# Resource allocation scheme for 5G C-RAN: a Swarm Intelligence based approach

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## Abstract

The recent fifth generation (5G) system enabled a highly promising evolution of Cloud Radio Access Network (C-RAN). Unlike the conventional Radio Access Network (RAN), the C-RAN decouples the baseband processing unit (BBU) from the remote radio head (RRH) by allowing BBUs from multiple Base Stations (BSs) to operate into a centralized BBU pool on a remote cloud-based infrastructure and a scalable deployment of light-weight RRHs. In this paper, we propose an efficient resource allocation scheme for 5G C-RAN called Bee-Ant-CRAN. The challenge addressed is to design a logical joint mapping between User Equipment (UE) and RRHs as well as between RRHs and BBUs. This is done adaptively to network load conditions, in a way to reduce the overall network costs while maintaining the user QoS and QoE. The network load has been formulated as a mixed integer nonlinear problem with a number of constraints. Then, the formulated optimization problem is decomposed into two stage resource allocation problem: UE-RRH association and RRH-BBU mapping. Therefore, a modified Artificial Bee Colony is developed as a swarm intelligence based approach to build the UE-RRH mapping (resource allocation). Moreover, an ameliorated Ant Colony Optimization algorithm is proposed to solve the RRH-BBU mapping (clustering) problem. Computational results demonstrate that our proposed Bee-Ant-CRAN scheme reduces the resource wastage and significantly improves the spectral efficiency as well as the throughput.

*Keywords:* C-RAN, Clustering, Swarm Intelligence, RRH, BBU, Resource Allocation, 5G

## 1. Introduction

### 1.1. Background

In recent years, wireless communications are subjected to a tremendous growth in traffic demand due to the explosion of the Internet and its contents. The advances in the Electronics and Telecommunication technology have led to the development of powerful devices with high communication and networking capabilities. This growing challenge faced by mobile operators in the explosive increase of data traffic is principally due to the prevalence of mobile devices, streamed audio and video services as well as others services related to the Internet of Things (IoT). To meet this more and more increasing demand of data transmission, the mobile network technologies must be able to increase their capacities.

At first glance, supporting the continuously growing end-users' needs in terms of traffic demands that continuously changeover the time and space, the new generation networks are based on the increase in the number of cells while reducing the cells size, increasing the density of the network without forgetting the interference management. Moreover, the used Time Division Duplex (TDD) systems introduce not negligible fluctuations of traffic in both DownLink (DL) and UpLink (UL). These factors involved operators to review the design, deployment mode and the management of telecommunication networks. Since mobile Internet traffic is continuously surging, operators are obliged to deploy more Base Stations (BSs) in order to meet users needs. In other words, these capabilities can be increased by adding more cells into existing networks creating more complex Heterogeneous and Small cell Networks (HetSNets), or by integrating techniques such as Multiple Input Multiple Output (MIMO), which allow a number of antennas to simultaneously serve clients using the same time-frequency resources [1, 2, 3].

Therefore, cells may be organized in hierarchical structures: macro, micro, pico and femto cells. However, that hierarchy greatly increases the inter-cell interference, power consumption as well as costs of deployment and operation. Moreover, the deployment of additional sites per unit area leads to an increase in the CAPital eXpenditure (CAPEX) and OPErational EXpenditure (OPEX), without increasing operators' revenues. In fact, although traffic demand remains one of the driving forces in 5G, a less cost of both OPEX and CAPEX is fundamental. In addition, the density of BSs is very high in urban areas. It is therefore very difficult to add new BSs in such kind of area.

Furthermore, huge amounts of data are becoming an overwhelming part of the traffic, while the associated income is

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shrinking [4, 5]. Therefore, there is an increasing challenge in the operation of the upcoming 5G networks, especially for multimedia systems, services and applications [6, 7]. Similarly, the energy consumed by communication networks is growing rapidly. Finally, the available spectrum is scarce, thus limiting the possible throughput. Some technologies such as the Long-Term Evolution Unlicensed (LTE-U), which use a number of available unlicensed spectrum in order to increase the capacity of the 5G network, has been introduced. Unfortunately, this caused a severe interference with existing WiFi networks [8].

To meet these challenges, researchers and industry pushed the limit of the technological aspect and operators increased the deployment of RAN by introducing a promising centralized collaborative cloud based RAN named C-RAN [9, 10, 11], which is inspired by the green soft cloud access networks proposed in [12]. Indeed, emerging mobile networks and clouds need to merge and combine smoothly. For this reason, maximizing data rate of cellular transmissions for content sharing in collaborative mobile clouds while maintaining the energy efficiency has been investigated in [13], especially a low power resource allocation scheme for 5G based D2D [14] communications.

The C-RAN [15] has been introduced by the China Mobile Research Institute that is a new promising type of RAN architecture in order to help operators in addressing the aforementioned issues. In contrast to the traditional access networks, in the C-RAN system rather than being located on a single BS, this architecture decouples digital units (BBUs: Baseband Units) that implement the functionality of the MAC layer, from inexpensive radio units (RRHs: Remote Radio Heads) that only integrate the Radio Frequency (RF) frontend functions capable to acquire, process and transmit the signal, by relocating BBUs on a remote cloud-based infrastructure called the BBU Pool like it is illustrated in Fig. 1. Thereby, a BBU can be assigned to one or more RRHs. Similarly, by sharing their radio resources, a number of RRHs managed by a single BBU can form a single cluster especially for reducing the cost of maintenance, the computational load and for energy saving purpose. Furthermore, besides being reliable and relatively inexpensive, solutions for the interconnection of BBUs must allow high bandwidth and flexible topology for the interconnection of RRHs. Moreover, an optical backhaul network is used as a fronthaul to link BBUs and distributed RRHs via a Common Public Radio Interface (CPRI) connection. In other words, in the C-RAN architecture, treatments are moved from BSs toward the cloud, which is based on open platforms and has better virtualization capabilities for dynamic allocation of available resources [16, 17, 18].

Indeed, the global growth of the Cloud Computing market that principally following the pay-per-use model, has favored the deployment of regional, geographically distributed and interconnected data centers, making it possible to provide Cloud resource pools. In traditional architectures only about 15-20% of BSs operating in the current RAN architecture are loaded more than 50% [19, 20]. This causes a power wastage in current RAN. Thereby, shifting computing resources of BSs and radio communication features to cloud, allow the reduction of energy consumption and upgrading costs while enabling resource sharing and a coordinated joint signal processing in order to increase the spectral efficiency. This approach allows the reduction of OPEX since the computational load and the energy consumption are reduced compared in the traditional architecture.

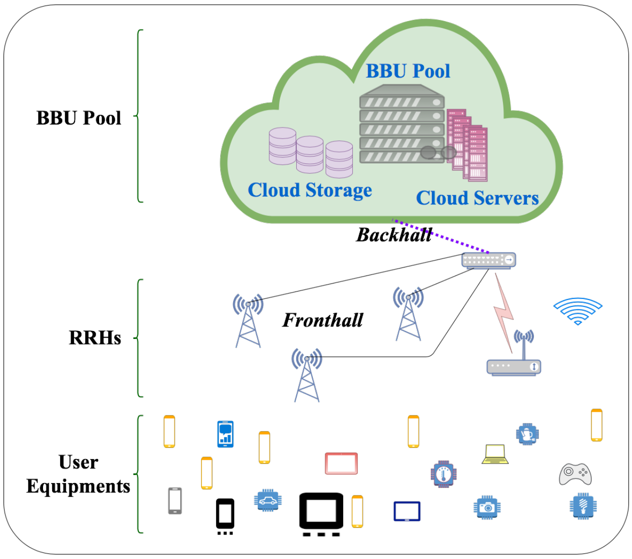
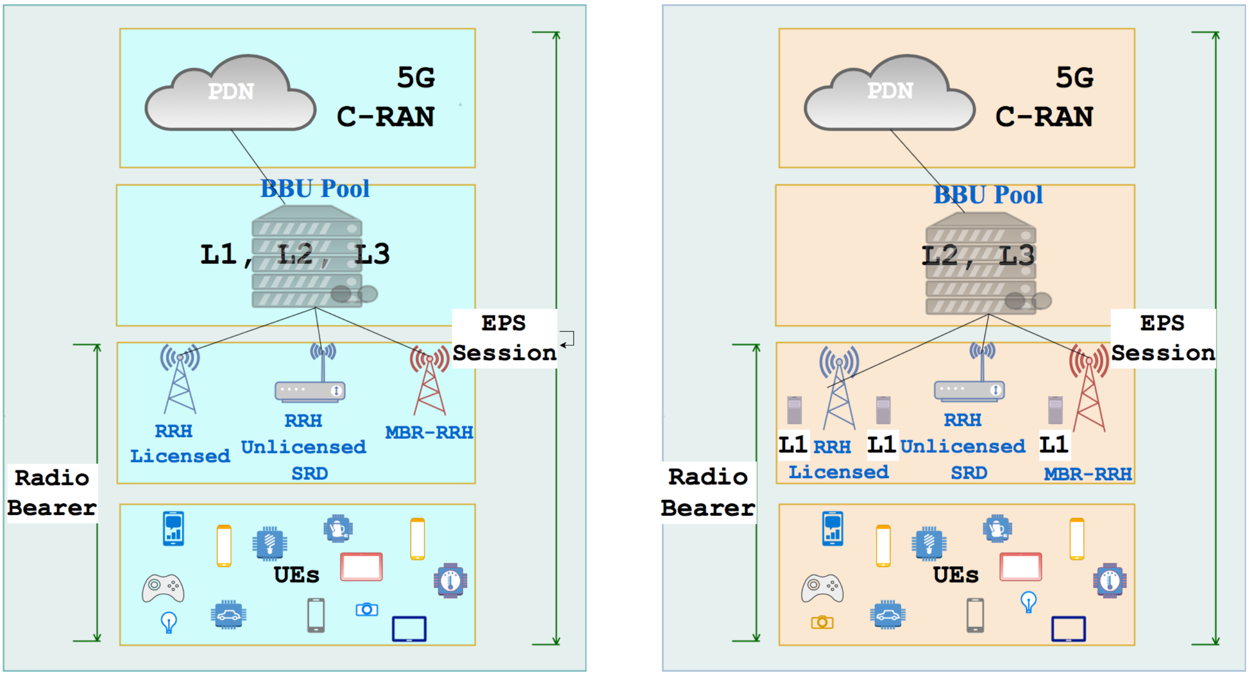



Figure 1: C-RAN Architecture

Morever, the units decoupling adopted by the C-RAN allows a centralized operation of BBUs and a scalable distributed deployment of RRHs on multiples sites. Thus, a BBU can be assigned to one or more RRHs. Similarly, RRHs managed by the same BBU can form a single cluster by sharing their radio resources [21, 22, 23]. These features allow a flexibility in resources allocation and a smart centralized management on the C-RAN architecture. However, the challenging issue is to design a logical mapping between each RRH and one or multiple managing BBUs. This design can be performed dynamically so as to optimize the resource consumption on the backhaul, taking into account the user profile, the load factor of the served cell and its size. This design includes two scenario. The first is the one-to-one mapping where each RRH is logically connected to a single BBU enables to transmit a different radio signal on RRHs like it is illustrated in Fig. 2a. The one-to-one mapping is also adapted to frequency reuse deployments, where only part of the available spectrum is used in the available cells [24]. Next, the second scenario that interests us is the one-to-many mapping where multiple RRHs are logically connected to a single BBU enables to transmit simultaneously the same radio signal on multiple antennas, i.e., RRHs (see Fig. 2b). This is typically adapted to Distributed Antenna System (DAS) deployments [25]. Of course, it suppose that RRHs are physically connected to the BBU using a low latency optical transport network.

### 1.2. Author's Contributions

A number of works that deal with the issue of UEs association and the RRHs mapping with BBUs exist in the litera-




one-to-one mapping one-to-many mapping

Figure 2: One-to-one vs One-to-many BBU-RRH mapping

ture. However, most of them address the problem separately. Yet, these problems are dependent in practice and should be addressed with joint mechanisms. Recent trends of using artificial intelligence to solve resource allocation based optimization problem in 5G C-RAN are emerging. Especially, a number of swarm intelligence based metaheuristics including Particle Swarm Optimization (PSO) [26], Genetic Algorithm (GA) [27, 28], Ant Colony Optimization (ACO) [29] and Artificial Bee Colony (ABC) [30], have been used to solve various optimization problems. In order to overcome the aforementioned challenges, in this paper, we jointly considered the problem RRH antenna with the BBU computation resources and proposed a power efficient resource allocation scheme for optimal C-RAN systems named Bee-Ant-CRAN. Inspired by the swarm intelligence, we designed a scheme for real time UE-RRH and RRH-BBU mapping based on a modified approach of ABC and ACO metaheuristics. In short, the main contributions of this paper can be summarized as follows:

- Formulation of the joint UE-RRH and RRH-BBU mapping for resource allocation in C-RAN as a multi-objective optimization problem with a number of constraints.
- Proposition of a modified ABC optimization scheme to find optimal UE-RRH mapping while providing a low latency and an optimal spectral efficiency.
- Adaptation of the Max-Min Ant System (MMAS) based on the ACO algorithm to provide optimal RRH-BBU mapping in order to handle the overall network traffic and maintain a high level of QoS while improving the throughput and reducing the power consumption.

### *1.3. Organization of the paper*

The rest of the paper is organized as follows. In section 2, a brief review of resource allocation schemes for C-RAN is presented. Section 3 describes the system model that includes our considered C-RAN architecture and the channel model. Section 4 presents the proposed multi-objective problem formulation, which include the power consumption model. The proposed SI based mechanisms for resource allocation in C-RAN are presented in section 5. The simulation results and discussions are presented in section 6. Finally, we conclude this work in section 7.

## 2. Related Work

C-RAN issues have been dealt with globally by the scientific and industrial community over the past few years and constitute a major component and even the major subject of certain ongoing or completed European cooperative projects such as 5G PPP phase one, 5G-Crosshaul, 5G-Xhaul, i-CIRRUS and FP7 Mobile Cloud Networking projects. Especially, the way to distribute the functions of the BSs between BBU and RRH, i.e., functional split, is addressed by these European consortia, whose results also feed the standardization to 3GPP/RAN. What is certain is that the cloud computing based, centralized and collaborative RAN system has been introduced to meet the explosive growth of mobile data traffic from access network technology.

Swarm Intelligence (SI) aims at designing biologically inspired algorithms by modeling individuals process that locally interact among themselves, exchanging knowledge through the swarm which results in a high emergent system with a high degree of self-organization. In networking, SI techniques have demonstrated their strength in facilitating a network to automatically reconfigure the network parameters in order to achieve an optimal network performance [30, 31, 32, 33, 34, 35]. Therefore, given to the visible features of SI, especially the self organization behavior, it may be suitable for the efforts made toward the standardization of the next generation 5G RAN [26].

The mapping between UEs and RRHs as well as the RRHs and BBUs mapping need to be carefully tackled in order to improve the network performances while reducing the network power consumption. Unfortunately, most existing recent studies in the literature on resource allocation and management in C-RAN address these mapping separately. Some related works on these mapping schemes are briefly discussed hereinafter.

Fakhri et al. [26] proposed a resource allocation scheme that enables a self organization in C-RAN. Authors used the concept of cell differentiation and integration to scale BBUs and RRHs in a semi static approach. Moreover, the load balancing of overall C-RAN system has been modeled as as an integer based optimization problem. To address the formulated load balancing optimization problem, a discrete Particle Swarm Optimization (PSO) has been proposed as a SI based approach. The simulation results show that their proposed scheme demonstrates significant throughput compared to a fixed C-RAN. In line with this work, Wang et al. [36] proposed an efficient joint BBU/RRH resource allocation in C-RAN. After the formulation of the of the jointly RRH antenna resource management and the BBU computation capabilities as an optimization problem, authors used a weighted minimum mean square error scheme to address the network wide beamforming vectors optimization and proceed to a proper UE-RRH mapping. In addition, in order to minimize the number of active BBU, especially for energy saving purpose, a bin packing problem based on the best fit decreasing scheme has been used. The results of simulation showed that their proposal in more energy efficient than existing classical schemes.

Boulos et al. [37] investigated the BBU-RRH mapping as a clustering problem, which has been formulated as a bin packing problem. A heuristic based scheme inspired from the best and worst fit decreasing strategies has been adopted in order to provide an optimal mapping. Moreover, Chen et al. [38] proposed a dynamic BU-RRH clustering scheme by taking the advantages of the borrow-and-lend approach to optimize the C-RAN system. Since traffic demand on RRHs are dynamically changing and therefore introduce a high flexibility on resources management, authors redefined the resource allocation scheme in C-RAN according to the sharing feature of BBUs. Concretely, authors proposed a mechanism to estimate the traffic load of the whole network and assigns a minimal number of shared BBUs that are assigned to aggregated RRHs for an efficient resources allocation. Like the scheme proposed by authors in [26] the results of simulation of the Chen's scheme significantly reduces the power wastage while improving the network throughput. In the same order of ideas, Zhu and Lei [39] introduced a traffic and interference-free dynamic BBU-RRH mapping for C-RAN TDD in which logical mapping between RRH and BBU are performed according to the traffic condition and asymmetric DL/UL resource allocation. To achieve that, authors developed a cross sub-frame coordinated scheduling and a beamforming scheme, which interact with each other to improve the performance of the C-RAN. The proposed algorithm is designed such a way that the BBU which is in much charged than a given limit is offloaded and the corresponding RRH is switched to another BBU. Unfortunately, the performance of their approach was not promising.

Shi et al. [40] designed a green C-RAN by proposing a framework that formulate the resource allocation problem as joint RRH selection and power minimization problem. In order to solve the formulated optimization problem, authors expressed a mixed integer non linear programming problem that aims at jointly selects RRHs to minimize the power consumption via beamforming. Moreover, the power consumption of the transport network is determined by a set of RRHs. Simulations performed by the authors showed that their scheme significantly reduce the power consumption in the whole C-RAN. Always for the sake of optimization, Taleb et al. [41] proposed a joint UE association and RRH clustering for C-RAN. Like the Shi's scheme, authors introduced a framework based on a mixed integer non linear programming problem. In order to avoid the exhaustive search and achieve a rapid convergence, the optimization has been decoupled into two sub optimization problems that have been solved separately. An heuristic based on the received SINR has been combined with exhaustive search were adopted to address the optimization problem. In the same order of idea, Yao and Ansari [42] proposed a QoS-aware joint BBU-RRH mapping as well as user association scheme for C-RAN, which aims at minimizing the energy cost of the whole system. Authors formulated the optimization problem as an integer linear programming problem, which is solved with a designed time efficient algorithm. Futhermore, Awais et al. [43] designed a joint user association for resource allocation scheme in C-RAN. Authors formulated a combinatorial optimization problem that is solved with an interference-aware greedy heuristic algorithm in order to jointly exploit the time-frequency resources of RRHs and optimize to schedule UEs. Simulation results showed that, their approach performs good throughput. Unfortunately, the RRH-BBU mapping is not considered in the authors' scheme.

Chien et al. [27] exploited an edge artificial intelligence to design a dynamic resource allocation and prediction for 5G C-CRAN. The scheme proposed by authors aims at designing an emerging network system that combines the features of edge computing and the robustness of the cloud computing to bottleneck problems. To achieve this goal, after the formulation of the resource allocation problem of multiple RRHs and BBUs, authors used the long short term memory to predict the traffic and the overall throughput. Moreover, authors used a GA-based algorithm to address the BBU resource allocation problem. The proposed mechanism that combines edge artificial intelligence features to dynamically configure BBU resources in order to deal with the constant network changes. The simulation of their proposed mechanism showed a non negligible gain in power consumption. In addition, the BBUs and RRHs re-associations problem, which cause frequent handovers for UEs connected to re-associated RRHs have been addressed by Boulos et al. [44]. Authors solved the dynamic aspect of the BBU-RRH mapping with a heuristic that provided a close performance to the optimal solution. Besides that, in order to reduce the impact of the BBU failure, Zhang et al. [28] proposed a BBU resource allocation scheme for C-RAN that aims at minimizing the computing resources used for processing the tasks of all cells. The optimization problem has been solved by a heuristic GA. However, authors introduced an additional cost in the coordination among BBUs.

