Multilayer Framework for Resource Orchestration in Next Generation Networks

Ermínio A. R. da Paixão, Albert E. Santos, Daniel da S. Souza, Diego L. Cardoso

***Abstract*—Due to the significant increase in data traffic and the large number of Internet Protocol (IP) devices, operators and researchers are seeking solutions to address the greater demand. One of the most attractive of these is Heterogeneous Cloud Radio Access Networks (H-CRAN), which has the capacity to solve problems of the current generation and add several improvements, such as centralized processing and greater energy efficiency. However, resource orchestration such as radio, mapping between radio and BaseBand Unit (BBU) and load balance in BBU pool are still of the utmost importance. This paper proposes a multilayer approach that enables Peak Remote Radio Head (PRRH)-underutilized reconfiguration model and optimized mapping between PRRH and BBU, with the aim of achieving high availability, energy savings and a reduction in high-speed processing. Obtained results were compared with other approaches in the literature and showed that our model offers a more efficient means of mitigating the problems addressed in this paper.**

***Index Terms*—H-CRAN, Resource Orchestration, Load Balance, Multilayer.**

I. Introduction

The growth in the number of connected devices in the network, with valid IPs by 2023, is estimated to be 29.3 billion devices, about 3.6 devices per person [1]. Also in this survey, it was found that the support for mobile telephony will correspond to 71% of the global market by 2023, an increase of 5% compared with 2018. This underlines that it is expected there will be an exponential increase in Internet-connected User Equipment (UE) globally, and this will reach 5.3 billion by 2023, a rise of 1.4 billion UE compared with 2018.

With the emergence of more network-oriented devices and applications, there is a need to restructure the architecture, since the current Distributed Radio Access Network (D-RAN) cannot be adapted to the new requirements, since it incurs high costs of capital expenditure and higher operational processing rates with an increase in the number of Base Stations (BSs) [2]. In response to the new challenges raised by the current mobile networks, Centralized Radio Access Network (C-RAN) has emerged as a possible solution, since it is able to centralize the UE processing, improve the energy efficiency and has the capacity to restructure the network data [3]. In addition, another promising technology is the Software Defined Network (SDN) which incorporates new features and applicability, such as self-adjusting scheduling, centralized management and a low cost deployment strategy [4].

The C-RAN architecture has robust requirements, such as low latency, low jitter, and high infrastructure deployment costs that are difficult to achieve [5]. However, all these obstacles can be overcome by H-CRAN which makes it possible to integrate the decentralized Heterogeneous Networks (HetNets) and C-RAN architectures, with the aim of meeting the requirements of signal processing, centralized workload management, and energy efficiency [5].

One of the main points of discussion in these new architectures is the question of deployment, because when planning the total capacity of a mobile network and the number of BSs, an attempt is usually made to meet the maximum traffic capacity. In this scenario all the BSs remain active regardless of the change in load throughout the day, thus incurring high energy costs and leading to an underutilization of equipment. This pattern of behavior is described as the Tidal Effect [6].

It is stipulated that processing rate for each BBU must be the total number of simultaneously active UEs in the sectors of the BBUs [7]. However, with regard to hardware or software, there is a restriction in the number of active UEs in the BBU, called the Hard Capacity (HC), which if not met can lead to a loss of data or decline in performance. Thus, networks must support the concept of Self-Organization (SO) so that they can address the problem of resource mapping efficiently.

In light of this, this paper proposes a framework for H-CRAN/SDN networks that integrates the monitoring of the network, the optimization of PRRHs and the efficient orchestration of resources in the BBU pool, even in different traffic conditions, aiming to maximize the UE experience, as well as reduce the number of operational resources. A bio-inspired multi-objective approach is adopted for this, and, in its first stage the Simulated Annealing On/Off algorithm (SAoff) is responsible for the intelligent disconnection and re-distribution of UEs among the remaining PRRHs. In the second stage, the Balance Particle Swarm Optimization (BPSO) algorithm is executed, and is responsible for re-orchestrating the resources of the PRRHs in the BBU. The whole process is monitored and carried out by a manager called the SDN Controller.

