

# A Comparison of Knapsack Optimisation and CRE/ABS for MLB in Dense Self Organising Small Cells

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## Abstract

We investigate the performance of a new approach for mobility load balancing (MLB) and user association in future 5G dense small cell networks. This Self Organising Network (SON) approach uses a Knapsack Optimisation (KO) algorithm to evenly distribute users across a network of small cells. It is shown that the new technique achieves substantial improvements (better than four times reduction) in blocking ratios compared to the case when no MLB strategy is deployed. Comparisons with other MLB approaches relying on Cell Range Expansion (CRE) and Almost Blank Subframes (ABS) are presented highlighting the effectiveness of the new approach as a centralised self optimisation technique for future dense self organising small cells.

**Keywords**—Small Cells; Self-Organising Networks (SON); Mobility Load Balancing (MLB); Knapsack Optimisation (KO); CRE; ABS; Wireless network planning and optimisation.

## 1. Introduction

The ever increasing demands for advanced and bandwidth hungry broadband services as well as enhanced Quality of Experience (QoE) for the end users together with spectrum efficiency and reduced energy consumption, have resulted in several challenges in designing and planning next generation “5G” wireless networks [1,2]. The use of network densification through the deployment of low power small cells, whether by a mobile network operator or an end user, is recognised as one of the key strategies towards achieving the 5G vision and targets. By densely deploying additional small cell [3-5] nodes within the local area range and bringing the network closer to end users, the performance and capacity are significantly improved. This in turn allows future systems to achieve higher aggregate data rates at lower energy levels, while retaining seamless connectivity and mobility resulting in improved QoE and user satisfaction of the services being delivered by the network.

SESAME (Small cELLS coordination for Multi-tenancy and Edge services) [6] is a project that targets innovations around three central elements in 5G: i) the placement of network intelligence and applications in the network edge through Network Functions Virtualisation (NFV) and Edge Cloud Computing; ii) the substantial evolution of the Small Cell concept, already mainstream in 4G but expected to deliver its full potential in the challenging high density 5G scenarios; and iii) the consolidation of multi-tenancy in communications infrastructures, allowing several operators/service providers to engage in new sharing models of both access capacity and edge computing capabilities resulting in a Small Cell as a Service (SCaaS) concept. Typical examples of use cases include deployment of small cell nodes to serve a busy large business or shopping centre, service provision to a sudden concentration of users in hotspots such as in a stadium, a conference centre, an exhibition or a carnival venue with users generating high data rate real time multimedia content.

With the dense and dynamic deployment of a large number of small cell nodes in a network, there is an essential need to adopt Self Organizing Networks (SON) technologies and advanced radio resource management capabilities [7-9] to facilitate network management and to reduce or ultimately remove the need for human intervention in the planning, deployment, optimisation and maintenance of the network infrastructure. Adoption of SON techniques also known as Self-X (self-planning, self-optimization and self-healing) result in rapid and efficient deployment of network nodes and considerable reduction in capital (CAPEX) and operational (OPEX) costs. SESAME proposes the Cloud-Enabled Small Cell (CESC) concept, a new multi-operator enabled Small Cell that integrates a virtualised execution platform (the Light DC (Data Center)) for deploying Virtual Network Functions (NVFs), supporting powerful Self-X management and executing novel applications and services within the access network infrastructure.

One of the main self-optimisation strategies in a SON is Mobility Load Balancing (MLB) [10-11]. MLB addresses the problem of uneven traffic distribution in mobile networks. The main target of MLB and traffic steering algorithms is to enable overloaded cells to re-direct a percentage of their load to neighbouring less loaded cells hence alleviating congestion problems. The expected gains from MLB algorithms are highest when participating cells exhibit different usage patterns with respect to time. The resulting increased network efficiency using MLB, postpones the deployment of additional network capacity hence reducing capital costs (CAPEX). This is traditionally done through Cell Range Expansion (CRE), achieved by either cell coverage and/or mobility parameter adjustments. The CRE based distributed approach may lead to network performance degradation due to the frequency reuse of one adopted in LTE based networks. Re-allocating a user to a base station other than the one offering the highest signal level, as CRE sometimes does, may result in increased interference levels. Suitable self-organizing MLB strategies should automatically react to varying traffic and dynamic mobility patterns and should also take into account multiple tenancy as neighbouring cells can generally belong to any tenant or operator. In multi-tenant Radio Access Network (RAN) deployments, where shared resources are allocated based on static or dynamic Service Level Agreements (SLA), the formulation of the “user-association” problem needs to take full account of multiple (and possibly conflicting) service types and requirements, as additional/new sets of constraints need to be met. We present in this paper, a new Knapsack Optimisation (KO) approach to MLB and the user association problem for dense small cell deployments. The generality of this KO based centralised approach makes it suitable to answer the several constraints that need to be met in a cluster of small cells densely deployed network wide and also suitable for implementation in a Light DC as proposed by SESAME. The paper is organized as follows: Section 1 sets the scene and highlights the need for new optimized MLB techniques specifically targeting small cells. Section 2 presents the mathematical framework of the MLB-KO approach. Section 3 presents examples of simulation use cases and comparisons with CRE and ABS highlighting the effectiveness of the approach. Finally, conclusions are summarised in Section 4.