Furthermore, these concepts and schemes intended to optimize resource allocation in C-RAN can be extended to develop the Software Defined Network (SDN) and the Network Function Virtualization (NFV) solutions for C-RAN [45, 46, 47]. Unfortunately, the traditional 5G C-RAN architecture are not yet able to deal with huge network requirements. In summary, most of existing resource allocation schemes in C-RAN are not yet capable to take the full advantage of the concept of centralized virtual BSs. The large scale RRHs and BBUs resource allocation problem still needs to be considered.

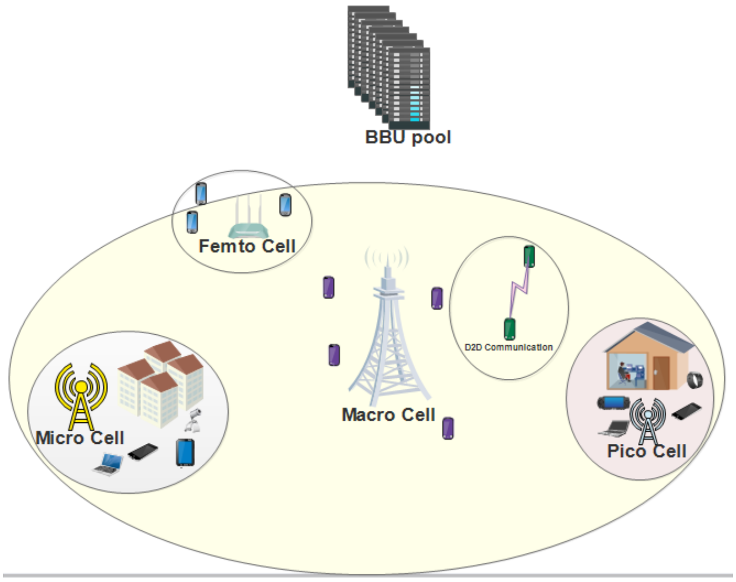



Figure 3: 5G C-CRAN Heterogeneous System

## 3. System Model

### 3.1. C-RAN Architecture

The C-RAN introduced a design in which the resource allocation scheme is redefined by introducing the resource sharing in BBUs. Thus, the BBUs and RRHs mapping can dynamically change to address the issue of resource wastage. Therefore, RRHs only utilize the per-user request according to the traffic demand of RRHs with a more flexible resources allocation. This section describes the network model and formulates the clustering problem.

In this paper, we consider an architecture of C-RAN that consist of three parts: a centralized BBU pool on the cloud that contains a number of BBUs, the RANs allowed by a number of distributed RRHs in order to adapt the traffic load and load balancing, and the fronthaul that allows connection between BBUs and RRHs via a CPRI. Given to the adopted C-RAN architecture, each BBU on the BBU pool can handle one or more RRHs depending on the network load condition. Moreover, since all BBUs are migrated in the cloud in the C-RAN architecture, the deployed RRHs become less complex, more scalable and energy efficient with a significant gain in CAPEX and OPEX. However, the logical mapping between centralized BBUs and distributed RRHs is not static but dynamic. It depends on the traffic load and some particular network conditions faced by operators.

Furthermore, in a heterogeneous C-RAN system proposed here (see Fig. 3), macro cells have to coexist with micro, pico and femto cells. Therefore, we consider a heterogeneous and flexible C-RAN that enables two kinds of cells: macro and pico. On the one hand, the macro cell is an ordinary hexagonal cell in which a macro RRH is deployed in order to allow a wide coverage. On the other hand, a large number of pico cells are deployed within a given operator's macro cell network as subcells. These pico cells are located in the edge areas of the macro cell in order to increase the macro cell's edge speed, data capacity as well as the network efficiency. Therefore, one BBU could serve many RRHs. However, due to limited processing of virtual machines [48] within the BBU Pool, the number of RRHs associated with one BBU is limited.

Unlike some schemes like those in [41, 49, 50], which assume that each UE is associated with at most one RRH, our proposal is designed such a way that each UE can be associated with more than one RRHs. In fact, the main benefit of C-RAN is the joint signal processing through CoMP technique, where several RRHs can cooperatively process the signals together. For energy saving purpose, a given BBU can be turned off when there is no traffic or when the traffic load decreases in RRHs. In addition, all BBUs are assumed to have the same capacities. Also, like adopted by works done in [36, 51], each pico RRH belonging to a macro RRH has a maximum cooperation range corresponding to that of their corresponding macro RRH. Therefore, all signals of others pico RRHs that are not belonging to a given macro RRHs will be considered as interference. For convenience, we assume that each pico RRH is deployed with a single antenna. In the same way, each UE is equipped by one receiving antenna. Thus, let us assume that the DL of our C-RAN system consists of all RRHs and all single antenna of UEs.

### 3.2. Channel Model

In this paper, we assume that the channels are modeled according to the Rayleigh fading and path loss. Certainly, the Ricean fading is more reasonable for pico, femto and most of unlicensed spectrum. However, the Rayleigh fading is also known to be a specialized model for stochastic fading and is sometimes considered as a special case of the more generalized concept of Ricean fading. Moreover, we assume that the channel state information between the RRHs and the UEs is perfect.

Let us define the BBU pool $\Upsilon$ made of $p$ BBUs is represented by the set $\Upsilon = \left\{B_{u_1}, B_{u_2}, \cdots B_{u_k}\right\}, k \in [1, p] \cap \mathbf{N}$. Each BBU in the BBU pool acts as a virtual base station that is a special virtual machine designed to process radio signals. We consider a network with $n$ macro cells, i.e., macro RRHs. So, we denote the set $\mathfrak{I}$ of macro cells as $\mathfrak{I} = \left\{M_{c_1}, M_{c_2}, \cdots, M_{c_n}\right\}$. Then, let us consider $\mathfrak{R}(M_{c_i}) = \left\{P_{c_1}, P_{c_2}, \cdots, P_{c_m}\right\}$, $i \in [1, n] \cap \mathbf{N}$ as the set of pico RRHs belonging to the macro RRH $M_{c_i}$, where $m = \left|M_{c_i}\right|$ is the length of the macro RRH $M_{c_i}$, i.e., the number of pico cells belonging to the macro RRH $M_{c_i}$. All the RRHs are connected to the BBU pool via fronthaul links, especially high-speed optical links. Let us define the set $\Psi(P_{c_j})$ of UEs belonging to the pico RRH $P_{c_j}$ by $\Psi(P_{c_j}) = \left\{U_{j,1}, U_{j,2}, \cdots, U_{j,l}\right\}$, $j \in [1, m] \cap \mathbf{N}$, $l \in [1, q] \cap \mathbf{N}$ and $q = \left|P_{c_j}\right|$ is the length of the $P_{c_j}$. In order to define the transmission rate of the tractable capacity of a UE $U_{j,l} \in \Psi(P_{c_j})$, let us give the received signal $y_{j,l}$ at a UE $U_{j,l} \in \Psi(P_{c_j})$ in Eq.(1).

$$y_{j,l} = \rho^{-\frac{1}{2}} h_j^l \left(d_j^l\right)^{-\frac{\beta}{2}} s_j^l + \sum_{P_{c_o} \in \mathfrak{R}'\left(M_{c_i}\right)} \rho^{-\frac{1}{2}} h_o^{l'} \left(d_o^{l'}\right)^{-\frac{\beta}{2}} s_o^{l'} + g_{j,l} \quad (1)$$

where, $\rho$ is the average signal-to-noise ratio (SINR); $h_j^l$ denotes the channel gain from the pico RRH $P_{c_j}$ to the UE $U_{j,l} \in \Psi(P_{c_j})$; $d_j^l$ is the distance between the pico RRH $P_{c_j}$ and the UE $U_{j,l} \in \Psi(P_{c_j})$; $s_j^l$ is the desired data for the UE $U_{j,l} \in \Psi(P_{c_j})$ from its corresponding RRH $P_{c_j}$; $\beta$ is the path loss exponent, $\mathfrak{R}'(M_{c_i})$ denotes the set of all the interfering pico RRHs; $h_o^{l'}$, $d_o^{l'}$, and $s_o^{l'}$ are defined similarly for a given interfering pico RRH $P_{c_o}$, $o \neq j$; $h_j^l$ and $h_o^l$ , $j \neq o$ follow the circularly-symmetric complex normal distribution, .i.e., $h_j^l$, $h_o^l$ $\sim \mathcal{CN}(0, 1)$. Also, $g_{j,l} \sim \mathcal{CN}(0, (\sigma_{j,l})^2)$ represents the additive Gaussian noise. Moreover, $\sigma_{j,l}$ is the root mean square voltage of the noise $g_{j,l}$ accompanied by the received signal $y_{j,l}$. Therefore, when associated with the RRH $P_{c_j}$, the SINR perceived by the UE, $U_{j,l}$ is given in Eq. (2) and $B$ the total bandwidth of the RRH is given in Eq. (3).

$$\gamma_{j,l} = \frac{\rho \cdot \left(d_j^l\right)^{-\beta} \times \left|h_j^l\right|^2}{(\sigma_{j,l})^2 + \sum\limits_{P_{c_o} \in \mathfrak{R}'\left(M_{c_i}\right)} \rho \cdot \left(d_o^{l'}\right)^{-\beta} \times \left|h_o^{l'}\right|^2} \quad (2)$$

$$B = \omega_j \times W_j \quad (3)$$

where, $\omega_j$ denotes the spectral efficiency and $W_j$ is the spectrum bandwidth in the RRH $P_{c_j}$.

Consequently, by considering interference as noise, according to Eq. (1), Eq. (2) and Eq. (3), the achievable rate in bit/s/Hz for the channel capacity $c_{j,l}$ or the transmission rate of the UE $U_{j,l} \in \Psi(P_{c_j})$ can be expressed as given in Eq. (4).

$$c_{j,l} = B \times log_2(1 + \gamma_{j,l}) \quad (4)$$

Otherwise, from Eq. (4), we can conclude that channel capacity is based on the perfect delay assumption. Therefore, the channel capacity cannot be used to characterize the QoS requirements of UEs. Moreover, coordinating pico RRHs of a given macro RRH while taking into account the others macro cells is necessary for avoiding inter/intra-cell interference. To achieve that, BBU's processing resources must be allocated according to the UEs' QoS needs, the channel state and the overall network beamforming vectors.

## 4. Formulation of the Optimization Problem

The requirements in terms of QoS warranties are strongly linked with the strategy of radio resource allocation such as the way of mapping RRHs with BBUs or UEs with RRHs. In this light, our goal is to maximize the achievable bit rate while minimizing the overall network energy consumption of our considered Bee-Ant-CRAN scheme. This trade-off is realized by jointly optimizing the UE-RRH association, RRH-BBU mapping and the computer resources allocation in BBUs while maximizing the energy efficiency the C-RAN. In most cases, this kind of problem is formalized with a multi-objective optimization scheme [24, 30, 35, 52, 53, 54, 55].

### *4.1. Constraints derivation*

According to prior assumptions, let us define the binary variable $a_{l,j}$ given in Eq. (5) representing the association status between the RRH $P_{c_j}$ and the UE, $U_{j,l}$.

$$a_{l,j} = \begin{cases} 1 & \text{if the UE } U_{j,l} \text{ is served by the RRH } P_{c_j} \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

Therefore, the total channel capacity $c_{j,l}^T$ is given in Eq. (6) and the the per-fronthaul capacity constraint $(C_1)$ can be expressed as given in Eq. (7).

$$c_{j,l}^T = \sum_{j=1}^{m} \sum_{l=1}^{q} c_{j,l} \quad (6)$$

$$\begin{aligned} (C_1): \sum_{l \in [1, |P_{c_j}|] \cap \mathbf{N}} a_{l,j} \times c_{j,l} \leqslant c_j^{FH} \\ \forall j \in [1, m] \cap \mathbf{N} \end{aligned} \quad (7)$$

where $c_j^{FH}$ is the maximum capacity of the fronthaul link on RRH $P_{c_j}$.

Let us define define the binary variable $d_k$ given in Eq. (14) that represents the operation mode of the BBU $B_{u_k} \in \Upsilon$.

$$d_k = \begin{cases} 1 & \text{if the } B_{u_k} \text{ is turned ON.} \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

Thereby, the total amount of transmission power at each RRH is limited by the maximum available power in the fronthaull that is represented by the threshold value $\delta$. The corresponding fronthaul capacity constraints $(C_2)$, $(C_3)$ and $(C_4)$ are given in Eq. (9), Eq. (10) and Eq. (11).

$$(C_2): \sum_{l\in[1,q]\cap\mathbf{N}} \left(d_j^l\right)^{-\frac{\beta}{2}} \leqslant d_k \times \delta \qquad \forall k \in [1,p]\cap\mathbf{N}, \forall j \in [1,m]\cap\mathbf{N} \tag{9}$$

$$(C_3): \left(d_j^l\right)^{-\frac{\beta}{2}} \leqslant a_{l,j} \times \delta \qquad \forall l \in [1,q]\cap\mathbf{N}, \forall j \in [1,m]\cap\mathbf{N} \tag{10}$$

$$(C_4): a_{l,j} \leqslant d_k \qquad \forall l \in [1,q]\cap\mathbf{N}, \forall j \in [1,m]\cap\mathbf{N}, \forall k \in [1,p]\cap\mathbf{N} \tag{11}$$

Furthermore, like considered by Luong et al. [56], we assume that the arrival of packets from the UE, $U_{j,l}$ at the BBU $B_{u_k}$ follow the Poisson process with an arrival rate $\lambda_{j,l}$. Moreover, without lost of generality, let us assume that each packet has the same length. As mentioned by Ari et al. [29], it is important to take into account the computing capacity of virtual machines. Thus, the computing capacity of the BBU $B_{u_k} \in \Upsilon$ is denoted by $C(B_{u_k})$. Let us consider $\mu_{k,l}$ as the capacity required to compute the packet originating from the UE, $U_{j,l}$. Then, the packet processing task at each BBU $B_{u_k}$ can be described as a *M/M/1* queue. Therefore, in that condition, the service time at each BBU follows the exponential distribution with the mean $\frac{1}{\mu_{k,l}}$ and the computing capability constraint $(C_5)$ is given in Eq. (12).

$$(C_5): \sum_{l\in[1,q]\cap\mathbf{N}} \mu_{k,l} \leq d_k \times C(B_{u_k}) \qquad \forall k \in [1,p]\cap\mathbf{N} \tag{12}$$

Now, let $\tau_{j,l}$ given in Eq. (13) be the average response time for processing each packet of the UE, $U_{j,l}$ by the BBU $B_{u_k}$.

$$\tau_{j,l} = \frac{1}{\mu_{k,l} - \lambda_{j,l}} \tag{13}$$

Let us define define the binary variable $e_{k,l}$ given in Eq. (14), which represents the user's packets assignment to a BBU for processing.

$$e_{k,l} = \begin{cases} 1 & \text{if the packets of the user } U_{j,l} \text{ are processed by the BBU } B_{u_k}. \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

Then, the constraint $(C_6)$ for the response time is given in Eq. (15) and the constraint $(C_7)$ given in Eq. (16) ensures that each user $U_{j,l}$ is served by at least one BBU $B_{u_k}$.

$$(C_6): \sum_{l\in[1,q]\cap\mathbf{N}} e_{k,l} \times \tau_{j,l} \leqslant \varepsilon \qquad \forall k \in [1,p]\cap\mathbf{N}, \forall j \in [1,m]\cap\mathbf{N} \tag{15}$$

where $\varepsilon$ is a defined threshold value that represents the capacity of the fronthaul.

$$(C_7): \sum_{l\in[1,q]\cap\mathbf{N}} e_{k,l} \geqslant 1 \qquad \forall k \in [1,p]\cap\mathbf{N} \tag{16}$$

### 4.2. *Power consumption derivation*

The power consumption model like those proposed by Auer et al. [57], Badic et al. [58] and Etoh et al. [59] for the traditional RAN architecture, cannot be directly used to model power consumption in C-RAN. Indeed, this is due to the fact that, in C-RAN RRHs and BBUs are decoupled, not located on the same site and the BBUs are running on virtual machines located in the cloud. Thus, in order to be realistic, the power consumption model of the studied architecture takes into account the power consumption at the fronthaul links, the power consumption at the RRHs and the power consumption at the BBU pool.

- The power consumption $P_j^{FH}$ at the fronthaul link on RRH $P_{c_j}$ is given by Eq. (17).

$$P_j^{FH} = \nu_j \times \sum_{l\in[1,q]\cap\mathbf{N}} a_{l,j} \times c_{j,l} \tag{17}$$

where $\nu_j$ is the scaling factor of the fronthaul in the RRH $P_{c_j}$.

- Let us define the binary variable $b_j$ given in Eq. (18) that represents the operating mode of the RRH $P_{c_j}$.

$$b_j = \begin{cases} 0 & \text{if the RRH } P_{c_j} \text{ is in sleep mode.} \\ 1 & \text{otherwise} \end{cases} \tag{18}$$

Like adopted in [40, 53], the power consumption $P_j^{RRH}$ at the RRH $P_{c_j}$ given in Eq. (21) consists of: data dependent power $P_j^{dd}$ Eq. (19), which is the power expended at the power amplifiers of the RRH depending of transmitted signals; and the data independent power $P_j^{di}$ Eq. (20), that is the power consumed by electronic components.

$$P_j^{dd} = \frac{1}{\eta_j} \cdot \rho^{-\frac{1}{2}} \times \sum_{l\in[1,q]\cap\mathbf{N}} \left(d_j^l\right)^{-\frac{\beta}{2}} \tag{19}$$

where $\eta_j \in [0,1]$ is the efficiency of the power amplifier.

$$P_j^{di} = b_j \times P_j^{ra} + (1 - b_j) \times P_j^{ri} \tag{20}$$

where $P_j^{ra}$ represents the fixed amount of consumed power when the RRH $P_{c_j}$ is active and $P_j^{ri}$ represents the required power for keeping the RRH $P_{c_j}$ in sleep mode.

$$P_j^{RRH} = P_j^{dd} + P_j^{di} \tag{21}$$

- The power consumption $P_j^{BBU}$ at the BBU $B_{u_k} \in \Upsilon$ is given Eq. (22).

$$P_k^{BBU} = d_k \times \zeta_k \cdot \mu_{k,l} \tag{22}$$

where $\zeta_k$ is the power consumption factor of the $B_{u_k}$.

Therefore, the power consumption model of our system is given in Eq. (23).

$$P(\mu, a, b, d, e) = \sum_{j=1}^{m} \left(P_j^{FH} + P_j^{RRH}\right) + \sum_{k=1}^{p} P_k^{BBU} \tag{23}$$

### *4.3. Multi-objective optimization*

In order to guarantee the QoS requirements, we defined the weighted cost function $f(c, P)$ in Eq. (24) by making a linear combination of channel capacity and power consumption for solving the joint problem of UE-RRH association, RRH-BBU mapping as well as the computer resources allocation.

$$f(c, P) = \alpha \times c_{j,l}^T - (1 - \alpha) \times P(\mu, a, b, d, e) \tag{24}$$

The problem $P_0$ is therefore formulated as given in Eq. (25).

$$\begin{aligned}(P_0): \quad & \max_{c,\mu,a,b,d,e} f(c, P) \\ & \text{subjected to} \\ & (C_1), (C_2), (C_3), (C_4), (C_5), (C_6) \text{ and } (C_7).\end{aligned} \tag{25}$$

where $a, b, d$ and $e$ are implicitly understood as being binary.