This paper is structured as follows: Section 2 examines the related works that are drawn on for this work, Section 3 shows the features of the architecture and the problem being investigated. Section 4 outlines the main characteristics of the algorithms used in this work and Section 5 describes the

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parameters that are used for the simulations carried out in this work. Section 6 analyzes the results and discussions, and Section 7 concludes with the final considerations of this work and makes suggestions for further research in the field.

II. Related Work

The use of HetNets has been widely discussed as a feasible solution meeting the requirements of 5G networks (CRAN and H-CRAN). However, the failure to deploy PRRHs correctly has led to a wide range of problems, from interference management to financial concerns, such as high deployment costs or a significant increase in energy consumption, factors that can make the use of this technology unfeasible. Thus, several works in the literature employ an intelligent-driven methodology for matters related to deployment and operations.

In [8] there is a discussion of the two-level energy efficiency optimization problem in an H-CRAN network. In the first stage, a dynamic shutdown algorithm for picocell is executed, based on a utility function which maintains the UE Quality Of Service (QoS). In the second stage, two algorithms are used to reduce the number of BBU servers, and thus save energy. Both these solutions achieved good results and ensured energy savings without losing QoS quality.

The study by [9], examines what measures need to be taken in the face of the exponential increase in global data traffic, since the current network structure will not be able to support this demand. The work also highlights the C-RAN architecture as a possible alternative, because of its higher processing power, capacity for reconfiguration and intelligent mapping of UE. This was investigated through a Key Performance Indicator (KPI), which seeks to reduce the number of blocked UEs so that it can optimize the QoS of the architecture. This involved using a Discrete Particle Swarm algorithm (DPSO) to match UE to the KPI and optimize the QoS. The results obtained for validation purposes were compared with those of the literature, and found that in periods of low traffic, it can turn off up to 99% of BSs.

Another work addresses the PRRH-BBU assignment problem in [10]. An optimization problem is formulated that models the allocation of resources at these two levels. At the level between cells and UEs, resources are distributed among UEs, who have different QoS requirements. As a result, the system must optimize the allocation of resources accordingly, while maintaining other features such as the availability of physical resources, QoS satisfaction, and continuity of service. At the PRRH and BBU level, computing requirements have to be processed instantaneously in the available BBU pool, while maintaining power consumption and optimizing computing resources.

The authors in [11] mathematically formulate a tidal traffic model and then propose tidal traffic-aware routing and spectrum allocation algorithms for elastic optical networks. Based on the traditional Routing and Spectrum Allocation (RSA) algorithm, the authors created Pre-Deviation RSA (PD-RSA) and Pre-Deviation K-Path Shorter RSA (PDK-RSA) algorithms to increase bandwidth efficiency in elastic optical networks.

It is clear from the analysis of the works conducted here, that although the resource allocation problems of PRRHs and BBUs have been addressed extensively (either separately or together), none of the above-mentioned studies has effectively dealt with the problem of mapping and load balancing nor have they taken into account the question of multi-level based decision-making, which is a determining factor for efficient resource orchestration. In view of this, it can be stated that this work makes two key research contributions: a) the implementation of a new algorithm for PRRH shutdown, based on Simulated Annealing; b) optimized BPSO-based load balancing algorithm for a redefinition of BBU-RRH mapping based on the results of the previous stage.

III. Proposed Scenario

Fig. 1 explains the framework established for this work. The map of available PRRHs, as well as the arrangement of UE, per hour, are used as input data for triggering the SAoff algorithm, which is responsible for turning off underutilized PRRHs. This PRRHs traffic has to be forwarded to a BBU, and, for this the BPSO is used for balancing the load between the BBU sectors, and thus reducing the number of blocked UEs between the BBU sectors. The proposed architecture is triggered at pre-established time intervals to ensure it always provides an appropriate configuration for each fluctuation of the UEs. The modules are described below:

1. Coverage Area: PRRHs are randomly placed, the UEs have the same traffic profiles and their traffic requirements were obtained from [6].

2. SDN controller: The SDN controller is the manager of all the processes in this diagram, as described below:

2.1. Traffic profile: Uses the traffic extracted from [6].

2.2. SAoff: This algorithm is explained in section IV.A.

2.3. Convert UE traffic to blocked UEs: UE data are converted to blocked UEs and sent to BBU pool.

2.4. Mapping UE: Maps the blocked UEs and determines where they will be allocated.

2.5. Initial UE-PRRH-BBU allocation: Starts the allocation of UE in the PRRHs and PRRHs in the BBUs.

2.6. Load Balancing on BBUs: Performs resource balancing on BBUs, which have a capacity that is determined by the KPI of the blocked UEs.