## **2. Knapsack Optimisation for MLB in Small Cells**

### **2.1 Background**

The main modelling approaches for the user association problem are based on a “utility” cost function maximisation that quantifies the satisfaction that a certain metric is met. Examples of such approaches include game theory, stochastic geometry and combinatorial optimisation. Combinatorial optimisation has the advantage of being a generalised approach for the utility maximisation problem. Several techniques relying on combinatorial optimisation were previously investigated and reported e.g. [12-21] all tackling the user association problem from different perspectives and with different targets. Knapsack

Optimisation KO [22] is a combinatorial optimisation technique that, to our knowledge has not been reported previously for the target application of this paper (MLB for dense small cell deployments). KO is a natural solution to the problem of associating a number of end users to a number of small cells with the aim of achieving efficient MLB throughout the network under specific constraints as will be described below. The knapsack problem can be described as follows: Given a knapsack with a fixed capacity and a set of items, each item is associated with an individual profit and a weight. The problem is to select a subset of items such that the total profit of the selected items is maximised without exceeding the capacity. A more generalised form is the Multiple Knapsack Problem (MKP) where a set of knapsacks are considered rather than one.

## 2.2 System Model

Given  $N$  end users and  $M$  small cell base stations, then the generalised MKP can be formulated as follows:

Assign each user  $i$  with a weight  $w_i$  to exactly one small cell base station  $j$  such that the total capacity or throughput (i.e. the total profit in the context of MKP) of the network  $C$  is maximised and without assigning user weights greater than the individual capacity  $c_j$  of any individual small cell base station  $j$ . Considering LTE/LTE-A networks, the weight of user  $i$  if assigned to base station  $j$ :  $w_{ij}$  is defined as the required Physical Resource Blocks (PRB) by the user to achieve a certain target individual Quality of Service (QoS) while the profit  $p_{ij}$  is the achieved individual throughput which is a function of the Signal to Interference plus Noise Ratio (SINR) of user  $i$  when connected to base station  $j$ . This can be formulated as follows:

$$\max C = \sum_{j=1}^m \sum_{i=1}^n p_{ij} x_{ij} \quad (1)$$

$$\text{subject to } \sum_{i=1}^n w_{ij} x_{ij} \leq c_j, \quad j \in M = \{1, \dots, m\} \quad (2)$$

$$\sum_{j=1}^m x_{ij} = 1, \quad i \in N = \{1, \dots, n\} \quad (3)$$

$$\text{with } x_{ij} = \begin{cases} 1 & \text{if user } i \text{ is assigned to small cell base station } j; \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

The SINR of user  $i$  associated with small cell base station  $j$  can be written as:

$$SINR_{ij} = \frac{P_j |H_{ij}|^2}{\sum_{k=1, k \neq j}^m P_k |H_{ik}|^2 + \sigma_i^2} \quad (5)$$

where  $P$  is the transmission power of the base station,  $H$  is the channel transfer function between the user and the base station and includes the effects of path loss, shadowing, antenna patterns and other losses and  $\sigma^2$  is the thermal noise power at the user's receiver.

An additional constraint is added to the optimisation problem to ensure that the individual user's SINR is above a certain minimum threshold value to reject users suffering from excessively bad radio channel conditions and/or interference from unnecessarily overloading the target small cell base station.

$$SINR_{ij} \geq SINR_{threshold} \quad (6)$$

When  $N$  and  $M$  increase, the MKP problem becomes NP-hard [22]. A possible approach to solve the above optimisation problem is to use the Greedy algorithm. This is implemented by sorting all the users in a decreasing order of their profit to weight ratios before associating them to individual small cells.

Examples highlighting the effectiveness of the KO approach for MLB in dense small cells and comparisons with CRE and ABS are presented in the following section.