### *4.4. Complexity of the optimization problem*

Due to the binary variables $a$, $b$ and $e$, the optimization problem defined in Eq. (25) is a mixed integer nonlinear problem that is generally known to be an NP-hard problem [36, 41, 51, 53, 60]. The intuitive approach to get an optimal solution of such optimization problem may be through exhaustive search. However, exploring all the space of possible UE-RRH mapping as well as those of RRH-BBU mapping leads to exponential complexity. Therefore, due to its extremely computational behavior, the exhaustive search becomes hard to implement and should be avoided in the context of large scale C-RANs.

### *4.5. Decomposition of the optimization problem*

In order to address the complexity of the $P_0$, we present in this section a decomposition approach that divides $P_0$ into two stage resource allocation problem in order to reach optimal and stable solutions. The main idea of this decomposition is to separate the cost function $f(c, P)$ given in Eq. (24) into sub cost functions. In this light, given the fact that the computing capabilities of each BBU within the BBU Pool are the same. Also, the number of used working BBUs in the C-RAN should be minimal for energy saving purpose. Therefore, we can divide the cost function $f(c, P)$ into two sub cost functions as given in Eq. (26). As schematized in the Fig. 4, the first sub cost function $f_1(c, P_j^{FH}, P_j^{RRH})$ given in given in Eq. (27) represents the UE-RRH optimization problem $P_1$ and the second sub cost function $f_2(\mu, P_k^{BBU})$ given Eq. (28) in represents BBU scheduling problem $P_2$. Moreover, the sub cost function $f_1(c, P_j^{FH}, P_j^{RRH})$ includes the data transmission rate of the each UE, the power consumption of the fronthaull as well as the power consumption of each RRH. The sub cost function $f_2(\mu, P_k^{BBU})$ includes the power consumption of each BBU.

$$f(c, P) = f_1(c, P_j^{FH}, P_j^{RRH}) + f_2(\mu, P_k^{BBU}) \tag{26}$$

$$(P_1): \; f_1(c, P_j^{FH}, P_j^{RRH}) = \alpha \times c_{j,l}^T + (1 - \alpha) \times \sum_{j=1}^{m} \left(P_j^{FH} + P_j^{RRH}\right) \tag{27}$$

$$(P_2): \; f_2(\mu, P_k^{BBU}) = (1 - \alpha) \times \sum_{k=1}^{p} P_k^{BBU} \tag{28}$$

$P_1$ is related to the UE-RRH mapping and the and $P_2$ is about the RRH-BBU mapping problem. To address these issue we propose a swarm intelligence based approach.

## 5. Swarm Intelligence based Approach

### *5.1. Background*

Formally, in the context of mobile networks, clustering or mapping can be seen as the way of grouping a set of elements in such a way that objects belonging to the same group are more similar to each other than to those in other groups, by respecting a number of well defined criteria. These elements can be assimilated to UEs, RRHs and BBUs. Thus, a cluster can be seen as a group of UEs led by a RRH. Therefore, it is possible to define a second level of clusters that associate a group of objects, says RRHs, with up-level objects, says BBUs. In brief, clustering allows us to have an abstraction of prototypes or representatives' elements from individual elements in the same clusters that be managed as a single object. Unfortunately, deciding on what object should belong to a given cluster is not an easy task [30, 35, 61]. There is not an polynomial algorithm that is able to regroup elements in disjoint clusters [34, 62]. In another words, power efficient clustering is a well known NP-hard optimization problem for complex and dynamic cloud-based cellular network environments [63].

Increasingly, SI based approaches have been regularly used to solve a number of optimization problems in many areas including wireless networks, radio interference mitigation and cloud computing [29, 30, 64, 65, 66, 67, 68, 69]. These SI based approaches such as ACO [70], PSO [34], Bacterial Foraging Optimization (BFO) [62] and most recently ABC [71] have been extensively used as population based metaheuristic thanks to their desirable features of being adaptive for solving optimization problems [35]. Moreover, a number of results [32, 33, 35, 72, 73, 74] demonstrates the effectiveness of the the ABC metaheuristic and its competitiveness compared to other SI based algorithms [75]. In the same order of ideas, the ACO

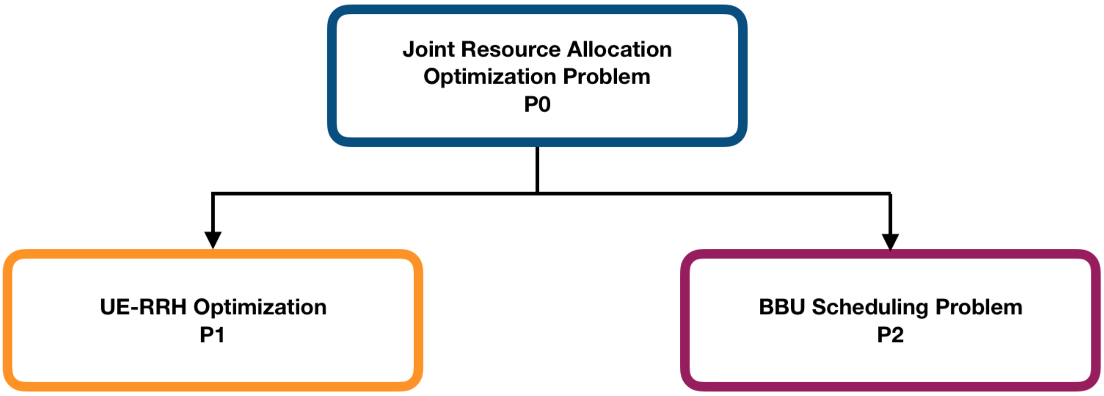



Figure 4: The two-stage resource allocation problem

features have been used to address a number of optimization problems in order to make optimal decision clustering problems [70]. In this light, we present in this section the adopted approach for the UE-RRH mapping that uses the ABC features and RRH-BBU mapping, which is based on a modified ACO algorithm.

### 5.2. UE-RRH mapping: a modified ABC based scheme

The ABC algorithm firstly introduced by Karaboga [76] was designed for numerical optimization problems. This metaheuristic is based on honeybees that are fascinating and highly organized insects capable of individual cognitive actions and self-organization [30]. The ABC is based on three essential components on which the minimal model of foraging behaviors has been designed. It includes: employed foragers, unemployed foragers and food sources. The first, also known as worker bees, are associated with given food sources and the second are in two kinds: onlookers and scouts. Onlookers are associated with a food source based on the information on the quality of the food source received from employed bees. The scouts are always in looking for new food sources to exploit. Besides, the onlooker bees and unemployed foragers are responsible of carrying out the exploitation process in the search space while the control of the exploration process are assured by scouts.

Furthermore, metaheuristic algorithms usually depend on the number and the choice of control parameters that condition their performance. In the ABC algorithm, these parameters includes: the colony size, i.e., the number of food sources; the maximum number of cycle that is a stopping criterion; and the limit that is equivalent to the number of trials after which a given food source is abandoned. Moreover, contrary to a number of SI based metaheuristics that take possible solutions among population individuals, in the ABC, the possible solutions, (i.e., the $j-th$ initial population of size $SN$) $X_j = \{x_{j1}, x_{j2}, \cdots, x_{jl}\}$, $j = 1, 2, \cdots, SN$, that is a $l$-dimensional vector, are represented by the food sources. Also, the quality of the food source, i.e., the possible solution is evaluated by a fitness function that is obtained from the value of the objective function $f_1$ given in Eq. (27).

In this section we develop a modified ABC based scheme for our proposed UE-RRH mapping. In the ABC, the convergence rate mainly depends on the balance between exploitation and exploration processes, which are two contradictory processes. Indeed, the exploration process allows to search closely in the various unknown regions in the possible solution space in order to found the global optimum while, the exploitation process ensure that the better solutions is obtained from the knowledge of the previous good solutions.

However, in the original ABC optimization, the new candidate solution is not in advance expected to be better than the previous since the candidate solution is chosen such a way that the probability to select a random good solution and that of selecting a random bad solution are the same. Therefore, the exploitation process of the initial ABC becomes very poor while the exploration process is excellent. In this light, we propose a modified version of the initial ABC. Inspired by the PSO metaheuristic described by Kennedy [77] and in order to improve the exploitation process of the initial ABC, we take the advantage in the concept of the global best solution (called *gbest*) of the PSO in the evaluation of the new candidate solution. Hence, the main steps of our UE-RRH mapping based modified ABC algorithm are shown hereinafter. For simplicity reasons in the clustering process, let us consider one macro cell $M_{c_i} \in \mathfrak{I}$ with a number of pico RRHs.

#### 5.2.1. Initialization phase

The three parameters of the ABC as well as the initial population are initialized in this step. The number of food sources $SN$ that is equal to the number of employed bees or onlooker bees, is equivalent to the length $m$ of the pico RRHs $X_j = P_{c_j} \in \Psi(M_{c_i})$ given in Eq. (29). The number of trials until the abandonment of a food source, i.e., the *limit* and the stopping criterion $\Delta \in \mathbf{N}$ should be properly chosen in the simulation. Therefore, the population is initialized with $m$ pico RRHs $P_{c_j}$ (the food sources), which is a $l$-dimensional vectors.

$$X_j = \{x_{j1}, x_{j2}, \cdots, x_{jl}\},\ j = 1, 2, \cdots, m \tag{29}$$

where $x_{j1} = P_{c_1}, x_{j2} = P_{c_2}, \cdots, x_{jl} = P_{c_m},\ j \in [1, m] \cap \mathbf{N}$.

*5.2.2. Employed bee phase*

In this step, each employed bee, i.e., the RRH $x_{jl} \in X_j$, generates a new solution $v_{jl}$ (see Eq. 33) in the neighborhood of its present position by taking advantage of the information of the global best (*gbest*) solution of the PSO in order to improve the exploitation process of the ABC. Three weighting factors $\varpi$, $\varrho$ and $\varsigma$ respectively given in Eq. (30), Eq. (31) and Eq. (32) are introduced in the evaluation of the new candidate solution for balancing the search selections and controlling the convergence speed of the modified ABC algorithm.

$$\varpi = \frac{\vartheta}{1 + \theta} \tag{30}$$

$$\varrho = \vartheta \times \left(\frac{1 - \theta}{\vartheta}\right)^{\frac{t}{\Delta}} \tag{31}$$

$$\varsigma = \theta \times \left(\frac{\vartheta}{1 - \vartheta}\right)^{\frac{t}{\Delta}} \tag{32}$$

where $\vartheta$ and $\theta$ are constant that should properly chosen; $t \in [1, \Delta] \cap \mathbf{N}$ represents the number of the current cycle, i.e., iteration.

$$v_{jl} = \varpi \times x_{jl} + \varrho \times \phi_{jl}(x_{jl} - x_{kl}) + \varsigma \times \Phi_{jl}(z_l - x_{jl}) \tag{33}$$

where :

- $k$ represents the number of a neighbor, $k \in [1, m] \cap \mathbf{N} \wedge k \neq l$.
- $\phi_{jl} = rand(-r;\ +r)$. For simplicity reason, we take $r = 1$.
- $\Phi_{jl} \in [0, C]$, $C > 0$ is a uniform random number. $C$, which is a non-negative constant that must not be a too big, plays a capital role in balancing the exploitation and the exploration processes of the candidate solution. By suggested by Cao et al. [31], we take $C = 1.5$ for a good setting.
- $z_l$ is the $l$-th element of the global best solution.
- $\varsigma \times \Phi_{jl}(z_l - x_{jl})$ is the global best (*gbest*) term that guides the new solution $v_{jl}$ towards best solution and therefore improves the exploitation process of the ABC.

*5.2.3. Onlooker bee phase*

Then, the $j$-th food source position is represented by the vector $X_j = \{x_{j1}, x_{j2}, \cdots, x_{jl}\}^T$ and the fitness ($f_1$) of the food source located at position $X_j$ is $f_1(X_j)$, where $f_1$ is the cost function given in Eq. (27). Finally, employed bees share their knowledge about the fitness value, with the onlooker bees. Each onlooker has to select a food source according to the goodness probability $p_j$ given by Eq. (34). In other words, if the probability value at $v_j$ is better than that at $X_j$, the employed bee will quit the old solution $X_j$ and memorizes the new one $v_j$.

$$p_j = \frac{f_1(v_j)}{\sum\limits_{n=1}^{m} f_1(v_n)} \tag{34}$$

*5.2.4. Scout bee phase*

During the employed and onlooker bees phases, food sources are exploited until their exhaustion. If a food source $X_j$ can not be improved when reaching the limit parameter $\Delta$, i.e., the fitness value is not improved at the end of the number of cycles, the scout bee randomly generate a solution, i.e., food source in order to update the old one according to Eq. (35).

$$x_{jl}^{new} = q_j + rand(0; 1) \times (r_j - q_j) \tag{35}$$

where, $X_j$ is the abandoned food source and $q_j \leqslant x_{jl} \leqslant r_j$.

*5.2.5. UE-RRH mapping algorithm*

The proposed UE-RRH mapping algorithm is given thereafter in Algorithm 1. The main relationship between the our proposed modified ABC-based protocol and the original ABC protocol lies in the position update process of the ABC algorithm, which is used in the optimization of the UEs assignment to RRHs. The proposed algorithm performs in three step. The first step consists of initialization. The second step is dedicated to the UEs allocation to RRHs. Indeed, each $U_{j,l} \in \Psi(P_{c_j}),\ j \in [1,\ m] \cap \mathbb{N},\ l \in [1, q] \cap \mathbf{N}$ is assigned to $x_{jl} \in X_j$ such a way that the network wide beamforming vector have a maximum of non zero terms. This means that the UE, $U_{j,l}$ receives a useful signal from a given RRH $P_{c_j}$. Moreover, this approach suppose that the beamforming vector is not affected by other constraints such as the fronthaul capacity. Then the optimal set of RRHs are determined by the proposed modified ABC algorithm. The last step consists of identifying the non required RRHs and put them into idle mode.

*5.3. RRH-BBU mapping: an ameliorated ACO scheme*

In order to balance the wide network load, the system should determine the new RRH-BBU configurations at each period of time. After the UE-RRH mapping achieved by the Algorithm 1, the system could now proceed to the RRH-BBU mapping. At the end of each network cycle, the system will reconfigure itself by taking into consideration information on traffic load, i.e., the UE-RRH mapping view, and the QoS requirements. Concretely, at time $t$ if the BBU-RRH mapping is known, then a new RRH-BBU mapping should takes place at time $t+1$ in order to balance the traffic variation in an adaptive way. Moreover, in other to avoid latency, the load balancing cycle, which is the time between $t$ and $t + 1$, may not be more than a millisecond.

To achieve the RRH-BBU mapping, the ACO features have been used for making the optimal mapping. The ACO [70] is a well-known SI based search technique that mainly aims at optimizing a wide variety of combinatorial problems. Moreover, the ACO is a stochastic local search scheme, which has been

**Algorithm 1** . Joint UE-RRH mapping algorithm

Begin
1. Initialization:
2. Generate the initial population $X_j,\ j \in [1,\ m] \cap \mathbb{N}$
3. according to Eq. (29)
4. **Repeat**:
   **For** each UE $U_{j,l} \in \Psi(P_{c_j}),\ l \in [1, q] \cap \mathbf{N}$ **do**
5. Evaluate wide network beamforming vector
6. Assign the UE, $U_{j,l}$ to RRH $P_{c_j}$ based on the optimum beamforming vector
7. Launch the employee bee phase
   Proceed to the position update Eq. (33)
8. Launch the onlooker bee phase
   Evaluate the goodness probability $p_j$ Eq. (34)
9. **if** the fitness $f_1$ Eq. (27) is not improved **then**
10. Launch the scout bee phase Eq. (35)
11. **Until** convergence
12. idle non required RRHs
End

inspired by the pheromone trail laying as well as other behaviors of some ant species [29]. Unfortunately, the ACO become slower in terms of convergence while considering a large research space. In this light, in order to obtain a rapid convergence, we proposed a modified version of the Max-Min Ant System (MMAS) that is an improved version of the ant system, in order the achieve the RRH-BBU mapping. The proposed scheme performs in three main steps.

*5.3.1. Initialization step*

In this step, a number of parameters including the number of virtual BSs, i.e., the number of BBUs, the number of ants, the pheromone trail, the heuristic information as well as the maximum iteration number, are initialized. The pheromone values $\chi_{k,l}(o),\ k \in [1, p] \cap \mathbb{N},\ l \in [1, q] \cap \mathbb{N}$ of the BBU $B_{u_k}$ at iteration $o$ are computed according to the formula given in Eq. (36). Therefore, at iteration $o$, the pheromone trail is represented by the matrix $\chi_{k,l}(o)$. In addition, the heuristic information $\eta_{k,l}(o)$ that is seen as the capacity of a BBU $B_{u_k}$ to process the workload of a given RRH $P_{c_m} \in \Re(M_{c_i})$ is defined in Eq. (37).

$$\chi_{k,l}(o) = \frac{1}{\sum_{k=1}^{p} \varphi_k} \times (\xi_k + \varphi_k \cdot \psi_k) \times d_k \tag{36}$$

where $\varphi_k$ is the processor million instructions per second (MIPS), $\psi_k$ is the number of computing units in the BBU $B_{u_k}$, $d_k$ given in Eq. (18) is the operation mode of the BBU $B_{u_k} \in \Upsilon$ and $\xi_k$ is the available rate flow on the BBU $B_{u_k}$.

$$\eta_{k,l}(o) = \frac{1}{z(P_{c_j})} \times (\upsilon \times \varphi_k \cdot \psi_k) \times e_{k,l} \tag{37}$$

where $z(P_{c_j})$ is the total amount of basic unit of time-frequency resources, i.e., physical resource block, which can be allocated to all UEs $U_{j,l},\ j \in [1, m] \cap \mathbf{N},\ l \in [1, q] \cap \mathbf{N}$ mapped to the RRH $P_{c_j} \in \Psi(P_{c_j})$, $\upsilon$ is a weight factor that should be properly chosen and $e_{k,l}$ is the binary variable given in Eq. (13).

*5.3.2. Construction step*

Like it is done in the original ACO, the construction step consists of a colony of ants that are independently engaged in designing a solution by using the pheromone matrix constructed in Eq. (36) and the heuristic information derived in Eq. (37). To achieve the construction each ant will generate an array of RRH-BBU mapping that will be considered as an initial solution. These ants will iteratively construct the optimal mapping according to the probability function given in Eq. (38).

$$p_{k,l}(o) = \frac{1}{\sum_{l=1}^{q} \left( z(P_{c_j}) \times \chi_{k,l}(o) \right)} \times (\chi_{k,l}(o) \cdot \eta_{k,l}(o)) \tag{38}$$

*5.3.3. Updates step*

In the updating pheromone trails step, the solutions computed during the construction step are improved. Indeed, in order to improve these solutions, at iteration $o+1$, the pheromone matrix $\chi_{k,l}(o+1)$ is updated by the formula given in Eq. (41) according to the amount $\Delta\chi_{k,l}$ (see Eq. (40)) of pheromones produced by the best ant that has been obtained during the construction step, which is inversely proportional to the flow function $f_{k,l}(o)$ given in Eq. (39).

$$f_{k,l}(o) = \frac{1}{\sum_{l=1}^{q} p_{k,l}(o) \cdot z(P_{c_j}) + \sum_{k=1}^{p} \varphi_k} \times (\xi_k \times \phi_k \cdot \psi_k) \tag{39}$$

$$\Delta\chi_{k,l} = \frac{1}{f_{k,l}} \tag{40}$$

$$\tau_{k,l}(o+1) = \kappa \times \chi_{k,l}(o) + \Delta\chi_{k,l} \tag{41}$$

where $0 \leqslant \kappa < 1$ is a parameter that express the trail persistence.