2.7. Load Balancing on BBU sectors: Carries out resource balancing among the BBU sectors.

2.8. BPSO: Used to optimize load balancing; Its operation is described in Section IV.B.

2.9. Re-orchestrated Resources: After going through all the balancing stages, the re-orchestrated resources are revealed in their respective BBUs and sectors.

The sequence diagram shows the operating stages of the SDN controller within the framework of BBU pool load balancing. In the first stage, the data decisions are transmitted; in the second stage these data are distributed among the available BBUs and the third is responsible for restructuring the resources among the sectors of the BBUs. The stages followed in this diagram are shown in Fig. 2.

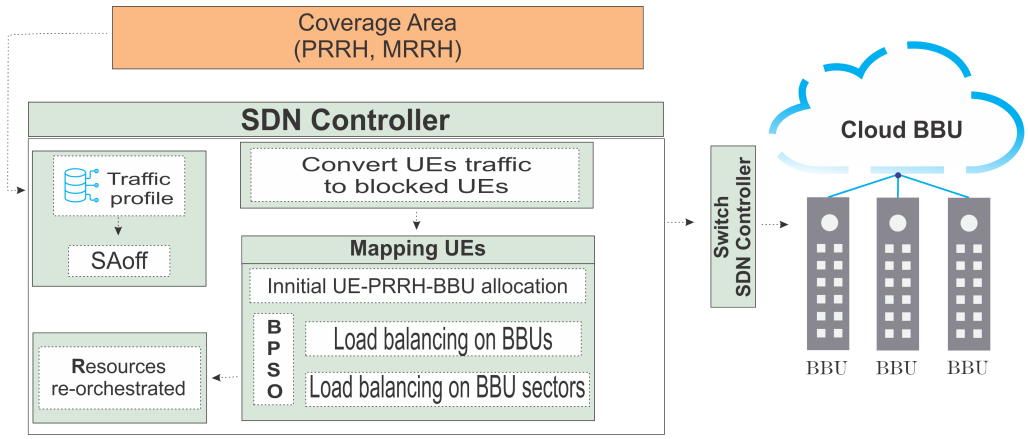

Fig. 1. Proposed framework.

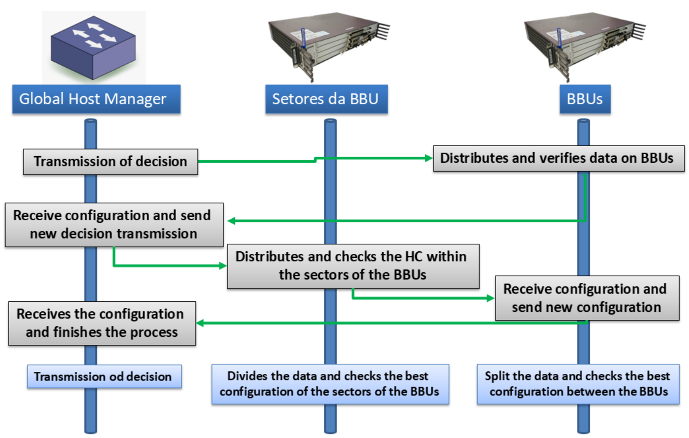

Fig. 2. BBU mapping and balancing process.

IV. Optimization Algorithms

In this section, the choice of the algorithms used and their characteristics will be outlined in detail. According to [12], bio-inspired algorithms are among the best for solving optimization-based problems, especially Nondeterministic Polynomial (NP)-hard problems.

Two search algorithms were used for this study. The first algorithm is SA which in this work is referred to as SAoff, and is based on annealing. This method is used for the improvement of steel, by heating it to high temperatures [13]. The second is PSO which will be called BPSO. This mimics the social habits of animals, such as insects, fish and birds. Each potential solution (called particles) is also assigned a randomized velocity, and then are "flown" through hyperspace. Each particle tracks its coordinates in hyperspace and is linked to the best solution (fitness) that it has reached so far [14].

