its seen that as soon as the train enters the track (time=0s), the MSAP connects to the first RRH and thus both starts their journey at the same time. But for a greater speed, the MSAP reaches the track end faster, this is because as speed increases, Δt, indicating the time between a shift in MSAP-RRH connection decreases.

- In Fig 4b, for the same speed $300ms^{-1}$, we see that the first MSAP to enter the train track (j=J) connects to RRH 1 immediately while the last MSAP takes a time of $(J-1)\times\Delta t$ before it appears in the range of the first RRH. Similarly the last MSAP leaves the track later then the first.

VII. CONCLUSION

In this paper, for a down-link transmission with mmWave backhaul enabled CRAN, we studied the placement of a minimum number of required RRHs along the train track, to provide backhaul support to the users connected to the MSAPs. For this, we formed a Maximum Coverage Problem (MCP), which ensured that an RRH connects to a maximum number of MSAPs. Using the results from MCP, we found the number of RRH needed to cover the whole track and placed them uniformly. Then for a single time instant, we performed joint time slot and power allocation for the placed RRHs to maximize the resource efficiency of the network. Branch and Bound Algorithm (BnBA) was proposed and the scalability and optimality for the optimal and suboptimal Iterative Resource Efficient Allocation Algorithm (IREAA) were also studied. It was found that BnBA algorithm provided an optimal solution, it was less scalable in terms of complexity. Whereas, IREAA reduced the problem complexity; however, being suboptimal.

REFERENCES

[1] B. Ai *et al.*, "Challenges toward wireless communications for high-speed railway," *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 5, pp. 2143–2158, Oct. 2014.

[2] B. Lannoo, D. Colle, M. Pickavet, and P. Demeester, "Radio-over-fiber-based solution to provide broadband Internet access to train passengers," *IEEE Commun. Mag.*, vol. 45, no. 2, pp. 56–62, Feb. 2007.

[3] Y. Lin, L. Shao, Z. Zhu, Q. Wang, and R. K. Sabhikhi, "Wireless network cloud: Architecture and system requirements," *IBM J. Res. Develop.*, vol. 54, no. 1, pp. 4:1–4:12, 2010.

[4] A. Checko *et al.*, "Cloud RAN for mobile networks—A technology overview," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 1, pp. 405–426, 1st Quart., 2015.

[5] Y. Chen, S. Zhang, S. Xu, and G. Y. Li, "Fundamental trade-offs on green wireless networks," *IEEE Commun. Mag.*, vol. 49, no. 6, pp. 30–37, Jun. 2011.

[6] J. Tang, D. K. C. So, E. Alsusa, and K. A. Hamdi, "Resource efficiency: A new paradigm on energy efficiency and spectral efficiency tradeoff," *IEEE Trans. Wireless Commun.*, vol. 13, no. 8, pp. 4656–4669, Aug. 2014.

[7] Y. Niu, Y. Li, D. Jin, L. Su, and A. V. Vasilakos, "A survey of millimeter wave communications (mmWave) for 5G: Opportunities and challenges," *Wireless Netw.*, vol. 21, no. 8, pp. 2657–2676, 2015.

[8] J. Bartelt, G. Fettweis, D. Wubben, M. Boldi, and B. Melis, "Heterogeneous backhaul for cloud-based mobile networks," in *Proc. IEEE 78th Veh. Technol. Conf. (VTC)*, Sep. 2013, pp. 1–5.

[9] X. Ge, H. Cheng, M. Guizani, and T. Han, "5G wireless backhaul networks: Challenges and research advances," *IEEE Netw.*, vol. 28, no. 6, pp. 6–11, Nov./Dec. 2014.

[10] S. Hur, T. Kim, D. J. Love, J. V. Krogmeier, T. A. Thomas, and A. Ghosh, "Millimeter wave beamforming for wireless backhaul and access in small cell networks," *IEEE Trans. Commun.*, vol. 61, no. 10, pp. 4391–4403, Oct. 2013.

[11] C. Dehos, J. L. González, A. De Domenico, D. Kténas, and L. Dussopt, "Millimeter-wave access and backhauling: The solution to the exponential data traffic increase in 5G mobile communications systems?" *IEEE Commun. Mag.*, vol. 52, no. 9, pp. 88–95, Sep. 2014.