*5.3.4. RRH-BBU mapping algorithm*

The proposed RRH-BBU mapping is given in Algorithm 2. After the initialization of the pheromone matrix and the others parameters. Then, the set of non idle RRHs is obtained from the output of Algorithm 1. Moreover, each ant in the ant colony is associated with a resource, i.e., a RRH. Then, the mapping of RRHs with BBUs are performed in lines 6-13 until convergence. At the end of iteration, the optimal array of RRH-BBU mapping are obtained and the last step consists of identifying the non required BBUs and put them into idle mode.

## 6. Simulation Results

In this section, we present the computational results, analysis as well as discussion, in order to show the effectiveness of our proposed UE-RRH and RRH-BBU mapping schemes.

**Algorithm 2** . The RRH-BBU mapping algorithm

Begin
1. Initialize parameters
   the number $p$ of BBUs in the BBU pool $\Upsilon$
   the amount of ants $A_a$
   the maximum number of iterations $it_{max}$
   the weight factor $\upsilon$
   the trail persistence $\kappa$
2. Initialize pheromone trail matrix $\chi_{k,l}$
3. Build the set of non idle RRHs with the output of Algorithm 1
4. Associate each RRHs with an ant
5. Initialize the iteration index ($o = 1$)
6. **Repeat**:
   **For** each ant **do**
7. Compute the pheromone matrix $\chi_{k,l}(o)$ Eq. (36)
8. Compute the heuristic information $\eta_{k,l}(o)$ Eq. (37)
9. Generate an array of RRH-BBU according to Eq. (38)
   **End for**
10. Compute the flow function $f_{k,l}$ Eq. (39)
11. Proceed to the update of pheromone matrix Eq. (41)
12. Increment the iteration index ($o = o + 1$)
13. **Until** ($o > it_{max}$)
14. idle non required BBUs

End

To achieve that, we evaluated our proposed resource allocation scheme (Bee-Ant-CRAN) by simulations on Matlab with the MOESK tool. Moreover, we compared our proposed Bee-Ant-CRAN with the Zhu and Lei [39], Chen et al. [38] and the CDI-CRAN [26] in terms of active RRHs/BBUs, packet throughput, power consumption, spectrum efficiency, and packet loss. Detailed simulation parameters are summarized in Tab. 1 and the Bee-Ant-CRAN parameters are shown in Tab. 2. The ABC and ACO parameters proposed in the Tab. 2 are properly chosen. Indeed, the values of the parameters adopted for the modified version of the MMAS used to achieve the RRH-BBU mapping have been carefully taken from the study of Ari et al. [29]. Moreover, the values of the parameters adopted for the proposed modified ABC mechanism for UEs association have are properly chosen after benchmarking with eleven stressful functions.

Furthermore, our goal is to test the performance of the proposed Bee-Ant-C-RAN in cases of small and large C-RAN networks with the same amount of BBUs. For this reason, in order to discuss the effects of the simulation results on a system bandwidth of 15 MHz, a carrier frequency of 5 GHz and a limited number of BBUs, we consider two scenario in the simulation. The scenario A consists of a C-RAN with nineteen RRHs and the scenario B consists of a C-RAN with forty-nine RRHs. Both scenarios consist of five BBUs. In addition, we consider a uniform distribution of UEs within each cell in a high dense and less dense cells context.

Besides that, we consider that the UEs arrivals follows the Poisson process with a rate of $\lambda_{UE}$. Then, owing to the dynamical spatio-temporal nature of the UEs' traffic, a more realistic scenario where the user downlink (DL) packet arrivals follow a Poisson process with the rate $\lambda_{DL}$. According to the $\frac{\lambda_{DL}}{\lambda_{UL}}$ ratio of packets arrival rate, the uplink (UL) packet arrival rate $\lambda_{UL} = \frac{1}{2} \times \lambda_{DL}$. In addition, according to the 3GPP TS 22.261 version 15.5.0 Release 15 [78], which presents the 5G service requirements for next generation new services and markets, the traffic model in terms of different data requirements is considered.

Table 1: Simulation parameters

| **Parameter** | **Value** | |
|---|---|---|
| Cell radius | 500 m | |
| Multipath Fading | 3GPP TU channel | |
| System bandwidth | 15 MHz | |
| Carrier frequency | 5 GHz | |
| Log normal shadowing | -8 dB | |
| Penetration loss | -20 dB | |
| Noise power density | -174 dBm/Hz | |
| Maximum RRHs TX power | 30 dBm | |
| Power consumption of RRH | Static: 84 W | idle: 56 W |
| Number of BBUs | Scenario A: 5 | Scenario B: 5 |
| Number of RRHs | Scenario A: 19 | Scenario B: 49 |

Table 2: Bee-Ant-C-RAN parameters

| **Parameter** | **Value** |
|---|---|
| $it_{max}$ | 1000 |
| $\Delta$ | 3000 |
| $C$ | 1.5 |
| $\varrho$ | 1.2 |
| $\theta$ | 0.8 |
| $\kappa$ | 0.3 |

### 6.1. Active RRH/BBU

We first evaluated the performance of the Bee-Ant-CRAN in terms of number of RRHs/BBUs in a considered network load. The obtained results have been compared with those obtained in the schemes proposed by Chen et al., 2018 as well as Zhu and Lei, 2013. We achieved this experiment by varying the number of cells, 9, 19, 29, 39 and 49 RRHs and the objective is to evaluate the number of BBUs for each considered number of RRHs. Moreover, in order to be close to the reality, we considered the same network load, i.e., the same amount of DL packets arrival rate generated by all the UEs in a given cell. Fig. 5 shows the number of active RRHs/BBUs with respect to the traffic loads in the whole network. It can be seen that in the proposed Bee-Ant-CRAN, with 9 RRHs, we need only 2 BBUs while the scheme of Zhu and Lei performs a mapping with all the 5 available BBUs. Moreover, the scheme of Chen et al. performs a mapping with 4 BBUs and the CDI-CRAN needs 3 BBUs to perform a mapping with 9 RRHs. By considering 19 RRHs, the proposed Bee-Ant-CRAN use 4 BBUs out of the 5 available while the compared scheme use all the 5 available BBUs. Beyond 19 RRHs, all the compared schemes including the Bee-Ant-CRAN use all 5 available BBUs in the mapping process.

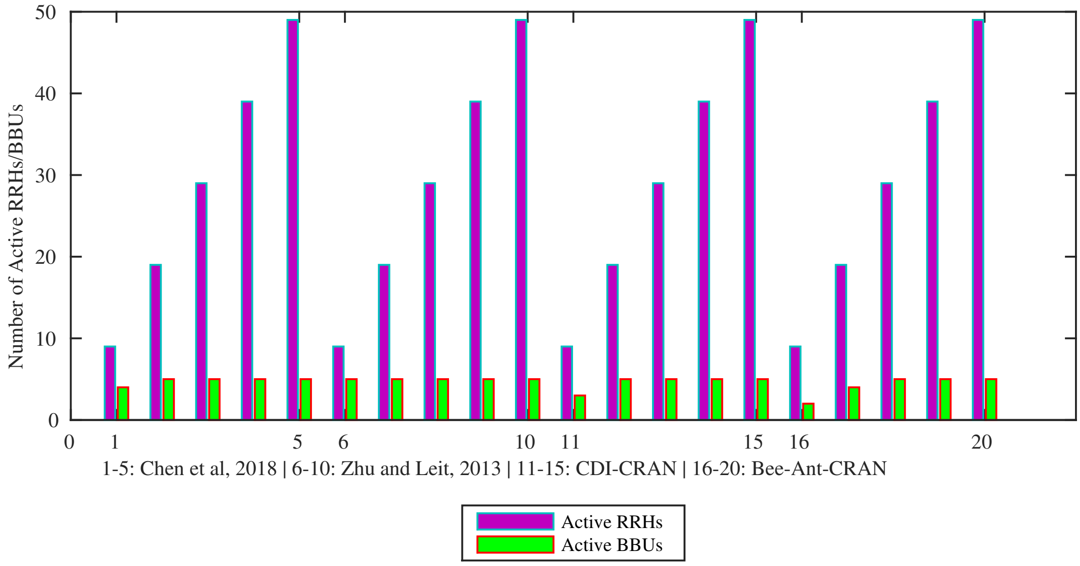
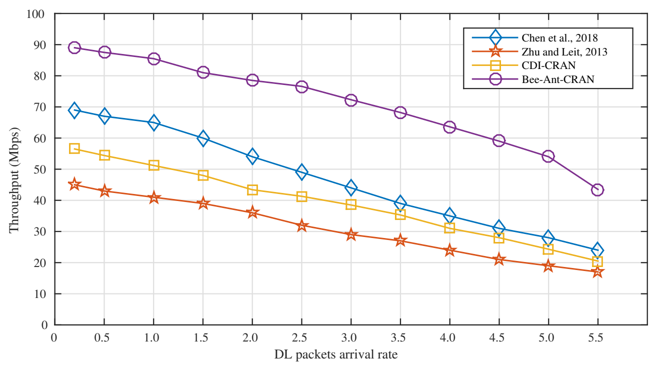


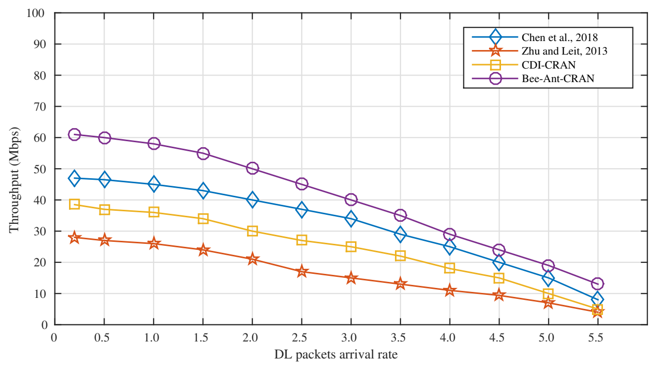

Figure 5: Number of active RRHs/BBUs with respect to the network load

### 6.2. *Throughput*

In Fig. 6, the obtained results of overall network throughput under DL packets arrival rate are presented. We conducted the simulation under scenarios with few (scenario A) and several number of RRHs (scenario B). Fig. 6a and Fig. 6b show the results of throughput for our proposed Bee-Ant-CRAN respectively in scenario A and scenario B, compared with the CDI-CRAN and the schemes proposed by Chen et al., 2018 as well as Zhu and Lei, 2013. As it can be observed from the curves in the both scenarios, the packet throughput of our proposal is better than the compared. When the number of RRHs is large, i.e., scenario B (Fig. 8b), and when the DL packets arrival rate increases, the overall network throughput tends to decrease rapidly. However, in scenario A (Fig. 8a) with a few amount of RRHs, the overall network throughput according to the DL packets arrival rate does not fluctuate much with a substantial gain in the Bee-Ant-CRAN while it quickly decrease in the compared schemes. This indicates efficient resource allocation the during the RRH-BBU mapping presented in Algorithm 2 and the during the network scheduling, theses resources are under optimal utilization.




(a) scenario A

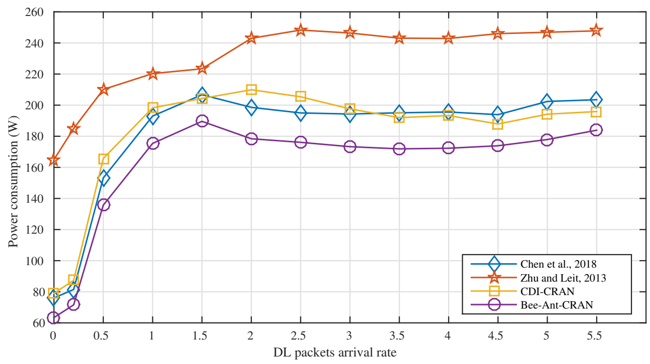



(b) scenario B

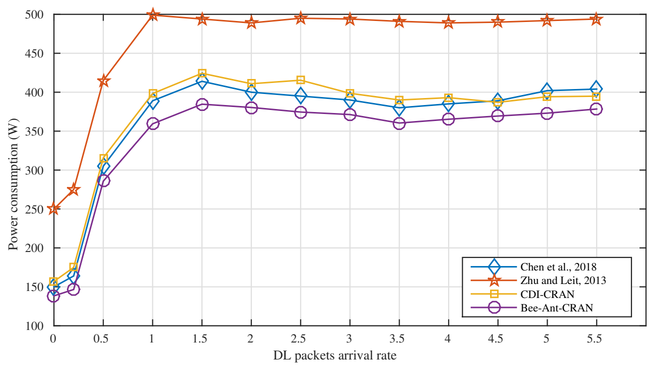
Figure 6: Network throughput

### 6.3. *Power consumption*

The proposed power consumption model (see Section 4.2) has been evaluated and compared with the with the CDI-CRAN and the schemes proposed by Chen et al., 2018 as well as Zhu and Lei, 2013. In order to be close to the traffic changing, the Bee-Ant-CRAN mapping schemes ensure that the minimum and sufficient number of BBUs are used according to the traffic requirements at the fronthall. Moreover, the average power consumed by the fronthall, the RRHs as well as the active BBUs is evaluated according to our considered network C-RAN and the proposed model given in Eq. (10). Fig.7 shows the obtained results for the power consumption for the proposed Bee-Ant-CRAN and the compared schemes. It can be observed from Fig.7 that our proposed Bee-Ant-CRAN performs well in the both scenario relative to the compared schemes. Apart from the scheme proposed by Zhu and Lei, which outputted poor results, the CDI-CRAN scheme and that of Chen et al. are less greedy in energy consumption. Furthermore, despite the quantity of deployed RRHs in scenario A (Fig. 7a) and scenario B (Fig. 7b), the total power consumption for the overall network remains lower in the proposed Bee-Ant-CRAN.




(a) scenario A

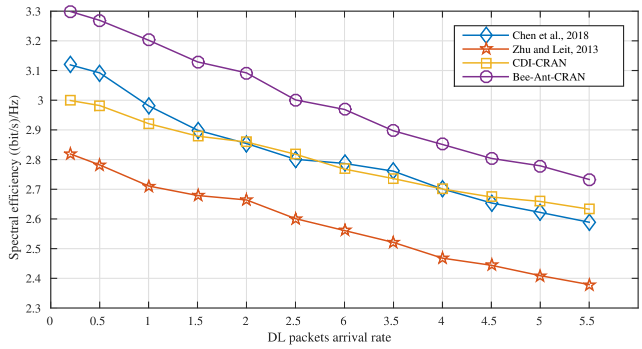



(b) scenario B

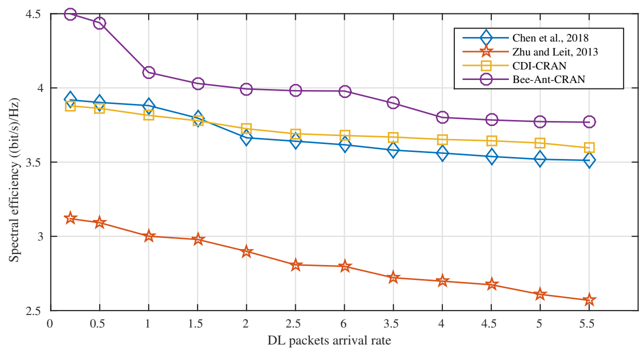
Figure 7: Power consumption

### 6.4. Spectral efficiency

In this paper, the spectral efficiency, which refers to the information rate that can be transmitted over a specific bandwidth, measures the net bit rate, i.e., the maximum throughput divided by the available bandwidth of the channel. We performed the simulation of the spectral efficiency under the DL packets arrival rate in the Bee-Ant-CRAN and compared the obtained with those obtained while evaluating the schemes proposed by Chen et al., 2018, Zhu and Lei, 2013 as well as the CDI-CRAN scheme. From Fig. 8, it can be observed in booth scenario A (Fig. 8a) and scenario B (Fig. 8b) that the spectral efficiency in the proposed Bee-Ant-CRAN scheme is low as the packets arrival rate decreases. This is due to the fact that a high number of deployed RRHs may increases interference. Fortunately, we take the advantage in the use of the overlap area managed by same BBU in order to increase the spectral efficiency of the Bee-Ant-CRAN that is in general better than the compared schemes.




(a) scenario A

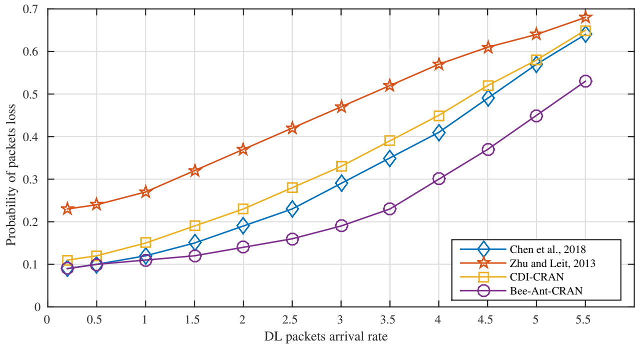



(b) scenario B

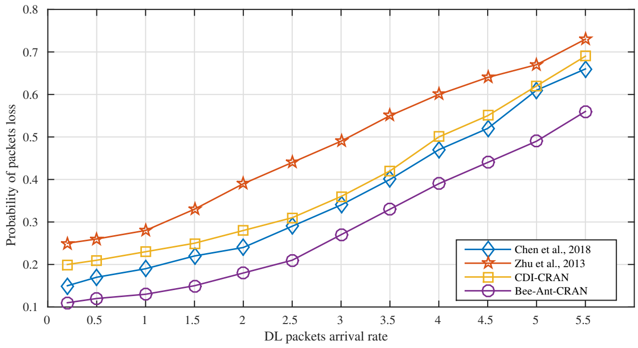
Figure 8: Spectral efficiency

### 6.5. Packet loss

The performance evaluation of the proposed Bee-Ant-CRAN resource allocation scheme in terms of probability of packet loss under the DL packets arrival rate have been achieved. The obtained results for the Bee-Ant-CRAN compared to the schemes proposed by Chen et al., Zhu and Lei, as well as the CDI-CRAN scheme, are highlighted in Fig. 9. In both scenario A and scenario B, the evolution of probabilities of packets loss under the DL packets arrival rate for the considered C-CRAN systems are plotted in Fig. 9a and Fig. 9b. From the curves, it can be observed that in general the packets loss rate in the proposed Bee-Ant-CRAN schemes is low relative to the compared schemes. This is thanks to the proposed UE-RRH mapping scheme that exploits the optimal position update scheme adopted during the employed bee phase. Furthermore, the scheme proposed by Chen et al., 2018 as well as the CDI-CRAN have in average less packets loss. Unfortunately, the Zhu and Lei scheme have a great loss rate in the boot scenario.




(a) scenario A




(b) scenario B

Figure 9: Packets loss

## 7. Conclusion

In this paper, we investigated the joint UE-RRH and RRH-BBU mapping as well as the computer resources allocation problem for optimal resource allocation in C-RAN with the objective of reducing the overall cost in terms of power consumption, the fronthall capacity for a good throughput and the optimal number of needed BBUs especially for profitability purpose. Moreover, we modeled our resource allocation scheme by taking the advantage enabled by some efficient features and convergence behaviors of swarm intelligence based optimization. A power consumption model to estimate the overall network power utilization has been proposed. Furthermore, the resource allocation problem in 5G C-RAN have been formulated as a multi-objective optimization problem. Given the high performance complexity generated by the obtained mixed integer nonlinear problem, a decomposition into two subproblems of the whole resource allocation problem in order to reach optimal and stable solutions and minimal QoS requirements has been proposed. A modified ABC that optimally balance the exploitation and exploration processes of the original ABC algorithm has been modeled to address the UE-RRH mapping subproblem. While, the RRH-BBU mapping subproblem has been solved thanks to an improved version of the ant system based on the ACO features. The performance of the proposed Bee-Ant-CRAN has been evaluated and compared to three resource allocation schemes for C-RAN systems. The results of simulation demonstrated the effectiveness of our proposal. As a future work, we plan to study the effects of introducing virtual BSs at the edge of the C-RAN in the overall performance.