A. Simulated Annealing on/off (SAoff)

Fig. 3 and Algoritmo 1 illustrates how SAoff works. The SAoff starts the search for the optimal solution using a random initial solution represented by a vector of size equal to the maximum number of PRRHs. This vector has binary values that correspond to the on/off state of the PRRH, where 1 represents the active PRRH and 0 represents the off state. To generate new solutions, SAoff modifies the binary values of this vector. It is worth noting that the SAoff must be performed for each period of study, separately, thus turning on only the PRRHs needed for that specific demand. This solution is evaluated through its objective function, which is calculated by equation 1.

$$MIN\_TPRRH_{(i)} = \sum_{j=0}^{n} A_j \tag{1}$$

subject to

$$BP_{(i)}\_MAX <= x \tag{2}$$

Where:
$TPRRH_{(i)}$ is the total number of PRRHs on at hour *i*;
n is total number of PRRHs in the network;
A is binary variable that indicates whether PRRH *j* is active or not;
$BP(i)$: is the maximum blocking probability for hour *i*.

The blocking Probability is calculated according to the equation 3:

$$BP_{(i)} = \frac{Nc_{(i)}}{Tuc_{(i)}} \tag{3}$$

Where:
$Nc(i)$ is number of users not covered at hour *i*;
$Tu(i)$ is total users available on the network.

The stopping criterion used in this algorithm is given by equation 1, that is, a vector with the smallest combination of PRRHs that must be active, in each period. Rest of the parameters can be found in Table I.

B. Balance Particle Swarm Optimization (BPSO)

The objective function of the algorithm 2 was changed, where the algorithm starts by creating a swarm of particles where each particle corresponds to a candidate solution. Then the particles randomly ascertain the solution area with different velocities. After passing through the *fitness* of the algorithm the particles are directed to their best fitness values. The velocity of an individual particle is changed stochastically in

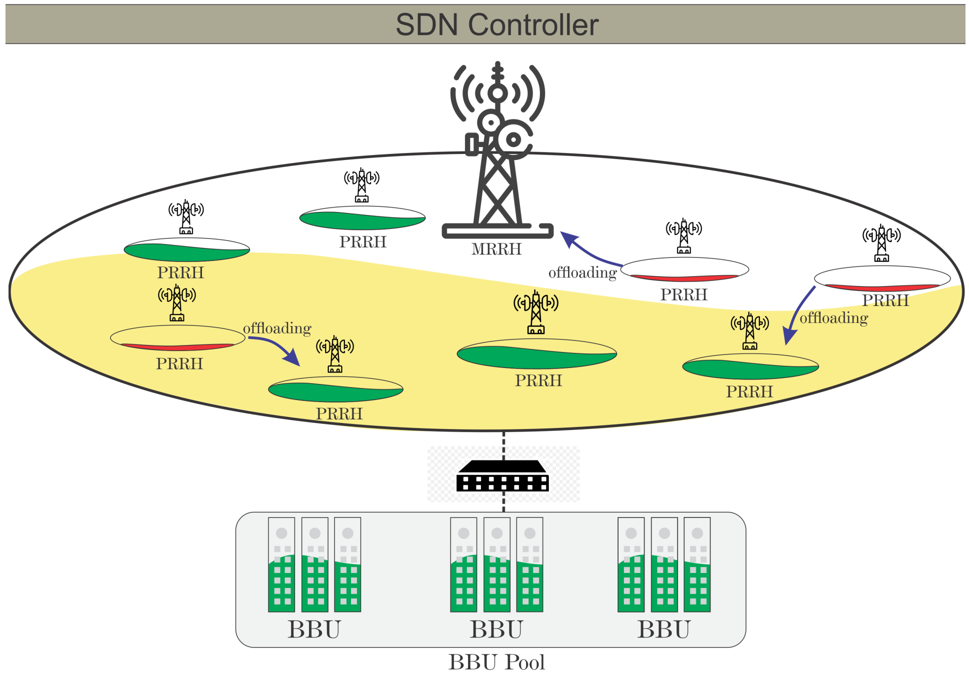

Fig. 3. SAoff.