[12] T. S. Rappaport *et al.*, "Millimeter wave mobile communications for 5G cellular: It will work!" *IEEE Access*, vol. 1, pp. 335–349, May 2013.

[13] G. Fettweis, F. Guderian, and S. Krone, "Entering the path towards terabit/s wireless links," in *Proc. Design, Automat. Test Eur.*, 2011, pp. 1–6.

[14] O. Trullols, M. Fiore, C. Casetti, C. F. Chiasserini, and J. M. B. Ordinas, "Planning roadside infrastructure for information dissemination in intelligent transportation systems," *Comput. Commun.*, vol. 33, no. 4, pp. 432–442, 2010.

[15] B. Aslam, F. Amjad, and C. C. Zou, "Optimal roadside units placement in urban areas for vehicular networks," in *Proc. IEEE Symp. Comput. Commun. (ISCC)*, Jul. 2012, pp. 423–429.

[16] S. Mehar, S. M. Senouci, A. Kies, and M. M. Zoulikha, "An optimized roadside units (RSU) placement for delay-sensitive applications in vehicular networks," in *Proc. IEEE 12th Annu. Consum. Commun. Netw. Conf. (CCNC)*, Jun. 2015, pp. 121–127.

[17] B. Aslam and C. C. Zou, "Optimal roadside units placement along highways," in *Proc. IEEE Consum. Commun. Netw. Conf. (CCNC)*, Jan. 2011, pp. 814–815.

[18] Y. Sun, X. Lin, R. Lu, X. Shen, and J. Su, "Roadside units deployment for efficient short-time certificate updating in vanets," in *Proc. IEEE Consum. Commun. Netw. Conf. (CCNC)*, May 2010, pp. 1–5.

[19] D. Vageesh, M. Patra, and C. S. R. Murthy, "Joint placement and sleep scheduling of grid-connected solar powered road side units in vehicular networks," in *Proc. IEEE 12th Int. Symp. Modeling Optim. Mobile, Ad Hoc, Wireless Netw. (WiOpt)*, May 2014, pp. 534–540.

[20] P. Patil and A. Gokhale, "Voronoi-based placement of road-side units to improve dynamic resource management in vehicular ad hoc networks," in *Proc. Int. Conf. Collaboration Technol. Syst. (CTS)*, May 2013, pp. 389–396.

[21] O. B. Karimi, J. Liu, and C. Wang, "Seamless wireless connectivity for multimedia services in high speed trains," *IEEE J. Sel. Areas Commun.*, vol. 30, no. 4, pp. 729–739, May 2012.

[22] S. Xu, G. Zhu, C. Shen, Y. Lei, and Z. Zhong, "Delay-aware online service scheduling in high-speed railway communication systems," *Math. Problems Eng.*, vol. 2014, Mar. 2014, Art. no. 248174.

[23] C. W. Lee, M. C. Chuang, M. C. Chen, and Y. S. Sun, "Seamless handover for high-speed trains using femtocell-based multiple egress network interfaces," *IEEE Trans. Wireless Commun.*, vol. 13, no. 12, pp. 6619–6628, Dec. 2014.

[24] M.-S. Pan, T.-M. Lin, and W.-T. Chen, "An enhanced handover scheme for mobile relays in LTE-A high-speed rail networks," *IEEE Trans. Veh. Technol.*, vol. 64, no. 2, pp. 743–756, Feb. 2015.

[25] M. Peng, Y. Li, J. Jiang, J. Li, and C. Wang, "Heterogeneous cloud radio access networks: A new perspective for enhancing spectral and energy efficiencies," *IEEE Wireless Commun.*, vol. 21, no. 6, pp. 126–135, Dec. 2014.

[26] M. Peng, K. Zhang, J. Jiang, J. Wang, and W. Wang, "Energy-efficient resource assignment and power allocation in heterogeneous cloud radio access networks," *IEEE Trans. Veh. Technol.*, vol. 64, no. 11, pp. 5275–5287, Nov. 2014.