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# Resource allocation scheme for 5G C-RAN: a Swarm Intelligence based approach

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**Abstract**

The recent fifth generation (5G) system enabled a highly promising evolution of Cloud Radio Access Network (C-RAN). Unlike the conventional Radio Access Network (RAN), the C-RAN decouples the baseband processing unit (BBU) from the remote radio head (RRH) by allowing BBUs from multiple Base Stations (BSs) to operate into a centralized BBU pool on a remote cloud-based infrastructure and a scalable deployment of light-weight RRHs. In this paper, we propose an efficient resource allocation scheme for 5G C-RAN called Bee-Ant-CRAN. The challenge addressed is to design a logical joint mapping between User Equipment (UE) and RRHs as well as between RRHs and BBUs. This is done adaptively to network load conditions, in a way to reduce the overall network costs while maintaining the user QoS and QoE. The network load has been formulated as a mixed integer nonlinear problem with a number of constraints. Then, the formulated optimization problem is decomposed into two stage resource allocation problem: UE-RRH association and RRH-BBU mapping. Therefore, a modified Artificial Bee Colony is developed as a swarm intelligence based approach to build the UE-RRH mapping (resource allocation). Moreover, an ameliorated Ant Colony Optimization algorithm is proposed to solve the RRH-BBU mapping (clustering) problem. Computational results demonstrate that our proposed Bee-Ant-CRAN scheme reduces the resource wastage and significantly improves the spectral efficiency as well as the throughput.

*Keywords:* C-RAN, Clustering, Swarm Intelligence, RRH, BBU, Resource Allocation, 5G

## 1. Introduction

### *1.1. Background*

In recent years, wireless communications are subjected to a tremendous growth in traffic demand due to the explosion of the Internet and its contents. The advances in the Electronics and Telecommunication technology have led to the development of powerful devices with high communication and networking capabilities. This growing challenge faced by mobile operators in the explosive increase of data traffic is principally due to the prevalence of mobile devices, streamed audio and video services as well as others services related to the Internet of Things (IoT). To meet this more and more increasing demand of data transmission, the mobile network technologies must be able to increase their capacities.

At first glance, supporting the continuously growing end-users' needs in terms of traffic demands that continuously changeover the time and space, the new generation networks are based on the increase in the number of cells while reducing the cells size, increasing the density of the network without forgetting the interference management. Moreover, the used Time Division Duplex (TDD) systems introduce not negligible fluctuations of traffic in both DownLink (DL) and UpLink (UL). These factors involved operators to review the design, deployment mode and the management of telecommunication networks. Since mobile Internet traffic is continuously surging, operators are obliged to deploy more Base Stations (BSs) in order to meet users needs. In other words, these capabilities can be increased by adding more cells into existing networks creating more complex Heterogeneous and Small cell Networks (HetSNets), or by integrating techniques such as Multiple Input Multiple Output (MIMO), which allow a number of antennas to simultaneously serve clients using the same time-frequency resources [1, 2, 3].

Therefore, cells may be organized in hierarchical structures: macro, micro, pico and femto cells. However, that hierarchy greatly increases the inter-cell interference, power consumption as well as costs of deployment and operation. Moreover, the deployment of additional sites per unit area leads to an increase in the CAPital eXpenditure (CAPEX) and OPErational EXpenditure (OPEX), without increasing operators' revenues. In fact, although traffic demand remains one of the driving forces in 5G, a less cost of both OPEX and CAPEX is fundamental. In addition, the density of BSs is very high in urban areas. It is therefore very difficult to add new BSs in such kind of area.

Furthermore, huge amounts of data are becoming an over-

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whelming part of the traffic, while the associated income is shrinking [4, 5]. Therefore, there is an increasing challenge in the operation of the upcoming 5G networks, especially for multimedia systems, services and applications [6, 7]. Similarly, the energy consumed by communication networks is growing rapidly. Finally, the available spectrum is scarce, thus limiting the possible throughput. Some technologies such as the Long-Term Evolution Unlicensed (LTE-U), which use a number of available unlicensed spectrum in order to increase the capacity of the 5G network, has been introduced. Unfortunately, this caused a severe interference with existing WiFi networks [8].

To meet these challenges, researchers and industry pushed the limit of the technological aspect and operators increased the deployment of RAN by introducing a promising centralized collaborative cloud based RAN named C-RAN [9, 10, 11], which is inspired by the green soft cloud access networks proposed in [12]. Indeed, emerging mobile networks and clouds need to merge and combine smoothly. For this reason, maximizing data rate of cellular transmissions for content sharing in collaborative mobile clouds while maintaining the energy efficiency has been investigated in [13], especially a low power resource allocation scheme for 5G based D2D [14] communications.

The C-RAN [15] has been introduced by the China Mobile Research Institute that is a new promising type of RAN architecture in order to help operators in addressing the aforementioned issues. In contrast to the traditional access networks, in the C-RAN system rather than being located on a single BS, this architecture decouples digital units (BBUs: Baseband Units) that implement the functionality of the MAC layer, from inexpensive radio units (RRHs: Remote Radio Heads) that only integrate the Radio Frequency (RF) frontend functions capable to acquire, process and transmit the signal, by relocating BBUs on a remote cloud-based infrastructure called the BBU Pool like it is illustrated in Fig. 1. Thereby, a BBU can be assigned to one or more RRHs. Similarly, by sharing their radio resources, a number of RRHs managed by a single BBU can form a single cluster especially for reducing the cost of maintenance, the computational load and for energy saving purpose. Furthermore, besides being reliable and relatively inexpensive, solutions for the interconnection of BBUs must allow high bandwidth and flexible topology for the interconnection of RRHs. Moreover, an optical backhaul network is used as a fronthaul to link BBUs and distributed RRHs via a Common Public Radio Interface (CPRI) connection. In other words, in the C-RAN architecture, treatments are moved from BSs toward the cloud, which is based on open platforms and has better virtualization capabilities for dynamic allocation of available resources [16, 17, 18].

Indeed, the global growth of the Cloud Computing market that principally following the pay-per-use model, has favored the deployment of regional, geographically distributed and interconnected data centers, making it possible to provide Cloud resource pools. In traditional architectures only about 15-20% of BSs operating in the current RAN architecture are loaded more than 50% [19, 20]. This causes a power wastage in current RAN. Thereby, shifting computing resources of BSs and radio communication features to cloud, allow the reduction of energy consumption and upgrading costs while enabling resource sharing and a coordinated joint signal processing in order to increase the spectral efficiency. This approach allows the reduction of OPEX since the computational load and the energy consumption are reduced compared in the traditional architecture.

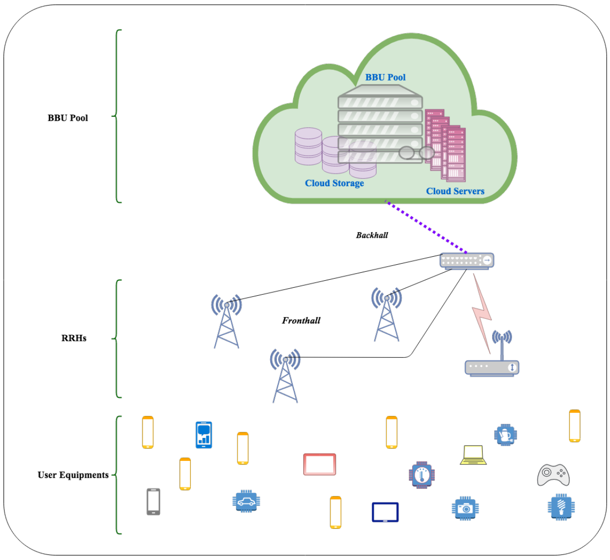



Figure 1: C-RAN Architecture

Morever, the units decoupling adopted by the C-RAN allows a centralized operation of BBUs and a scalable distributed deployment of RRHs on multiples sites. Thus, a BBU can be assigned to one or more RRHs. Similarly, RRHs managed by the same BBU can form a single cluster by sharing their radio resources [21, 22, 23]. These features allow a flexibility in resources allocation and a smart centralized management on the C-RAN architecture. However, the challenging issue is to design a logical mapping between each RRH and one or multiple managing BBUs. This design can be performed dynamically so as to optimize the resource consumption on the backhaul, taking into account the user profile, the load factor of the served cell and its size. This design includes two scenario. The first is the one-to-one mapping where each RRH is logically connected to a single BBU enables to transmit a different radio signal on RRHs like it is illustrated in Fig. 2a. The one-to-one mapping is also adapted to frequency reuse deployments, where only part of the available spectrum is used in the available cells [24]. ~~Indeed, like in the context of traditional cellular networks, the Fractional Frequency Reuse (FFR) is the used mechanism for the radio resource management in this scenario. Obviously, some techniques for inter-cell interference should be addressed while adopting the FFR. Of course, the point-to-point MIMO is automatically included in the FFR. However, others techniques such as Coordinated Multi-Point (CoMP), Inter-Cell Interference Coordination (ICIC) and MU-MIMO (Multi User-MIMO), implemented with the Long Term Evolution Advanced (LTE-A) to increase the spectral efficiency and throughput, can be associated with the FFR~~ Next, the second scenario that interests us is the one-to-many mapping where multiple RRHs are logically connected to a single BBU enables to transmit simultanoeusly the same radio signal on multiple antennas, i.e., RRHs (see Fig. 2b). This is typically adapted to Distributed Antenna System (DAS) deployments [25]. Of course, it suppose that RRHs are physically connected to the BBU using a low latency optical transport network. ~~Contrary to the FFR that is mainly focused on underutilized small cells, this technique is adopted by a wide range of operators since it enables a large coverage for both outdoors and indoors.~~

### 1.2. Author's Contributions

A number of works that deal with the issue of UEs association and the RRHs mapping with BBUs exist in the literature. However, most of them address the problem separately. Yet, these problems are dependent in practice and should be addressed with joint mechanisms. Recent trends of using artificial intelligence to solve resource allocation based optimization problem in 5G C-RAN are emerging. Especially, a number of swarm intelligence based metaheuristics including Particle Swarm Optimization (PSO) [26], Genetic Algorithm (GA) [27, 28], Ant Colony Optimization (ACO) [29] and Artificial Bee Colony (ABC) [30], have been used to solve various optimization problems. ~~are potentials metaheuristics that promise best solution of optimization problems in acceptable time and computing resources.~~ In order to overcome the aforementioned challenges, in this paper, we jointly considered the problem RRH antenna with the BBU computation resources and proposed a power efficient resource allocation scheme for optimal C-RAN systems named Bee-Ant-CRAN. Inspired by the swarm intelligence, we designed a scheme for real time UE-RRH and RRH-BBU mapping based on a modified approach of ABC and ACO metaheuristics. In short, the main contributions of this paper can be summarized as follows:

- Formulation of the joint UE-RRH and RRH-BBU mapping for resource allocation in C-RAN as a multi-objective optimization problem with a number of constraints.
- Proposition of a modified ABC optimization scheme to find optimal UE-RRH mapping while providing a low latency and an optimal spectral efficiency.
- Adaptation of the Max-Min Ant System (MMAS) based on the ACO algorithm to provide optimal RRH-BBU mapping in order to handle the overall network traffic and maintain a high level of QoS while improving the throughput and reducing the power consumption.

### 1.3. Organization of the paper

The rest of the paper is organized as follows. In section 2, a brief review of resource allocation schemes for C-RAN is presented. Section 3 describes the system model that includes our considered C-RAN architecture and the channel model. Section 4 presents the proposed multi-objective problem formulation, which include the power consumption model. The proposed SI based mechanisms for resource allocation in C-RAN are presented in section 5. The simulation results and discussions are presented in section 6. Finally, we conclude this work in section 7.

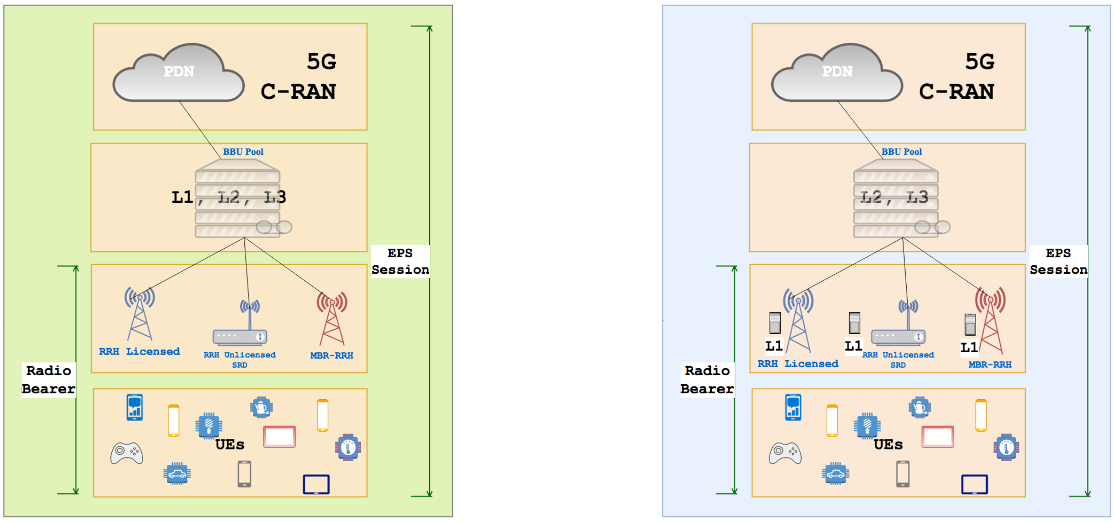
## 2. Related Work

C-RAN issues have been dealt with globally by the scientific and industrial community over the past few years and constitute a major component and even the major subject of certain ongoing or completed European cooperative projects such as 5G PPP phase one, 5G-Crosshaul, 5G-Xhaul, i-CIRRUS and FP7 Mobile Cloud Networking projects. Especially, the way to distribute the functions of the BSs between BBU and RRH, i.e., functional split, is addressed by these European consortia, whose results also feed the standardization to 3GPP/RAN. What is certain is that the cloud computing based, centralized and collaborative RAN system has been introduced to meet the explosive growth of mobile data traffic from access network technology.

Swarm Intelligence (SI) aims at designing biologically inspired algorithms by modeling individuals process that locally interact among themselves, exchanging knowledge through the swarm which results in a high emergent system with a high degree of self-organization. In networking, SI techniques have demonstrated their strength in facilitating a network to automatically reconfigure the network parameters in order to achieve an optimal network performance [30, 31, 32, 33, 34, 35]. Therefore, given to the visible features of SI, especially the self organization behavior, it may be suitable for the efforts made toward the standardization of the next generation 5G RAN [26].

The mapping between UEs and RRHs as well as the RRHs and BBUs mapping need to be carefully tackled in order to improve the network performances while reducing the network power consumption. Unfortunately, most existing recent studies in the literature on resource allocation and management in C-RAN address these mapping separately. Some related works on these mapping schemes are briefly discussed hereinafter.

Fakhri et al. [26] proposed a resource allocation scheme that enables a self organization in C-RAN. Authors used the concept of cell differentiation and integration to scale BBUs and RRHs in a semi static approach. Moreover, the load balancing of overall C-RAN system has been modeled as as an integer based optimization problem. To address the formulated load balancing optimization problem, a discrete Particle Swarm Optimization (PSO) has been proposed as a SI based approach. The simulation results show that their proposed scheme demonstrates significant throughput compared to a fixed C-RAN. In line with this work, Wang et al. [36] proposed an efficient joint BBU/RRH resource allocation in C-RAN. After the formulation of the of the jointly RRH antenna resource management and the BBU computation capabilities as an optimization problem, authors used a weighted minimum mean square error scheme to address the network wide beamforming vectors optimization and proceed to a proper UE-RRH mapping. In addition, in order to minimize the number of active BBU, especially for energy saving purpose, a bin packing problem based on the best fit decreasing scheme has been used. The results of




one-to-one mapping

one-to-many mapping

Figure 2: One-to-one vs One-to-many BBU-RRH mapping

simulation showed that their proposal in more energy efficient than existing classical schemes.

Boulos et al. [37] investigated the BBU-RRH mapping as a clustering problem, which has been formulated as a bin packing problem. A heuristic based scheme inspired from the best and worst fit decreasing strategies has been adopted in order to provide an optimal mapping. Moreover, Chen et al. [38] proposed a dynamic BU-RRH clustering scheme by taking the advantages of the borrow-and-lend approach to optimize the C-RAN system. Since traffic demand on RRHs are dynamically changing and therefore introduce a high flexibility on resources management, authors redefined the resource allocation scheme in C-RAN according to the sharing feature of BBUs. Concretely, authors proposed a mechanism to estimate the traffic load of the whole network and assigns a minimal number of shared BBUs that are assigned to aggregated RRHs for an efficient resources allocation. Like the scheme proposed by authors in [26] the results of simulation of the Chen's scheme significantly reduces the power wastage while improving the network throughput. In the same order of ideas, Zhu and Lei [39] introduced a traffic and interference-free dynamic BBU-RRH mapping for C-RAN TDD in which logical mapping between RRH and BBU are performed according to the traffic condition and asymmetric DL/UL resource allocation. To achieve that, authors developed a cross sub-frame coordinated scheduling and a beamforming scheme, which interact with each other to improve the performance of the C-RAN. The proposed algorithm is designed such a way that the BBU which is in much charged than a given limit is offloaded and the corresponding RRH is switched to another BBU. Unfortunately, the performance of their approach was not promising.

Shi et al. [40] designed a green C-RAN by proposing a framework that formulate the resource allocation problem as joint RRH selection and power minimization problem. In order to solve the formulated optimization problem, authors expressed a mixed integer non linear programming problem that aims at jointly selects RRHs to minimize the power consumption via beamforming. Moreover, the power consumption of the transport network is determined by a set of RRHs. Simulations performed by the authors showed that their scheme significantly reduce the power consumption in the whole C-RAN. Always for the sake of optimization, Taleb et al. [41] proposed a joint UE association and RRH clustering for C-RAN. Like the Shi's scheme, authors introduced a framework based on a mixed integer non linear programming problem. In order to avoid the exhaustive search and achieve a rapid convergence, the optimization has been decoupled into two sub optimization problems that have been solved separately. An heuristic based on the received SINR has been combined with exhaustive search were adopted to address the optimization problem. In the same order of idea, Yao and Ansari [42] proposed a QoS-aware joint BBU-RRH mapping as well as user association scheme for C-RAN, which aims at minimizing the energy cost of the whole system. Authors formulated the optimization problem as an integer linear programming problem, which is solved with a designed time efficient algorithm. Futhermore, Awais et al. [43] designed a joint user association for resource allocation scheme in C-RAN. Authors formulated a combinatorial optimization problem that is solved with an interference-aware greedy heuristic algorithm in order to jointly exploit the time-frequency resources of RRHs and optimize to schedule UEs. Simulation results showed that, their approach performs good throughput. Unfortunately, the RRH-BBU mapping is not considered in the authors' scheme.