### 3. Simulation Results and Discussion

#### 3.1 An Illustrative Two-Cell Scenario

We first consider a relatively simple case of a two small cells in an LTE network. Users are randomly located around the centre of each cell with a uniform distribution. The load (weight) of each user is obtained through a uniformly distributed random variable with an average value of five PRB. Users' speeds are randomly generated using a uniform distribution with an average speed of 30 km/h. Log normal shadowing with a mean value of 4 dB is considered. The first cell is intentionally made to be heavily overloaded ( $>$  cell maximum capacity) while the second cell has a spare capacity. An illustration of the simulation scenario is shown in Fig.1 and a summary of the main simulation parameters is shown in Table 1.

TABLE 1 MAIN SIMULATION PARAMETERS FOR THE TWO-CELL SCENARIO

Number of cells	2
Cell radius	20 and 10 m
Number and location of users	35 and 10 users uniformly distributed
Cell maximum capacity	100
User load	Variable with uniform distribution Average= 5 PRB
User speed	Variable with uniform distribution Average = 30 km/h
Carrier Frequency	2 GHz
Bandwidth	20 MHz
Small Cell Transmit Power	23 dBm
Noise Power Spectral Density (PSD)	-174 dBm/Hz
Path loss (in dB)	$140.1+36.7 \text{ Log}_{10}$ (distance in km)
Log normal shadowing mean value	4 dB

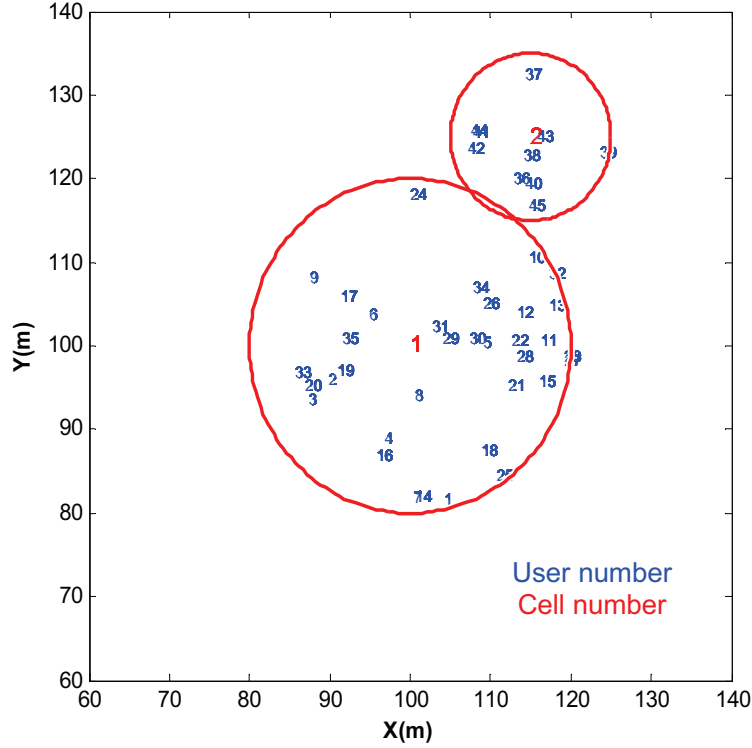
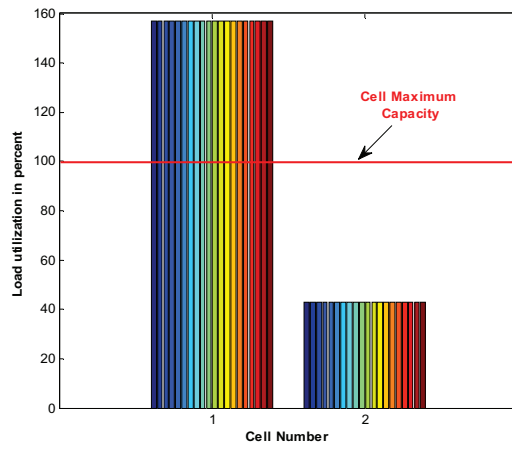


Fig. 1 Network topology example with two cells and 45 users

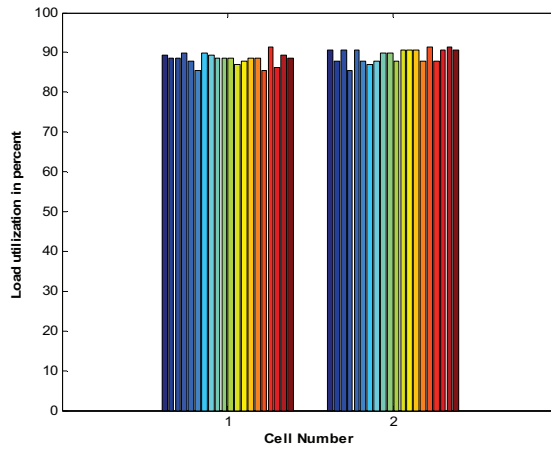
The metric used to assess the effectiveness of Mobility Load Balancing using Knapsack Optimisation (MLB-KO) is the Blocking Ratio (BR). BR is defined as the number of blocked (unserved) users  $U_b$  divided by the total number of users  $U_t$  in the network (or the cluster of participating small cells).