[27] Q.-T. Vien, T. A. Le, B. Barn, and C. V. Phan, "Optimising energy efficiency of non-orthogonal multiple access for wireless backhaul in heterogeneous cloud radio access network," *IET Commun.*, vol. 10, no. 18, pp. 2516–2524, 2016.

[28] Q. Liu, G. Wu, Y. Guo, and Y. Zhang. (2015). "Energy efficient resource allocation for control data separation architecture based h-cran with heterogeneous fronthaul." [Online]. Available: https://arxiv.org/abs/1511.01969

[29] M. Peng, Y. Yu, H. Xiang, and H. V. Poor, "Energy-efficient resource allocation optimization for multimedia heterogeneous cloud radio access networks," *IEEE Trans. Multimedia*, vol. 18, no. 5, pp. 879–892, May 2016.

[30] Q. Liu, G. Wu, Y. Guo, Y. Zhang, and S. Hu, "Energy efficient resource allocation for control data separated heterogeneous-CRAN," in *Proc. Global Commun. Conf. (GLOBECOM)*, Dec. 2016, pp. 1–6.

ZAEEMA IFTIKHAR received the B.S. degree in electrical engineering from the National University of Computer and Emerging Sciences (NUCES), Pakistan. She is currently pursuing the M.S. degree in electrical engineering in telecommunications and networking with the National University of Science and Technology (NUST), Pakistan, under the supervision of Dr. H. K. Qureshi. Her M.S. thesis is on Resource Efficient Allocation and RRH Placement for Backhaul of Moving Small Cells. Her research interests include wireless communication systems and 5G Networks.

SOBIA JANGSHER received the B.E. degree in electronics engineering and the M.S. degree in communication system engineering from the National University of Science and Technology (NUST), Pakistan, and the Ph.D. degree in wireless communication from The University of Hong Kong, Hong Kong. Her M.S. thesis was on Adaptive Transmission of Video Over MIMO Channels, under the supervision of Dr. S. A. Khayam, and her Ph.D. thesis was on Resource Allocation in Moving Small Cell Network, under the supervision of Prof. V. O. K Li. She is currently an Assistant Professor with the Institute of Space Technology, Islamabad, Pakistan. Her research interest includes resource allocation in future wireless communication systems.

HASSAAN KHALIQ QURESHI (M'16–SM'18) received the M.Sc. degree (Hons.) in electrical engineering from the Blekinge Institute of Technology, Sweden, in 2006, and the Ph.D. degree in electrical engineering from the City, University of London, U.K., in 2011. He held an Erasmus Mundus Postdoctoral Fellowship with Frederick University, Cyprus. Prior to starting his Ph.D. degree, he was a Research Assistant with City, University of London. He is currently serving as an Associate Professor with the School of Electrical Engineering and Computer Science (SEECS), National University of Sciences and Technology (NUST), Islamabad, Pakistan. His main research interests include wireless networks, wireless channel modeling, blockchains, network reliability, D2D communications, the Internet of Things (IOTs), network intrusion detection systems, and energy provisioning issues for infrastructure-less networks. He serves as a TPC Member for various IEEE conferences and journals. He was a recipient of the EU Erasmus Mundus Staff Research Mobility Program.

MOAYAD ALOQAILY received the M.Sc. degree in electrical and computer engineering from Concordia University, Montreal, QC, Canada, in 2012, and the Ph.D. degree in electrical and computer engineering from the University of Ottawa, in 2016. He was the President of the Electrical Engineering Graduate Student Association (EEGSA), University of Ottawa, from 2014 to 2016. He was an Instructor with the Systems and Computer Engineering Department, Carleton University, Ottawa, Canada, in 2017. He has been with Gnowit, Inc., since 2016. From 2017 to 2018, he was an Assistant Professor with the Computer Engineering Department, College of Engineering and Technology, American University of the Middle East (AUM), Kuwait. He is currently an Assistant Professor of computer engineering with the Faculty of Engineering, Canadian University Dubai, United Arab Emirates. His current research interests include connected vehicles, intelligent transportation systems, cloud and edge computing, vehicular cloud computing, 5G networks, and wireless communications/networks. He is actively working on different IEEE events. He was the IEEE Photonics Society Chair for the year 2016/2017. He is also a Professional Engineer Ontario (P.Eng.).