Chien et al. [27] exploited an edge artificial intelligence to design a dynamic resource allocation and prediction for 5G C-CRAN. The scheme proposed by authors aims at designing an emerging network system that combines the features of edge computing and the robustness of the cloud computing to bottleneck problems. To achieve this goal, after the formulation of the resource allocation problem of multiple RRHs and BBUs, authors used the long short term memory to predict the traffic and the overall throughput. Moreover, authors used a GA-based algorithm to address the BBU resource allocation problem. The proposed mechanism that combines edge artificial intelligence features to dynamically configure BBU resources in order to deal with the constant network changes. The simulation of their proposed mechanism showed a non negligible gain in power consumption. In addition, the BBUs and RRHs re-associations problem, which cause frequent handovers for UEs connected to re-associated RRHs have been addressed by Boulos et al. [44]. Authors solved the dynamic aspect of the BBU-RRH mapping with a heuristic that provided a close performance to the optimal solution. Besides that, in order to reduce the impact of the BBU failure, Zhang et al. [28] proposed a BBU resource allocation scheme for C-RAN that aims at minimizing the computing resources used for processing the tasks of all cells. The optimization problem has been solved by a heuristic GA. However, authors introduced an additional cost in the coordination among BBUs.

Furthermore, these concepts and schemes intended to optimize resource allocation in C-RAN can be extended to develop the Software Defined Network (SDN) and the Network Function Virtualization (NFV) solutions for C-RAN [45, 46, 47]. Unfortunately, the traditional 5G C-RAN architecture are not yet able to deal with huge network requirements. In summary, most of existing resource allocation schemes in C-RAN are not yet capable to take the full advantage of the concept of centralized virtual BSs. The large scale RRHs and BBUs resource allocation problem still needs to be considered.

## 3. System Model

### 3.1. C-RAN Architecture

The C-RAN introduced a design in which the resource allocation scheme is redefined by introducing the resource sharing in BBUs. Thus, the BBUs and RRHs mapping can dynamically change to address the issue of resource wastage. Therefore, RRHs only utilize the per-user request according to the traffic demand of RRHs with a more flexible resources allocation. This section describes the network model and formulates the clustering problem.

In this paper, we consider an architecture of C-RAN that consist of three parts: a centralized BBU pool on the cloud that contains a number of BBUs, the RANs allowed by a number of distributed RRHs in order to adapt the traffic load and load balancing, and the fronthaul that allows connection between BBUs and RRHs via a CPRI. Given to the adopted C-RAN architecture, each BBU on the BBU pool can handle one or more RRHs depending on the network load condition. Moreover, since all BBUs are migrated in the cloud in the C-RAN architecture, the deployed RRHs become less complex, more scalable and energy efficient with a significant gain in CAPEX and OPEX. However, the logical mapping between centralized BBUs and distributed RRHs is not static but dynamic. It depends on the traffic load and some particular network conditions faced by operators.

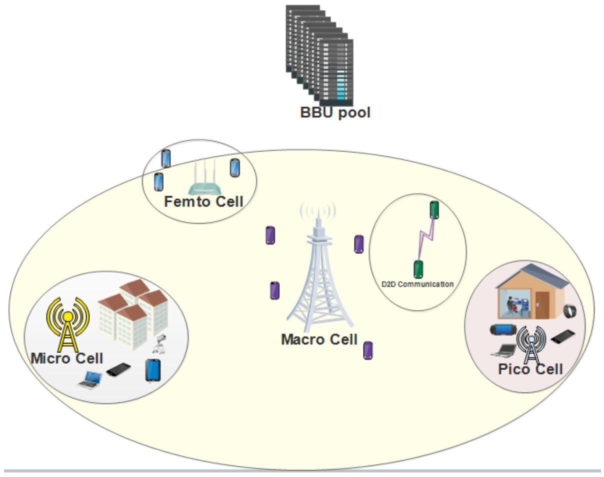



Figure 3: 5G C-CRAN Heterogeneous System

Furthermore, in a heterogeneous C-RAN system proposed here (see Fig. 3), macro cells have to coexist with micro, pico and femto cells. Therefore, we consider a heterogeneous and flexible C-RAN that enables two kinds of cells: macro and pico. On the one hand, the macro cell is an ordinary hexagonal cell in which a macro RRH is deployed in order to allow a wide coverage. On the other hand, a large number of pico cells are deployed within a given operator's macro cell network as subcells. These pico cells are located in the edge areas of the macro cell in order to increase the macro cell's edge speed, data capacity as well as the network efficiency. Therefore, one BBU could serve many RRHs. However, due to limited processing of virtual machines [48] within the BBU Pool, the number of RRHs associated with one BBU is limited.

Unlike some schemes like those in [41, 49, 50], which assume that each UE is associated with at most one RRH, our proposal is designed such a way that each UE can be associated with more than one RRHs. In fact, the main benefit of C-RAN is the joint signal processing through CoMP technique, where several RRHs can cooperatively process the signals together. For energy saving purpose, a given BBU can be turned off when there is no traffic or when the traffic load decreases in RRHs. In addition, all BBUs are assumed to have the same capacities. Also, like adopted by works done in [36, 51], each pico RRH belonging to a macro RRH has a maximum cooperation range corresponding to that of their corresponding macro RRH. Therefore, all signals of others pico RRHs that are not belonging to a given macro RRHs will be considered as interference. For convenience, we assume that each pico RRH is deployed with a single antenna. In the same way, each UE is equipped by one receiving antenna. Thus, let us assume that the DL of our C-RAN system consists of all RRHs and all single antenna of UEs.

### 3.2. Channel Model

In this paper, we assume that the channels are modeled according to the Rayleigh fading and path loss. Certainly, the Ricean fading is more reasonable for pico, femto and most of unlicensed spectrum. However, the Rayleigh fading is also known to be a specialized model for stochastic fading and is sometimes considered as a special case of the more generalized concept of Ricean fading. Moreover, we assume that the channel state information between the RRHs and the UEs is perfect.

Let us define the BBU pool $\Upsilon$ made of $p$ BBUs is represented by the set $\Upsilon = \left\{B_{u_1}, B_{u_2}, \cdots B_{u_k}\right\}, k \in [1, p] \cap \mathbf{N}$. Each BBU in the BBU pool acts as a virtual base station that is a special virtual machine designed to process radio signals. We consider a network with $n$ macro cells, i.e., macro RRHs. So, we denote the set $\mathfrak{I}$ of macro cells as $\mathfrak{I} = \left\{M_{c_1}, M_{c_2}, \cdots, M_{c_n}\right\}$. Then, let us consider $\mathfrak{R}(M_{c_i}) = \left\{P_{c_1}, P_{c_2}, \cdots, P_{c_m}\right\}$, $i \in [1, n] \cap \mathbf{N}$ as the set of pico RRHs belonging to the macro RRH $M_{c_i}$, where $m = \left|M_{c_i}\right|$ is the length of the macro RRH $M_{c_i}$, i.e., the number of pico cells belonging to the macro RRH $M_{c_i}$. All the RRHs are connected to the BBU pool via fronthaul links, especially high-speed optical links. Let us define the set $\Psi(P_{c_j})$ of UEs belonging to the pico RRH $P_{c_j}$ by $\Psi(P_{c_j}) = \left\{U_{j,1}, U_{j,2}, \cdots, U_{j,l}\right\}$, $j \in [1, m] \cap \mathbf{N}$, $l \in [1, q] \cap \mathbf{N}$ and $q = \left|P_{c_j}\right|$ is the length of the $P_{c_j}$. In order to define the transmission rate of the tractable capacity of a UE $U_{j,l} \in \Psi(P_{c_j})$, let us give the received signal $y_{j,l}$ at a UE $U_{j,l} \in \Psi(P_{c_j})$ in Eq.(1).

$$y_{j,l} = \rho^{-\frac{1}{2}} h_j^l \left(d_j^l\right)^{-\frac{\beta}{2}} s_j^l + \sum_{P_{c_o} \in \mathfrak{R}'\left(M_{c_i}\right)} \rho^{-\frac{1}{2}} h_o^{l'} \left(d_o^{l'}\right)^{-\frac{\beta}{2}} s_o^{l'} + g_{j,l} \quad (1)$$

where, $\rho$ is the average signal-to-noise ratio (SINR); $h_j^l$ denotes the channel gain from the pico RRH $P_{c_j}$ to the UE $U_{j,l} \in \Psi(P_{c_j})$; $d_j^l$ is the distance between the pico RRH $P_{c_j}$ and the UE $U_{j,l} \in \Psi(P_{c_j})$; $s_j^l$ is the desired data for the UE $U_{j,l} \in \Psi(P_{c_j})$ from its corresponding RRH $P_{c_j}$; $\beta$ is the path loss exponent, $\mathfrak{R}'(M_{c_i})$ denotes the set of all the interfering pico RRHs; $h_o^{l'}$, $d_o^{l'}$, and $s_o^{l'}$ are defined similarly for a given interfering pico RRH $P_{c_o}$, $o \neq j$; $h_j^l$ and $h_o^l$ , $j \neq o$ follow the circularly-symmetric complex normal distribution, .i.e., $h_j^l$, $h_o^l$ $\sim \mathcal{CN}(0, 1)$. Also, $g_{j,l} \sim \mathcal{CN}(0, (\sigma_{j,l})^2)$ represents the additive Gaussian noise. Moreover, $\sigma_{j,l}$ is the root mean square voltage of the noise $g_{j,l}$ accompanied by the received signal $y_{j,l}$. Therefore, when associated with the RRH $P_{c_j}$, the SINR perceived by the UE, $U_{j,l}$ is given in Eq. (2) and $B$ the total bandwidth of the RRH is given in Eq. (3).

$$\gamma_{j,l} = \frac{\rho \cdot \left(d_j^l\right)^{-\beta} \times \left|h_j^l\right|^2}{(\sigma_{j,l})^2 + \sum_{P_{c_o} \in \mathfrak{R}'\left(M_{c_i}\right)} \rho \cdot \left(d_o^{l'}\right)^{-\beta} \times \left|h_o^{l'}\right|^2} \quad (2)$$

$$B = \omega_j \times W_j \quad (3)$$

where, $\omega_j$ denotes the spectral efficiency and $W_j$ is the spectrum bandwidth in the RRH $P_{c_j}$.

Consequently, by considering interference as noise, according to Eq. (1), Eq. (2) and Eq. (3), the achievable rate in bit/s/Hz for the channel capacity $c_{j,l}$ or the transmission rate of the UE $U_{j,l} \in \Psi(P_{c_j})$ can be expressed as given in Eq. (4).

$$c_{j,l} = B \times log_2(1 + \gamma_{j,l}) \quad (4)$$

Otherwise, from Eq. (4), we can conclude that channel capacity is based on the perfect delay assumption. Therefore, the channel capacity cannot be used to characterize the QoS requirements of UEs. Moreover, coordinating pico RRHs of a given macro RRH while taking into account the others macro cells is necessary for avoiding inter/intra-cell interference. To achieve that, BBU's processing resources must be allocated according to the UEs' QoS needs, the channel state and the overall network beamforming vectors.

## 4. Formulation of the Optimization Problem

The requirements in terms of QoS warranties are strongly linked with the strategy of radio resource allocation such as the way of mapping RRHs with BBUs or UEs with RRHs. In this light, our goal is to maximize the achievable bit rate while minimizing the overall network energy consumption of our considered Bee-Ant-CRAN scheme. This trade-off is realized by jointly optimizing the UE-RRH association, RRH-BBU mapping and the computer resources allocation in BBUs while maximizing the energy efficiency the C-RAN. In most cases, this kind of problem is formalized with a multi-objective optimization scheme [24, 30, 35, 52, 53, 54, 55].

### *4.1. Constraints derivation*

According to prior assumptions, let us define the binary variable $a_{l,j}$ given in Eq. (5) representing the association status between the RRH $P_{c_j}$ and the UE, $U_{j,l}$.

$$a_{l,j} = \begin{cases} 1 & \text{if the UE } U_{j,l} \text{ is served by the RRH } P_{c_j} \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

Therefore, the total channel capacity $c_{j,l}^T$ is given in Eq. (6) and the the per-fronthaul capacity constraint ($C_1$) can be expressed as given in Eq. (7).

$$c_{j,l}^T = \sum_{j=1}^{m} \sum_{l=1}^{q} c_{j,l} \quad (6)$$

$$(C_1) : \sum_{l \in [1, |P_{c_j}|] \cap \mathbf{N}} a_{l,j} \times c_{j,l} \leqslant c_j^{FH} \quad \forall j \in [1, m] \cap \mathbf{N} \quad (7)$$

where $c_j^{FH}$ is the maximum capacity of the fronthaul link on RRH $P_{c_j}$.

Let us define define the binary variable $d_k$ given in Eq. (14) that represents the operation mode of the BBU $B_{u_k} \in \Upsilon$.

$$d_k = \begin{cases} 1 & \text{if the } B_{u_k} \text{ is turned ON.} \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

Thereby, the total amount of transmission power at each RRH is limited by the maximum available power in the fronthaull that is represented by the threshold value $\delta$. The corresponding fronthaul capacity constraints $(C_2)$, $(C_3)$ and $(C_4)$ are given in Eq. (9), Eq. (10) and Eq. (11).

$$\begin{aligned}(C_2): \sum_{l\in[1,q]\cap\mathbf{N}} \left(d_j^l\right)^{-\frac{\beta}{2}} \leqslant d_k \times \delta \\ \forall k \in [1,p]\cap\mathbf{N}, \forall j \in [1,m]\cap\mathbf{N}\end{aligned} \tag{9}$$

$$\begin{aligned}(C_3): \left(d_j^l\right)^{-\frac{\beta}{2}} \leqslant a_{l,j} \times \delta \\ \forall l \in [1,q]\cap\mathbf{N}, \forall j \in [1,m]\cap\mathbf{N}\end{aligned} \tag{10}$$

$$\begin{aligned}(C_4): \ & a_{l,j} \leqslant d_k \\ & \forall l \in [1,q]\cap\mathbf{N}, \forall j \in [1,m]\cap\mathbf{N}, \\ & \forall k \in [1,p]\cap\mathbf{N}\end{aligned} \tag{11}$$

Furthermore, like considered by Luong et al. [56], we assume that the arrival of packets from the UE, $U_{j,l}$ at the BBU $B_{u_k}$ follow the Poisson process with an arrival rate $\lambda_{j,l}$. Moreover, without lost of generality, let us assume that each packet has the same length. As mentioned by Ari et al. [29], it is important to take into account the computing capacity of virtual machines. Thus, the computing capacity of the BBU $B_{u_k} \in \Upsilon$ is denoted by $C(B_{u_k})$. Let us consider $\mu_{k,l}$ as the capacity required to compute the packet originating from the UE, $U_{j,l}$. Then, the packet processing task at each BBU $B_{u_k}$ can be described as a *M/M/1* queue. Therefore, in that condition, the service time at each BBU follows the exponential distribution with the mean $\frac{1}{\mu_{k,l}}$ and the computing capability constraint $(C_5)$ is given in Eq. (12).

$$\begin{aligned}(C_5): \sum_{l\in[1,q]\cap\mathbf{N}} \mu_{k,l} \leq d_k \times C(B_{u_k}) \\ \forall k \in [1,p]\cap\mathbf{N}\end{aligned} \tag{12}$$

Now, let $\tau_{j,l}$ given in Eq. (13) be the average response time for processing each packet of the UE, $U_{j,l}$ by the BBU $B_{u_k}$.

$$\tau_{j,l} = \frac{1}{\mu_{k,l} - \lambda_{j,l}} \tag{13}$$

Let us define define the binary variable $e_{k,l}$ given in Eq. (14), which represents the user's packets assignment to a BBU for processing.

$$e_{k,l} = \begin{cases} 1 & \text{if the packets of the user } U_{j,l} \text{ are} \\ & \text{processed by the BBU } B_{u_k}. \\ 0 & \text{otherwise}\end{cases} \tag{14}$$

Then, the constraint $(C_6)$ for the response time is given in Eq. (15) and the constraint $(C_7)$ given in Eq. (16) ensures that each user $U_{j,l}$ is served by at least one BBU $B_{u_k}$.

$$\begin{aligned}(C_6): \sum_{l\in[1,q]\cap\mathbf{N}} e_{k,l} \times \tau_{j,l} \leqslant \varepsilon \\ \forall k \in [1,p]\cap\mathbf{N}, \forall j \in [1,m]\cap\mathbf{N}\end{aligned} \tag{15}$$

where $\varepsilon$ is a defined threshold value that represents the capacity of the fronthaul.

$$\begin{aligned}(C_7): \sum_{l\in[1,q]\cap\mathbf{N}} e_{k,l} \geqslant 1 \\ \forall k \in [1,p]\cap\mathbf{N}\end{aligned} \tag{16}$$

### *4.2. Power consumption derivation*

The power consumption model like those proposed by Auer et al. [57], Badic et al. [58] and Etoh et al. [59] for the traditional RAN architecture, cannot be directly used to model power consumption in C-RAN. Indeed, this is due to the fact that, in C-RAN RRHs and BBUs are decoupled, not located on the same site and the BBUs are running on virtual machines located in the cloud. Thus, in order to be realistic, the power consumption model of the studied architecture takes into account the power consumption at the fronthaul links, the power consumption at the RRHs and the power consumption at the BBU pool.

- The power consumption $P_j^{FH}$ at the fronthaul link on RRH $P_{c_j}$ is given by Eq. (17).

$$P_j^{FH} = \nu_j \times \sum_{l\in[1,q]\cap\mathbf{N}} a_{l,j} \times c_{j,l} \tag{17}$$

  where $\nu_j$ is the scaling factor of the fronthaul in the RRH $P_{c_j}$.

- Let us define the binary variable $b_j$ given in Eq. (18) that represents the operating mode of the RRH $P_{c_j}$.

$$b_j = \begin{cases} 0 & \text{if the RRH } P_{c_j} \text{ is in sleep mode.} \\ 1 & \text{otherwise}\end{cases} \tag{18}$$

  Like adopted in [40, 53], the power consumption $P_j^{RRH}$ at the RRH $P_{c_j}$ given in Eq. (21) consists of: data dependent power $P_j^{dd}$ Eq. (19), which is the power expended at the power amplifiers of the RRH depending of transmitted signals; and the data independent power $P_j^{di}$ Eq. (20), that is the power consumed by electronic components.

$$P_j^{dd} = \frac{1}{\eta_j} \cdot \rho^{-\frac{1}{2}} \times \sum_{l\in[1,q]\cap\mathbf{N}} \left(d_j^l\right)^{-\frac{\beta}{2}} \tag{19}$$

  where $\eta_j \in [0,1]$ is the efficiency of the power amplifier.

$$P_j^{di} = b_j \times P_j^{ra} + (1-b_j) \times P_j^{ri} \tag{20}$$

  where $P_j^{ra}$ represents the fixed amount of consumed power when the RRH $P_{c_j}$ is active and $P_j^{ri}$ represents the required power for keeping the RRH $P_{c_j}$ in sleep mode.

$$P_j^{RRH} = P_j^{dd} + P_j^{di} \tag{21}$$

- The power consumption $P_j^{BBU}$ at the BBU $B_{u_k} \in \Upsilon$ is given Eq. (22).

$$P_k^{BBU} = d_k \times \zeta_k \cdot \mu_{k,l} \tag{22}$$

where $\zeta_k$ is the power consumption factor of the $B_{u_k}$.