Algorithm 1: SAoff Pseudocode

```
Generates the initial solucion x_i(i = 1, 2, ..., n)
Objective Function equation 1
begin
    σ(S) = 0
    while t < MaxGenerations do
        for i = 1 until n do
            for j = 1 until n do
                if I_j > I_i then
                    verifies the probability is less than
                     or equal to 0.1%
                end
                evaluate the solution
            end
        end
        Presents the solution
    end
end
```

TABLE I
SAOFF PARAMETERS

Parameters	Values
Hybridization rate	0.8
Mutation rate	0.1
blocking probability	10%
Number of iterations	100

each iteration and its update stems from the experience of the best historical position of the respective particle and the best position experience of neighboring particles, i.e., the global best position.

In this second step, the algorithm uses a performance indicator based on the one proposed in [9], to minimize the number of blocked UEs. The objective function of the algorithm was changed, to equally distribute the amount of UEs by the number of available sectors in the BBU pool. To do this, initially, a vector of UEs per sector is created, as modeled in equation 4.

$$U_{s(i)} = \sum_{j=1}^{N} C_j R_s, S = 1, 2, ..., K \quad (4)$$

Where:
$U_{s(i)}$ is the number of UEs in the sector;
N is the total PRRHs;
K is the total sectors;
C is the number of UEs connected in PRRH*j*;
R is a binary variable where it takes the value 1 if PRRH*j* is allocated to sector *s*;

For each period *i*, and for each sector *s*, a vector $U_{s(i)}$ is created, which is used in the objective function, respecting the maximum capacity of each sector, which is given by the variable *HC* (Hard Capacity). All $U_{s(i)}$ are tested to obtain the combination that generates the lowest possible $KPI_{(i)}$ value. This process involves reducing the number of blocked UEs and consequently maximizing QoS, as shown in equation 5.

$$MIN\_KPI_{(i)} = \sum_{s=1}^{k} (U_{s(i)} - HC), \quad (5)$$

$$(0, if(U_{s(i)} - HC) < 0) or((U_{s(i)} - HC) if(U_{s(i)} - HC) >= 0) \quad (6)$$

Where:
$KPI_{(i)}$ is the total number of UEs per sector on at hour *i*;
HC is the maximum capacity per BBU sector.

The output of the model is given by the vector: S_j^i={$S_1^i, S_2^i, ..., S_N^i$}, representing the sectors of the BBUs S_j^i and PRRHs that have been allocated to these sectors. Rest of the parameters can be found in Table II.

Algorithm 2: BPSO Pseudocode

```
Objective Function equation 2
Generates the initial particle pop
Determines the acceleration factor l c1 = 1.8
begin
    Initial Swarm
    while t < MaxGenerations do
        for i = 1 until n do
            for j = 1 until n do
                if I_j > I_i then
                    search i search for solutions j
                end
                Evaluates new solutions and updates
                  particles
            end
        end
        Rank the particles and find the best one
    end
end
```

TABLE II
BPSO PARAMETERS

Parameters	Values
Local acceleration factor(Pbest)	1.8
HC	200
Global acceleration factor (Gbest)	1.8
Total size	220
Number of interactions	100

V. SIMULATION

In this section, the details of the scenario implemented in this work will be outlined. These involved procedures that were carried out in a machine with an Intel(R) Core(TM) i5-3317u processor and with a 1.7GHz clock and 8GB DDR3 RAM. The simulator chosen to perform the simulations was Matlab[1], since it has vast documentation.

A. Network Parameters

Cellular coverage can be defined based on coverage, power, coding methods and propagation losses [15]. Effectively, the path loss can be measured from the Hata model and its COST231 extension for Carrier Frequency (CF) below 2 GHz and from the Stanford University Interim (SUI) model for CF above 2 GHz [16]. The Signal-to-Interference-Plus-Noise Ratio (SINR) of the downlink for a given sub-carrier N is assigned to UE k in the PRRH to which it is connected. This can be expressed as equation 7:

$$SINR_k = \frac{P_{k,b(j)}}{\sigma^2 + I_k} \tag{7}$$

[1]https://la.mathworks.com/products/matlab.html

Where $Pk, b(j)$ is the received power (in watts) on subcarrier N assigned to UE k by the PRRH $b(j)$ serving it, σ^2 is the thermal noise power and I_k is the intercellular interference from neighboring PRRHs. All the PRRHs are assumed to be transmitting at maximum power P. The received power at UE k of PRRH $b(j)$ can be calculated using equation 8, which expresses the received power of a UE k based on transmitted power and signal fading. The SUI [17] propagation model was used to calculate the fading signal.