Therefore, the power consumption model of our system is given in Eq. (23).

$$P(\mu, a, b, d, e) = \sum_{j=1}^{m} \left(P_j^{FH} + P_j^{RRH}\right) + \sum_{k=1}^{p} P_k^{BBU} \tag{23}$$

*4.3. Multi-objective optimization*

In order to guarantee the QoS requirements, we defined the weighted cost function $f(c, P)$ in Eq. (24) by making a linear combination of channel capacity and power consumption for solving the joint problem of UE-RRH association, RRH-BBU mapping as well as the computer resources allocation.

$$f(c, P) = \alpha \times c_{j,l}^T - (1 - \alpha) \times P(\mu, a, b, d, e) \tag{24}$$

The problem $P_0$ is therefore formulated as given in Eq. (25).

$$\begin{aligned} (P_0): \quad & \max_{c,\mu,a,b,d,e} f(c, P) \\ & \text{subjected to} \\ & (C_1), (C_2), (C_3), (C_4), (C_5), (C_6) \text{ and } (C_7). \end{aligned} \tag{25}$$

where $a, b, d$ and $e$ are implicitly understood as being binary.

*4.4. Complexity of the optimization problem*

Due to the binary variables $a$, $b$ and $e$, the optimization problem defined in Eq. (25) is a mixed integer nonlinear problem that is generally known to be an NP-hard problem [36, 41, 51, 53, 60]. The intuitive approach to get an optimal solution of such optimization problem may be through exhaustive search. However, exploring all the space of possible UE-RRH mapping as well as those of RRH-BBU mapping leads to exponential complexity. Therefore, due to its extremely computational behavior, the exhaustive search becomes hard to implement and should be avoided in the context of large scale C-RANs.

*4.5. Decomposition of the optimization problem*

In order to address the complexity of the $P_0$, we present in this section a decomposition approach that divides $P_0$ into two stage resource allocation problem in order to reach optimal and stable solutions. The main idea of this decomposition is to separate the cost function $f(c, P)$ given in Eq. (24) into sub cost functions. In this light, given the fact that the computing capabilities of each BBU within the BBU Pool are the same. Also, the number of used working BBUs in the C-RAN should be minimal for energy saving purpose. Therefore, we can divide the cost function $f(c, P)$ into two sub cost functions as given in Eq. (26). As schematized in the Fig. 4, the first sub cost function $f_1(c, P_j^{FH}, P_j^{RRH})$ given in given in Eq. (27) represents the UE-RRH optimization problem $P_1$ and the second sub cost function $f_2(\mu, P_k^{BBU})$ given Eq. (28) in represents BBU scheduling problem $P_2$. Moreover, the sub cost function $f_1(c, P_j^{FH}, P_j^{RRH})$ includes the data transmission rate of the each UE, the power consumption of the fronthaull as well as the power consumption of each RRH. The sub cost function $f_2(\mu, P_k^{BBU})$ includes the power consumption of each BBU.

$$f(c, P) = f_1(c, P_j^{FH}, P_j^{RRH}) + f_2(\mu, P_k^{BBU}) \tag{26}$$

$$(P_1): \; f_1(c, P_j^{FH}, P_j^{RRH}) = \alpha \times c_{j,l}^T + (1 - \alpha) \times \sum_{j=1}^{m} \left(P_j^{FH} + P_j^{RRH}\right) \tag{27}$$

$$(P_2): \; f_2(\mu, P_k^{BBU}) = (1 - \alpha) \times \sum_{k=1}^{p} P_k^{BBU} \tag{28}$$

$P_1$ is related to the UE-RRH mapping and the and $P_2$ is about the RRH-BBU mapping problem. To address these issue we propose a swarm intelligence based approach.

## 5. Swarm Intelligence based Approach

*5.1. Background*

Formally, in the context of mobile networks, clustering or mapping can be seen as the way of grouping a set of elements in such a way that objects belonging to the same group are more similar to each other than to those in other groups, by respecting a number of well defined criteria. These elements can be assimilated to UEs, RRHs and BBUs. Thus, a cluster can be seen as a group of UEs led by a RRH. Therefore, it is possible to define a second level of clusters that associate a group of objects, says RRHs, with up-level objects, says BBUs. In brief, clustering allows us to have an abstraction of prototypes or representatives' elements from individual elements in the same clusters that be managed as a single object. Unfortunately, deciding on what object should belong to a given cluster is not an easy task [30, 35, 61]. There is not an polynomial algorithm that is able to regroup elements in disjoint clusters [34, 62]. In another words, power efficient clustering is a well known NP-hard optimization problem for complex and dynamic cloud-based cellular network environments [63].

Increasingly, SI based approaches have been regularly used to solve a number of optimization problems in many areas including wireless networks, radio interference mitigation and cloud computing [29, 30, 64, 65, 66, 67, 68, 69]. These SI based approaches such as ACO [70], PSO [34], Bacterial Foraging Optimization (BFO) [62] and most recently ABC [71] have been extensively used as population based metaheuristic thanks to their desirable features of being adaptive for solving optimization problems [35]. Moreover, a number of results [32, 33, 35, 72, 73, 74] demonstrates the effectiveness of the the ABC metaheuristic and its competitiveness compared to other SI based algorithms [75]. In the same order of ideas, the ACO

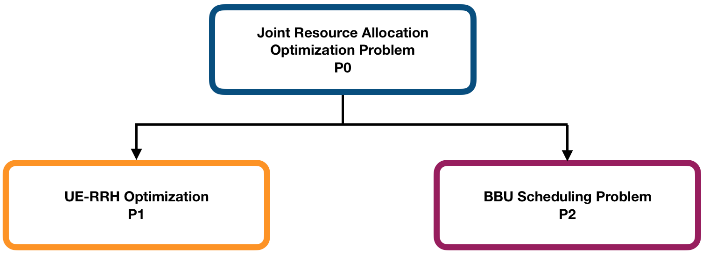



Figure 4: The two-stage resource allocation problem

features have been used to address a number of optimization problems in order to make optimal decision clustering problems [70]. In this light, we present in this section the adopted approach for the UE-RRH mapping that uses the ABC features and RRH-BBU mapping, which is based on a modified ACO algorithm.

### 5.2. UE-RRH mapping: a modified ABC based scheme

The ABC algorithm firstly introduced by Karaboga [76] was designed for numerical optimization problems. This metaheuristic is based on honeybees that are fascinating and highly organized insects capable of individual cognitive actions and self-organization [30]. The ABC is based on three essential components on which the minimal model of foraging behaviors has been designed. It includes: employed foragers, unemployed foragers and food sources. The first, also known as worker bees, are associated with given food sources and the second are in two kinds: onlookers and scouts. Onlookers are associated with a food source based on the information on the quality of the food source received from employed bees. The scouts are always in looking for new food sources to exploit. Besides, the onlooker bees and unemployed foragers are responsible of carrying out the exploitation process in the search space while the control of the exploration process are assured by scouts.

Furthermore, metaheuristic algorithms usually depend on the number and the choice of control parameters that condition their performance. In the ABC algorithm, these parameters includes: the colony size, i.e., the number of food sources; the maximum number of cycle that is a stopping criterion; and the limit that is equivalent to the number of trials after which a given food source is abandoned. Moreover, contrary to a number of SI based metaheuristics that take possible solutions among population individuals, in the ABC, the possible solutions, (i.e., the $j-th$ initial population of size $SN$) $X_j = \{x_{j1}, x_{j2}, \cdots, x_{jl}\},\ j = 1, 2, \cdots, SN$, that is a $l$-dimensional vector, are represented by the food sources. Also, the quality of the food source, i.e., the possible solution is evaluated by a fitness function that is obtained from the value of the objective function $f_1$ given in Eq. (27).

In this section we develop a modified ABC based scheme for our proposed UE-RRH mapping. In the ABC, the convergence rate mainly depends on the balance between exploitation and exploration processes, which are two contradictory processes. Indeed, the exploration process allows to search closely in the various unknown regions in the possible solution space in order to found the global optimum while, the exploitation process ensure that the better solutions is obtained from the knowledge of the previous good solutions.

However, in the original ABC optimization, the new candidate solution is not in advance expected to be better than the previous since the candidate solution is chosen such a way that the probability to select a random good solution and that of selecting a random bad solution are the same. Therefore, the exploitation process of the initial ABC becomes very poor while the exploration process is excellent. In this light, we propose a modified version of the initial ABC. Inspired by the PSO metaheuristic described by Kennedy [77] and in order to improve the exploitation process of the initial ABC, we take the advantage in the concept of the global best solution (called *gbest*) of the PSO in the evaluation of the new candidate solution. Hence, the main steps of our UE-RRH mapping based modified ABC algorithm are shown hereinafter. For simplicity reasons in the clustering process, let us consider one macro cell $M_{c_i} \in \Im$ with a number of pico RRHs.

#### 5.2.1. Initialization phase

The three parameters of the ABC as well as the initial population are initialized in this step. The number of food sources $SN$ that is equal to the number of employed bees or onlooker bees, is equivalent to the length $m$ of the pico RRHs $X_j = P_{c_j} \in \Psi(M_{c_i})$ given in Eq. (29). The number of trials until the abandonment of a food source, i.e., the *limit* and the stopping criterion $\Delta \in \mathbf{N}$ should be properly chosen in the simulation. Therefore, the population is initialized with $m$ pico RRHs $P_{c_j}$ (the food sources), which is a $l$-dimensional vectors.

$$X_j = \{x_{j1}, x_{j2}, \cdots, x_{jl}\},\ j = 1, 2, \cdots, m \tag{29}$$

where $x_{j1} = P_{c_1}, x_{j2} = P_{c_2}, \cdots, x_{jl} = P_{c_m},\ j \in [1, m] \cap \mathbf{N}$.

#### 5.2.2. Employed bee phase

In this step, each employed bee, i.e., the RRH $x_{jl} \in X_j$, generates a new solution $v_{jl}$ (see Eq. 33) in the neighborhood of its present position by taking advantage of the information of the global best (*gbest*) solution of the PSO in order to improve the exploitation process of the ABC. Three weighting factors $\varpi$, $\varrho$ and $\varsigma$ respectively given in Eq. (30), Eq. (31) and Eq. (32) are introduced in the evaluation of the new candidate solution for balancing the search selections and controlling the convergence speed of the modified ABC algorithm.

$$\varpi = \frac{\vartheta}{1+\theta} \tag{30}$$

$$\varrho = \vartheta \times \left(\frac{1-\theta}{\vartheta}\right)^{\frac{t}{\Delta}} \tag{31}$$

$$\varsigma = \theta \times \left(\frac{\vartheta}{1-\vartheta}\right)^{\frac{t}{\Delta}} \tag{32}$$

where $\vartheta$ and $\theta$ are constant that should properly chosen; $t \in [1, \Delta] \cap \mathbf{N}$ represents the number of the current cycle, i.e., iteration.

$$v_{jl} = \varpi \times x_{jl} + \varrho \times \phi_{jl}(x_{jl} - x_{kl}) + \varsigma \times \Phi_{jl}(z_l - x_{jl}) \tag{33}$$

where :

- $k$ represents the number of a neighbor, $k \in [1, m] \cap \mathbf{N} \wedge k \neq l$.
- $\phi_{jl} = rand(-r;\ +r)$. For simplicity reason, we take $r = 1$.
- $\Phi_{jl} \in [0, C]$, $C > 0$ is a uniform random number. $C$, which is a non-negative constant that must not be a too big, plays a capital role in balancing the exploitation and the exploration processes of the candidate solution. By suggested by Cao et al. [31], we take $C = 1.5$ for a good setting.
- $z_l$ is the $l$-th element of the global best solution.
- $\varsigma \times \Phi_{jl}(z_l - x_{jl})$ is the global best ($gbest$) term that guides the new solution $v_{jl}$ towards best solution and therefore improves the exploitation process of the ABC.

*5.2.3. Onlooker bee phase*

Then, the $j$-th food source position is represented by the vector $X_j = \{x_{j1}, x_{j2}, \cdots, x_{jl}\}^T$ and the fitness ($f_1$) of the food source located at position $X_j$ is $f_1(X_j)$, where $f_1$ is the cost function given in Eq. (27). Finally, employed bees share their knowledge about the fitness value, with the onlooker bees. Each onlooker has to select a food source according to the goodness probability $p_j$ given by Eq. (34). In other words, if the probability value at $v_j$ is better than that at $X_j$, the employed bee will quit the old solution $X_j$ and memorizes the new one $v_j$.

$$p_j = \frac{f_1(v_j)}{\sum_{n=1}^{m} f_1(v_n)} \tag{34}$$

*5.2.4. Scout bee phase*

During the employed and onlooker bees phases, food sources are exploited until their exhaustion. If a food source $X_j$ can not be improved when reaching the limit parameter $\Delta$, i.e., the fitness value is not improved at the end of the number of cycles, the scout bee randomly generate a solution, i.e., food source in order to update the old one according to Eq. (35).

$$x_{jl}^{new} = q_j + rand(0; 1) \times (r_j - q_j) \tag{35}$$

where, $X_j$ is the abandoned food source and $q_j \leqslant x_{jl} \leqslant r_j$.

*5.2.5. UE-RRH mapping algorithm*

The proposed UE-RRH mapping algorithm is given thereafter in Algorithm 1. The main relationship between the our proposed modified ABC-based protocol and the original ABC protocol lies in the position update process of the ABC algorithm, which is used in the optimization of the UEs assignment to RRHs. The proposed algorithm performs in three step. The first step consists of initialization. The second step is dedicated to the UEs allocation to RRHs. Indeed, each $U_{j,l} \in \Psi(P_{c_j})$, $j \in [1,\ m] \cap \mathbb{N}$, $l \in [1, q] \cap \mathbf{N}$ is assigned to $x_{jl} \in X_j$ such a way that the network wide beamforming vector have a maximum of non zero terms. This means that the UE, $U_{j,l}$ receives a useful signal from a given RRH $P_{c_j}$. Moreover, this approach suppose that the beamforming vector is not affected by other constraints such as the fronthaul capacity. Then the optimal set of RRHs are determined by the proposed modified ABC algorithm. The last step consists of identifying the non required RRHs and put them into idle mode.

**Algorithm 1** . Joint UE-RRH mapping algorithm

Begin
1. Initialization:
2. Generate the initial population $X_j$, $j \in [1,\ m] \cap \mathbb{N}$
3. according to Eq. (29)
4. **Repeat**:
**For** each UE $U_{j,l} \in \Psi(P_{c_j})$, $l \in [1, q] \cap \mathbf{N}$ **do**
5. Evaluate wide network beamforming vector
6. Assign the UE, $U_{j,l}$ to RRH $P_{c_j}$ based on the optimum beamforming vector
7. Launch the employee bee phase
Proceed to the position update Eq. (33)
8. Launch the onlooker bee phase
Evaluate the goodness probability $p_j$ Eq. (34)
9. **if** the fitness $f_1$ Eq. (27) is not improved **then**
10. Launch the scout bee phase Eq. (35)
11. **Until** convergence
12. idle non required RRHs
End

*5.3. RRH-BBU mapping: an ameliorated ACO scheme*

In order to balance the wide network load, the system should determine the new RRH-BBU configurations at each period of time. After the UE-RRH mapping achieved by the Algorithm 1, the system could now proceed to the RRH-BBU mapping. At the end of each network cycle, the system will reconfigure itself by taking into consideration information on traffic load, i.e., the UE-RRH mapping view, and the QoS requirements. Concretely, at time $t$ if the BBU-RRH mapping is known, then a new RRH-BBU mapping should takes place at time $t+1$ in order to balance the traffic variation in an adaptive way. Moreover, in other to avoid latency, the load balancing cycle, which is the time between $t$ and $t+1$, may not be more than a millisecond.

To achieve the RRH-BBU mapping, the ACO features have been used for making the optimal mapping. The ACO [70] is a well-known SI based search technique that mainly aims at optimizing a wide variety of combinatorial problems. Moreover, the ACO is a stochastic local search scheme, which has been inspired by the pheromone trail laying as well as other behaviors of some ant species [29]. Unfortunately, the ACO become slower in terms of convergence while considering a large research space. In this light, in order to obtain a rapid convergence, we proposed a modified version of the Max-Min Ant System (MMAS) that is an improved version of the ant system, in order the achieve the RRH-BBU mapping. The proposed scheme performs in three main steps.

*5.3.1. Initialization step*

In this step, a number of parameters including the number of virtual BSs, i.e., the number of BBUs, the number of ants, the pheromone trail, the heuristic information as well as the maximum iteration number, are initialized. The pheromone values $\chi_{k,l}(o)$, $k \in [1, p] \cap \mathbb{N}$, $l \in [1, q] \cap \mathbb{N}$ of the BBU $B_{u_k}$ at iteration $o$ are computed according to the formula given in Eq. (36). Therefore, at iteration $o$, the pheromone trail is represented by the matrix $\chi_{k,l}(o)$. In addition, the heuristic information $\eta_{k,l}(o)$ that is seen as the capacity of a BBU $B_{u_k}$ to process the workload of a given RRH $P_{c_m} \in \Re(M_{c_i})$ is defined in Eq. (37).

$$\chi_{k,l}(o) = \frac{1}{\sum\limits_{k=1}^{p} \varphi_k} \times (\xi_k + \varphi_k \cdot \psi_k) \times d_k \tag{36}$$

where $\varphi_k$ is the processor million instructions per second (MIPS), $\psi_k$ is the number of computing units in the BBU $B_{u_k}$, $d_k$ given in Eq. (18) is the operation mode of the BBU $B_{u_k} \in \Upsilon$ and $\xi_k$ is the available rate flow on the BBU $B_{u_k}$.

$$\eta_{k,l}(o) = \frac{1}{z(P_{c_j})} \times (\upsilon \times \varphi_k \cdot \psi_k) \times e_{k,l} \tag{37}$$

where $z(P_{c_j})$ is the total amount of basic unit of time-frequency resources, i.e., physical resource block, which can be allocated to all UEs $U_{j,l}$, $j \in [1, m] \cap \mathbf{N}$, $l \in [1, q] \cap \mathbf{N}$ mapped to the RRH $P_{c_j} \in \Psi(P_{c_j})$, $\upsilon$ is a weight factor that should be properly chosen and $e_{k,l}$ is the binary variable given in Eq. (13).

*5.3.2. Construction step*

Like it is done in the original ACO, the construction step consists of a colony of ants that are independently engaged in designing a solution by using the pheromone matrix constructed in Eq. (36) and the heuristic information derived in Eq. (37). To achieve the construction each ant will generate an array of RRH-BBU mapping that will be considered as an initial solution. These ants will iteratively construct the optimal mapping according to the probability function given in Eq. (38).

$$p_{k,l}(o) = \frac{1}{\sum\limits_{l=1}^{q} \left(z(P_{c_j}) \times \chi_{k,l}(o)\right)} \times (\chi_{k,l}(o) \cdot \eta_{k,l}(o)) \tag{38}$$

*5.3.3. Updates step*

In the updating pheromone trails step, the solutions computed during the construction step are improved. Indeed, in order to improve these solutions, at iteration $o+1$, the pheromone matrix $\chi_{k,l}(o+1)$ is updated by the formula given in Eq. (41) according to the amount $\Delta\chi_{k,l}$ (see Eq. (40)) of pheromones produced by the best ant that has been obtained during the construction step, which is inversely proportional to the flow function $f_{k,l}(o)$ given in Eq. (39).

$$f_{k,l}(o) = \frac{1}{\sum\limits_{l=1}^{q} p_{k,l}(o) \cdot z(P_{c_j}) + \sum\limits_{k=1}^{p} \varphi_k} \times (\xi_k \times \phi_k \cdot \psi_k) \tag{39}$$

$$\Delta\chi_{k,l} = \frac{1}{f_{k,l}} \tag{40}$$

$$\tau_{k,l}(o+1) = \kappa \times \chi_{k,l}(o) + \Delta\chi_{k,l} \tag{41}$$

where $0 \leqslant \kappa < 1$ is a parameter that express the trail persistence.

*5.3.4. RRH-BBU mapping algorithm*

The proposed RRH-BBU mapping is given in Algorithm 2. After the initialization of the pheromone matrix and the others parameters. Then, the set of non idle RRHs is obtained from the output of Algorithm 1. Moreover, each ant in the ant colony is associated with a resource, i.e., a RRH. Then, the mapping of RRHs with BBUs are performed in lines 6-13 until convergence. At the end of iteration, the optimal array of RRH-BBU mapping are obtained and the last step consists of identifying the non required BBUs and put them into idle mode.

## 6. Simulation Results

In this section, we present the computational results, analysis as well as discussion, in order to show the effectiveness of our proposed UE-RRH and RRH-BBU mapping schemes. To achieve that, we evaluated our proposed resource allocation scheme (Bee-Ant-CRAN) by simulations on Matlab with the MOESK tool. Moreover, we compared our proposed Bee-Ant-CRAN with the Zhu and Lei [39], Chen et al. [38] and the CDI-CRAN [26] in terms of active RRHs/BBUs, packet throughput, power consumption, spectrum efficiency, and packet loss. Detailed simulation parameters are summarized in Tab. 1 and the Bee-Ant-CRAN parameters are shown in Tab. 2. The ABC and

**Algorithm 2** . The RRH-BBU mapping algorithm

Begin
1. Initialize parameters
   the number $p$ of BBUs in the BBU pool $\Upsilon$
   the amount of ants $A_a$
   the maximum number of iterations $it_{max}$
   the weight factor $\upsilon$
   the trail persistence $\kappa$
2. Initialize pheromone trail matrix $\chi_{k,l}$
3. Build the set of non idle RRHs with the output of Algorithm 1
4. Associate each RRHs with an ant
5. Initialize the iteration index $(o = 1)$
6. **Repeat**:
   **For** each ant **do**
7. Compute the pheromone matrix $\chi_{k,l}(o)$ Eq. (36)
8. Compute the heuristic information $\eta_{k,l}(o)$ Eq. (37)
9. Generate an array of RRH-BBU according to Eq. (38)
   **End for**
10. Compute the flow function $f_{k,l}$ Eq. (39)
11. Proceed to the update of pheromone matrix Eq. (41)
12. Increment the iteration index $(o = o + 1)$
13. **Until** $(o > it_{max})$
14. idle non required BBUs

End

ACO parameters proposed in the Tab. 2 are properly chosen. Indeed, the values of the parameters adopted for the modified version of the MMAS used to achieve the RRH-BBU mapping have been carefully taken from the study of Ari et al. [29]. Moreover, the values of the parameters adopted for the proposed modified ABC mechanism for UEs association have are properly chosen after benchmarking with eleven stressful functions.

Furthermore, our goal is to test the performance of the proposed Bee-Ant-C-RAN in cases of small and large C-RAN networks with the same amount of BBUs. For this reason, in order to discuss the effects of the simulation results on a system bandwidth of 15 MHz, a carrier frequency of 5 GHz and a limited number of BBUs, we consider two scenario in the simulation. The scenario A consists of a C-RAN with nineteen RRHs and the scenario B consists of a C-RAN with forty-nine RRHs. Both scenarios consist of five BBUs. In addition, we consider a uniform distribution of UEs within each cell in a high dense and less dense cells context.

Besides that, we consider that the UEs arrivals follows the Poisson process with a rate of $\lambda_{UE}$. Then, owing to the dynamical spatio-temporal nature of the UEs' traffic, a more realistic scenario where the user downlink (DL) packet arrivals follow a Poisson process with the rate $\lambda_{DL}$. According to the $\frac{\lambda_{DL}}{\lambda_{UL}}$ ratio of packets arrival rate, the uplink (UL) packet arrival rate $\lambda_{UL} = \frac{1}{2} \times \lambda_{DL}$. In addition, according to the 3GPP TS 22.261 version 15.5.0 Release 15 [78], which presents the 5G service requirements for next generation new services and markets, the traffic model in terms of different data requirements is considered.

Table 1: Simulation parameters

| Parameter | Value | |
|---|---|---|
| Cell radius | 500 m | |
| Multipath Fading | 3GPP TU channel | |
| System bandwidth | 15 MHz | |
| Carrier frequency | 5 GHz | |
| Log normal shadowing | -8 dB | |
| Penetration loss | -20 dB | |
| Noise power density | -174 dBm/Hz | |
| Maximum RRHs TX power | 30 dBm | |
| Power consumption of RRH | Static: 84 W | idle: 56 W |
| Number of BBUs | Scenario A: 5 | Scenario B: 5 |
| Number of RRHs | Scenario A: 19 | Scenario B: 49 |

Table 2: Bee-Ant-C-RAN parameters

| Parameter | Value |
|---|---|
| $it_{max}$ | 1000 |
| $\Delta$ | 3000 |
| $C$ | 1.5 |
| $\varrho$ | 1.2 |
| $\theta$ | 0.8 |
| $\kappa$ | 0.3 |

### *6.1. Active RRH/BBU*

We first evaluated the performance of the Bee-Ant-CRAN in terms of number of RRHs/BBUs in a considered network load. The obtained results have been compared with those obtained in the schemes proposed by Chen et al., 2018 as well as Zhu and Lei, 2013. We achieved this experiment by varying the number of cells, 9, 19, 29, 39 and 49 RRHs and the objective is to evaluate the number of BBUs for each considered number of RRHs. Moreover, in order to be close to the reality, we considered the same network load, i.e., the same amount of DL packets arrival rate generated by all the UEs in a given cell. Fig. 5 shows the number of active RRHs/BBUs with respect to the traffic loads in the whole network. It can be seen that in the proposed Bee-Ant-CRAN, with 9 RRHs, we need only 2 BBUs while the scheme of Zhu and Lei performs a mapping with all the 5 available BBUs. Moreover, the scheme of Chen et al. performs a mapping with 4 BBUs and the CDI-CRAN needs 3 BBUs to perform a mapping with 9 RRHs. By considering 19 RRHs, the proposed Bee-Ant-CRAN use 4 BBUs out of the 5 available while the compared scheme use all the 5 available BBUs. Beyond 19 RRHs, all the compared schemes including the Bee-Ant-CRAN use all 5 available BBUs in the mapping process.

### *6.2. Throughput*

In Fig. 6, the obtained results of overall network throughput under DL packets arrival rate are presented. We conducted the simulation under scenarios with few (scenario A) and several number of RRHs (scenario B). Fig. 6a and Fig. 6b show

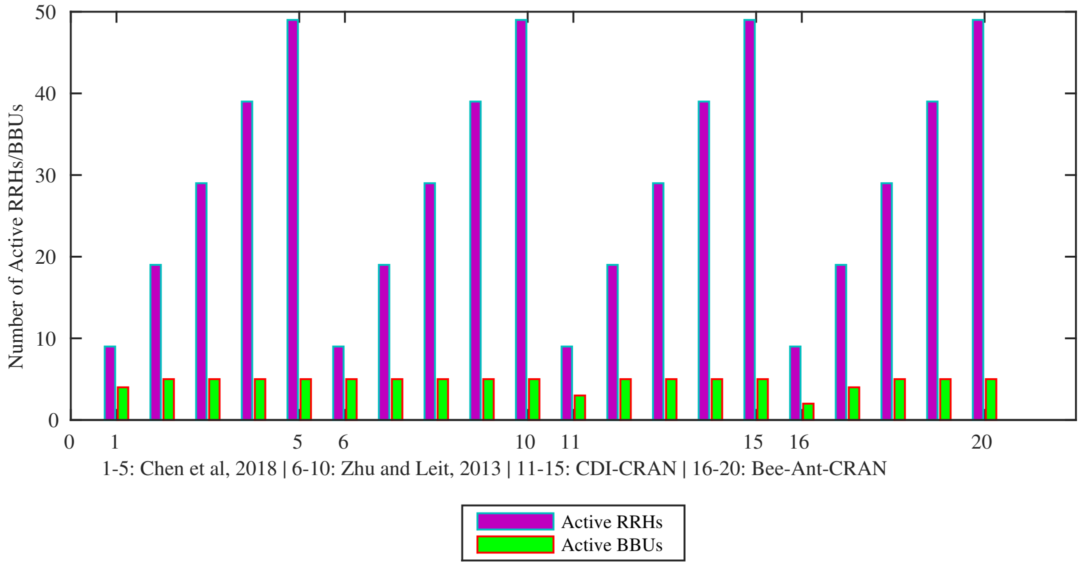
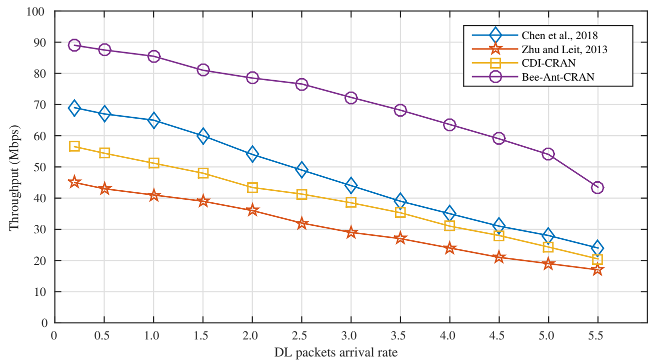



Figure 5: Number of active RRHs/BBUs with respect to the network load

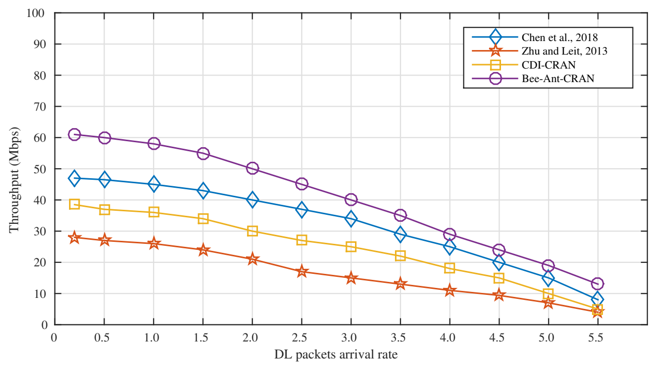
the results of throughput for our proposed Bee-Ant-CRAN respectively in scenario A and scenario B, compared with the CDI-CRAN and the schemes proposed by Chen et al., 2018 as well as Zhu and Lei, 2013. As it can be observed from the curves in the both scenarios, the packet throughput of our proposal is better than the compared. When the number of RRHs is large, i.e., scenario B (Fig. 8b), and when the DL packets arrival rate increases, the overall network throughput tends to decrease rapidly. However, in scenario A (Fig. 8a) with a few amount of RRHs, the overall network throughput according to the DL packets arrival rate does not fluctuate much with a substantial gain in the Bee-Ant-CRAN while it quickly decrease in the compared schemes. This indicates efficient resource allocation the during the RRH-BBU mapping presented in Algorithm 2 and the during the network scheduling, theses resources are under optimal utilization.

### 6.3. *Power consumption*

The proposed power consumption model (see Section 4.2) has been evaluated and compared with the with the CDI-CRAN and the schemes proposed by Chen et al., 2018 as well as Zhu and Lei, 2013. In order to be close to the traffic changing, the Bee-Ant-CRAN mapping schemes ensure that the minimum and sufficient number of BBUs are used according to the traffic requirements at the fronthall. Moreover, the average power consumed by the fronthall, the RRHs as well as the active BBUs is evaluated according to our considered network C-RAN and the proposed model given in Eq. (10). Fig.7 shows the obtained results for the power consumption for the proposed Bee-Ant-CRAN and the compared schemes. It can be observed from Fig.7 that our proposed Bee-Ant-CRAN performs well in the both scenario relative to the compared schemes. Apart from



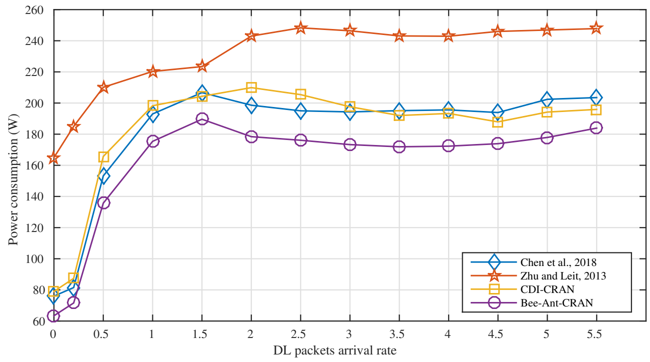

(a) scenario A



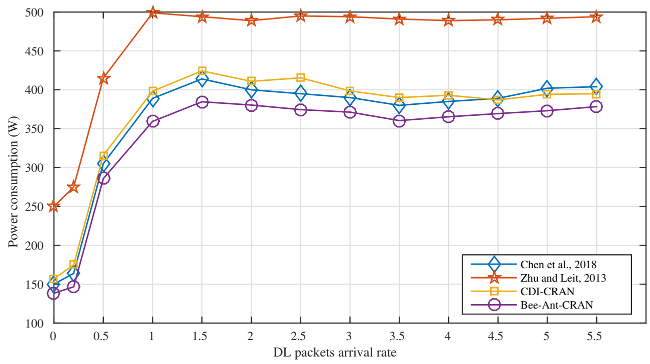

(b) scenario B

Figure 6: Network throughput

the scheme proposed by Zhu and Lei, which outputted poor results, the CDI-CRAN scheme and that of Chen et al. are less greedy in energy consumption. Furthermore, despite the quantity of deployed RRHs in scenario A (Fig. 7a) and scenario B (Fig. 7b), the total power consumption for the overall network remains lower in the proposed Bee-Ant-CRAN.




(a) scenario A

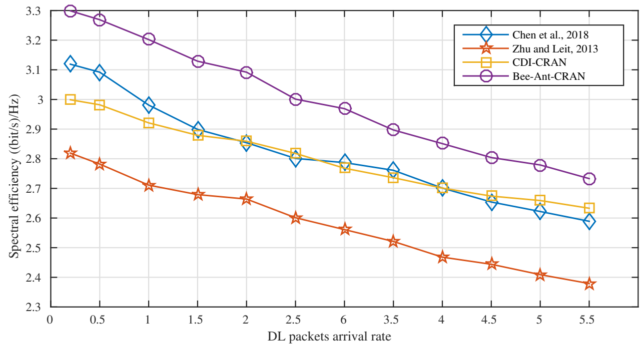



(b) scenario B

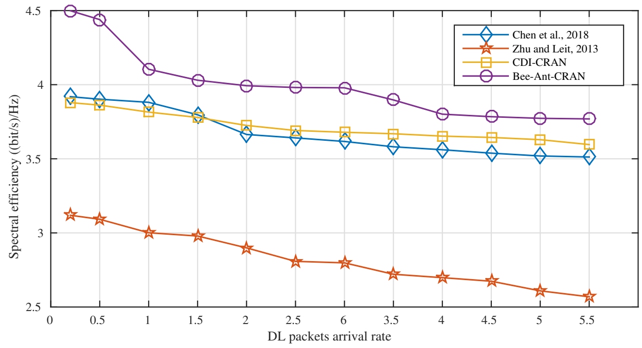
Figure 7: Power consumption

### 6.4. *Spectral efficiency*

In this paper, the spectral efficiency, which refers to the information rate that can be transmitted over a specific bandwidth, measures the net bit rate, i.e., the maximum throughput divided by the available bandwidth of the channel. We performed the simulation of the spectral efficiency under the DL packets arrival rate in the Bee-Ant-CRAN and compared the obtained with those obtained while evaluating the schemes proposed by Chen et al., 2018, Zhu and Lei, 2013 as well as the CDI-CRAN scheme. From Fig. 8, it can be observed in booth scenario A (Fig. 8a) and scenario B (Fig. 8b) that the spectral efficiency in the proposed Bee-Ant-CRAN scheme is low as the packets arrival rate decreases. This is due to the fact that a high number of deployed RRHs may increases interference. Fortunately, we take the advantage in the use of the overlap area managed by same BBU in order to increase the spectral efficiency of the Bee-Ant-CRAN that is in general better than the compared schemes.




(a) scenario A




(b) scenario B

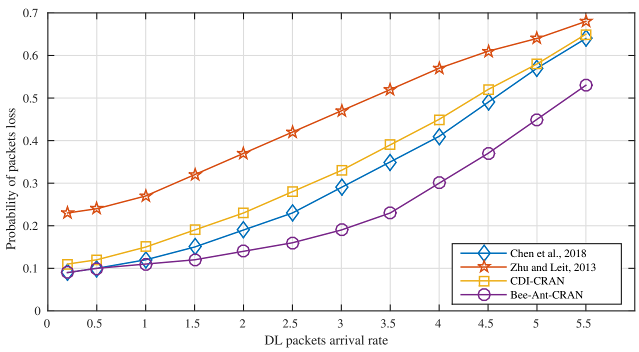
Figure 8: Spectral efficiency

### 6.5. *Packet loss*

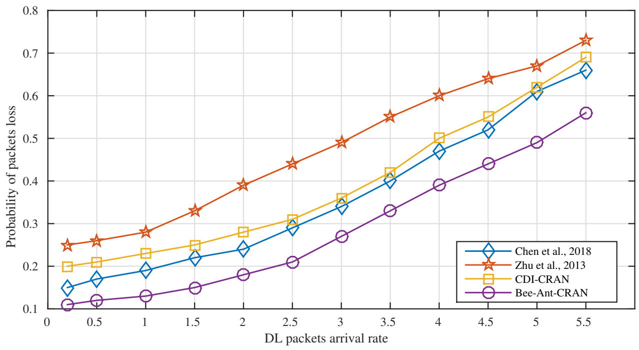
The performance evaluation of the proposed Bee-Ant-CRAN resource allocation scheme in terms of probability of packet loss under the DL packets arrival rate have been achieved. The obtained results for the Bee-Ant-CRAN compared to the schemes proposed by Chen et al., Zhu and Lei, as well as the CDI-CRAN scheme, are highlighted in Fig. 9. In both scenario A and scenario B, the evolution of probabilities of packets loss under the DL packets arrival rate for the considered C-CRAN systems are plotted in Fig. 9a and Fig. 9b. From the curves, it can be observed that in general the packets loss rate in the proposed Bee-Ant-CRAN schemes is low relative to the compared schemes. This is thanks to the proposed UE-RRH mapping scheme that exploits the optimal position update scheme adopted during the employed bee phase. Furthermore, the scheme proposed by Chen et al., 2018 as well as the CDI-CRAN have in average less packets loss. Unfortunately, the Zhu and Lei scheme have a great loss rate in the boot scenario.

## 7. Conclusion

In this paper, we investigated the joint UE-RRH and RRH-BBU mapping as well as the computer resources allocation problem for optimal resource allocation in C-RAN with the objective of reducing the overall cost in terms of power consumption, the fronthall capacity for a good throughput and the op-




(a) scenario A




(b) scenario B

Figure 9: Packets loss

timal number of needed BBUs especially for profitability purpose. Moreover, we modeled our resource allocation scheme by taking the advantage enabled by some efficient features and convergence behaviors of swarm intelligence based optimization. A power consumption model to estimate the overall network power utilization has been proposed. Furthermore, the resource allocation problem in 5G C-RAN have been formulated as a multi-objective optimization problem. Given the high performance complexity generated by the obtained mixed integer nonlinear problem, a decomposition into two subproblems of the whole resource allocation problem in order to reach optimal and stable solutions and minimal QoS requirements has been proposed. A modified ABC that optimally balance the exploitation and exploration processes of the original ABC algorithm has been modeled to address the UE-RRH mapping subproblem. While, the RRH-BBU mapping subproblem has been solved thanks to an improved version of the ant system based on the ACO features. The performance of the proposed Bee-Ant-CRAN has been evaluated and compared to three resource allocation schemes for C-RAN systems. The results of simulation demonstrated the effectiveness of our proposal. As a future work, we plan to study the effects of introducing virtual BSs at the edge of the C-RAN in the overall performance.

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