$$P_{k,b(j)} = \frac{10^{\frac{TP+G(k)-L_{SUI}}{10}}}{1000} \tag{8}$$

Where TP is total power of the incoming signal of interest, G is the Gain and L_{SUI} it is the value in dB of the fading signal which is calculated by the SUI propagation model, and expressed by the following equations:

$$L_{SUI} = A + 10\gamma log\frac{d}{d_o} + W, d > d_o, \tag{9}$$

$$A = 20log\frac{4\pi d_o}{\lambda}, \tag{10}$$

$$\gamma = a - bh_b + \frac{c}{h_b} \tag{11}$$

In which d is the distance from the PRRH to the measured point in meters, d_o is equal to 1 meter in accordance with [18]; λ is the wavelength in meters; γ is the exponent of the path loss; h_b is the height of the PRRH, which can be between 10 and 80 meters; a, b and c are the constants that depend on the type of terrain of the scenario; in this case, c was used (a = 3.6, b = 0.005 and c = 20); W is the shading effect, which can be between 8.2 and 10.6 dB.

It was assumed that each UE reaches the limit set by the Shannon capacity theorem, that is, the data rate for k is expressed as [18], where B is the system bandwidth equation 12.

$$C_k = Blog2(1 + SINR_k) \tag{12}$$

In the proposed scenario, a mobile H-CRAN network was implemented, where, the network flow was based on the UE profile of districts of New York City, which have an area is 4km long [6]. This scenario will make it possible to investigate a large amount of information that plays a vital role in traffic engineering, network design, load balancing and pricing, which can be observed in Fig.4. 100 PRRHs were randomly placed, one MRRH, one BBU pool with five resident BBUs and 3600 UEs with uniform characteristics, so that all the UEs could have the same requirements. The dimensions of the scenario were normalized according to the territorial limits of the New York [6] region. The rest of the parameters can be found in Table 3.

The problem discussed in this paper is divided into two phases. The first stage seeks to reduce the number of under-utilized PRRHs during their daily operation; this process is explained in Section IV.A. In the second, after obtaining the results from the first stage, a balancing between the active BBUs and their respective sectors; this methodology is explained in Section IV.B.

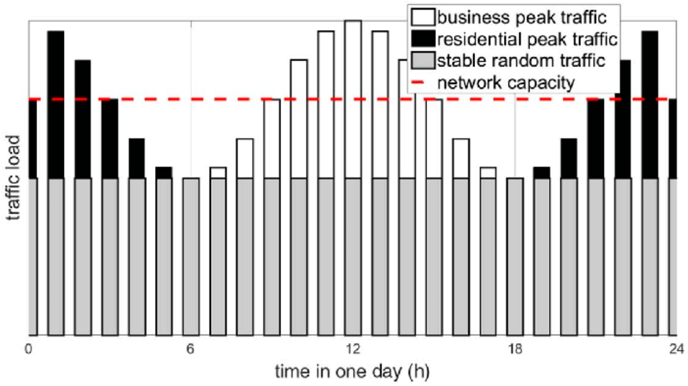

Fig. 4. Traffic Pattens per Hours from New York city [6].

TABLE III
SIMULATION PARAMETERS

Parameters	Values
Propagation loss (*MRRH*)	COST231
Propagation loss (*PRRH*)	SUI-TYPE A
Transmit Power (*MRRH*)	43 dBm
Transmit Power (*PRRH*)	23 dBm
Total Scene Area	4km²
PRRH Height	16m
Coverage area PRRH	150m
Coverage area MRRH	4km
Confidence Interval	95%
Number of Experiments	31

VI. RESULTS

In this section, the results obtained from our framework will be examined and compared with other approaches in the literature, LTE-A, HDSO and DPSO [3], [8], [9]. In Fig. 5 the averages of active PRRHs are displayed over a period of 24 hours, where it can be observed that the SAoff algorithm proved to be more effective in solving the problem being studied. On average, it maintained 89% of their active PRRHs, 9% less than HDSO and 10% less than LTE-A. In the period when there was a lower data flow, SAoff managed to turn off 44% of underutilized PRRHs, 20% more than HDSO and 44% more than LTE-A, thus showing the high capacity of the algorithm to deal with the heavy traffic of big cities.

In Fig. 6 the average throughput of the UEs in the network is analyzed. It can be seen that both the approaches discussed here can maintain the minimum throughput, although the SAoff can keep more UEs connected even with an average throughput 0.5% lower than HDSO. This fact can be attributed to the effectivce decision to keep the PRRHs active and, hence ensure a better distribution of resources among all the UEs.

In the context of load balancing between the sectors of the BBUs, three different techniques have been applied to mitigate the problem studied. The first is called Random Balance, which is an approach without any load balancing or intelligent mapping; the second, called BPSO, uses the two-level balancing system proposed here; finally, DPSO also uses intelligent balancing, as advocated by [9].

Fig. 7 presents the results obtained, where it can be seen that the convergence curve of UEs per sector of the BBUs in BPSO has a lower average than the other approaches,

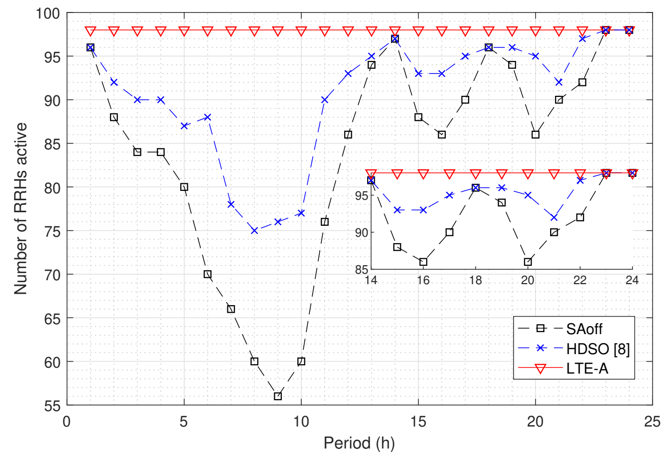

Fig. 5. Number of PRRHs in 24 hours.

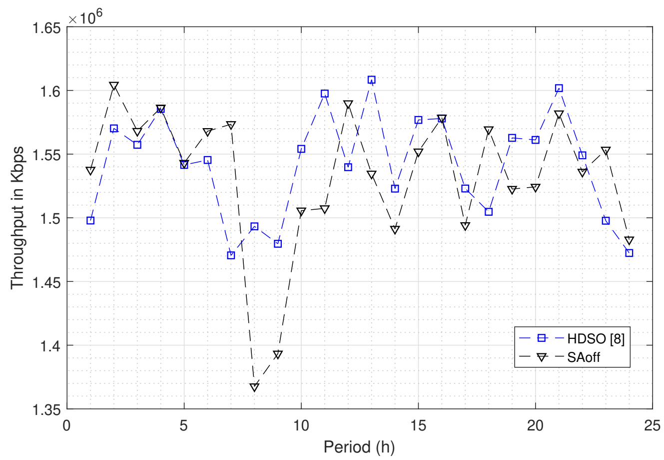

Fig. 6. Average UEs throughput rate during 24 hours.

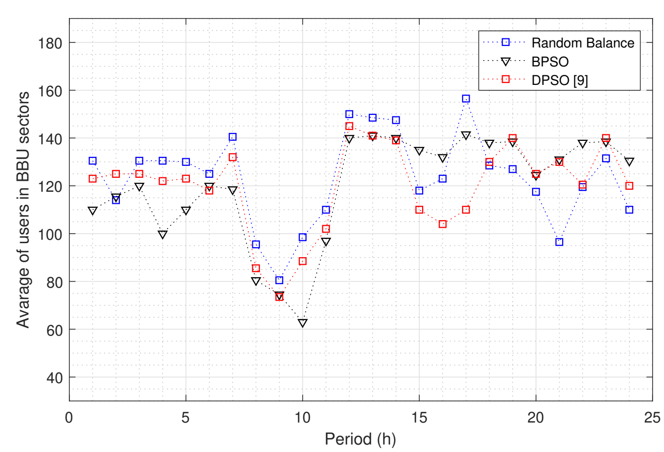

Fig. 7. Load balancing between BBU sectors.

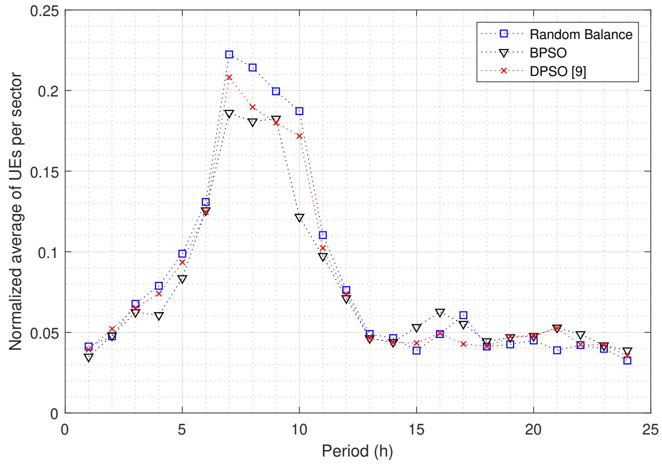

Fig. 8. Normalized average of UEs per sector in 24 hours.

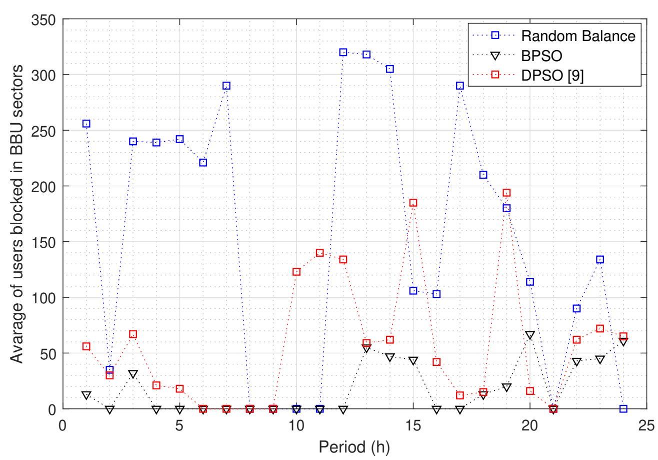

Fig. 9. Number of users blocked in 24 hours.

which results in a more balanced and optimized network, thus reducing the number of blocked UEs. In Fig.8 the average of UEs allocated in the sectors is presented but normalized by the current number of active UEs in a given hour, it can be seen that the algorithm better distributes users among the sectors, where it should be highlighted hours 15 to 17, where there was an increase in the number of users per sector when compared to the other approaches. This fact is attributed to the mapping process between RRHs and the sectors of BBUs, where a load coming from a RRH cannot be divided among different sectors.

This statement is supported by the average number of blocked UEs, which is shown in Fig. 9, over the 24h. The Random Balance which, using random assignment, averaged 153.8 blocked UEs, while DPSO averaged 57.2 and BPSO averaged 18.3. This represents a decrease of approximately 88.1% and 68% in the number of blocked UEs, respectively, thus demonstrating the effectiveness of the proposed resource orchestration.

VII. Conclusion

The constant increase in the number of cell phones and IP devices has driven the industry and academia to seek new solutions to meet this new demand. For this reason, the problem investigated in this paper is the intelligent orchestration of the resources of an H-CRAN network, through the intelligent turn off of PRRHs and optimized load balancing of UEs between the BBUs. In the context of PRRH sleep, the SAoff that had been designed, was able to 'sleep' more PRRHs than the algorithm used in the literature and maintain the stipulated QoS. Regarding resource balancing, BPSO averaged 68% fewer blocked users during the 24h analyzed when compared to DPSO, thus resulting in a more balanced network. In future work, it is recommended that the new KPIs should be incorporated to evaluate new factors and test the balancing in several scenarios.

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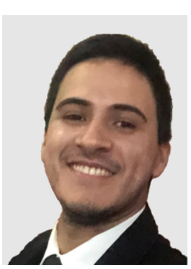

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