$$BR = \frac{U_b}{U_t} \times 100\% \quad (7)$$

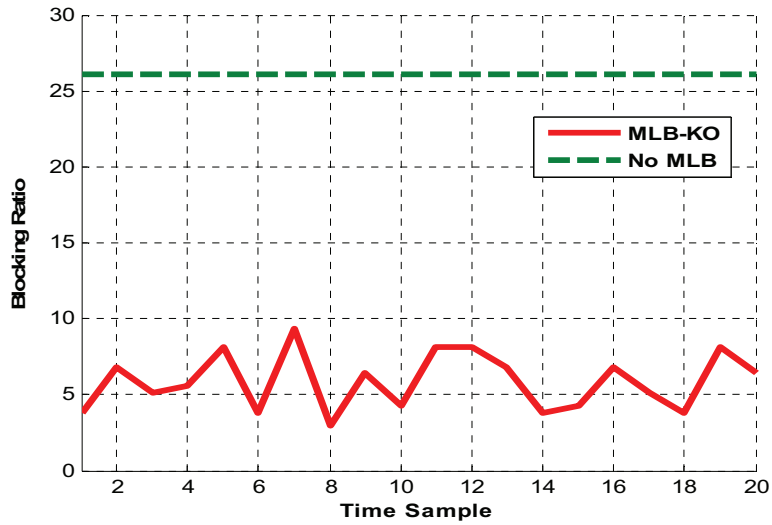
Fig.2 (a) shows the load of the two cells before implementing the KO approach. Cell 1 is overloaded and exceeds the maximum allowed capacity. The MLB-KO technique redistributes the users across the two cells subject to the above constraints to balance the loads resulting in a more even distribution as shown in Fig. 2(b). The technique is tested taking into account the effect of the variation of path loss and subsequently the individual SINR value of each user due to shadowing and random user speeds. The blocking ratio is calculated for every simulation time sample. It is concluded that the average blocking ratio drops from 26.06 % to 5.89% with MLB-KO resulting in more than four times improvement for the studied network topology as shown in Fig. 2 (c).



(a) Load Distribution with No MLB



(b) Load Distribution after MLB-KO



(c) Dynamic Variation of the Blocking Ratio

Fig. 2 Comparison of the Blocking Ratio before and after MLB-KO for the two cell scenario

### 3.2 Comparisons with CRE and ABS

We now compare the performance of the MLB-KO technique with approaches proposed for traffic steering and load balancing namely enhanced Inter Cell Interference Coordination (eICIC) as defined in the 3GPP release 11 standard. The eICIC strategies rely on CRE together with ABS.

CRE works by adding a positive bias to increase the coverage of a low power base station hence attracting edge users. Off-loaded users may experience unfavourable channel conditions and interference from biased cells. There is therefore a trade-off between load balancing and the achieved throughput depending on the bias value. ABS is a time domain technique that aims at improving the overall throughput of off-loaded users by sacrificing a part of the resources or throughput of unbiased cells. A user typically select a cell with a maximum ABS ratio (i.e. ratio of blank over total subframes).

A more challenging use case is now considered with a seven small cell scenario and 120 users unevenly distributed as illustrated in Fig. 3. Users are uniformly distributed from 5 to 35 per cell.

Three different CRE bias values were tested (6, 9 and 12 dB) together with an ABS ratio of 20%. The blocking ratio was calculated at every simulation time sample. Fig. 4 shows the load distribution among the seven cells (a) before MLB-KO, (b) after MLB-KO and (c) in the case when CRE with 9 dB bias and an ABS ratio of 20% are used. Fig. 5 shows the variation in BR resulting from path loss dynamics due to shadowing and users' speed. The average BR values are reported in Table 3 for the different studied techniques. It is concluded that the MLB-KO technique outperforms CRE/ ABS by at least 1.5 times for the 12 dB case increasing to 2.3 times for the 6 dB case and achieves more than four times improvement in BR compared to the case where no MLB scheme is implemented for the studied scenario.

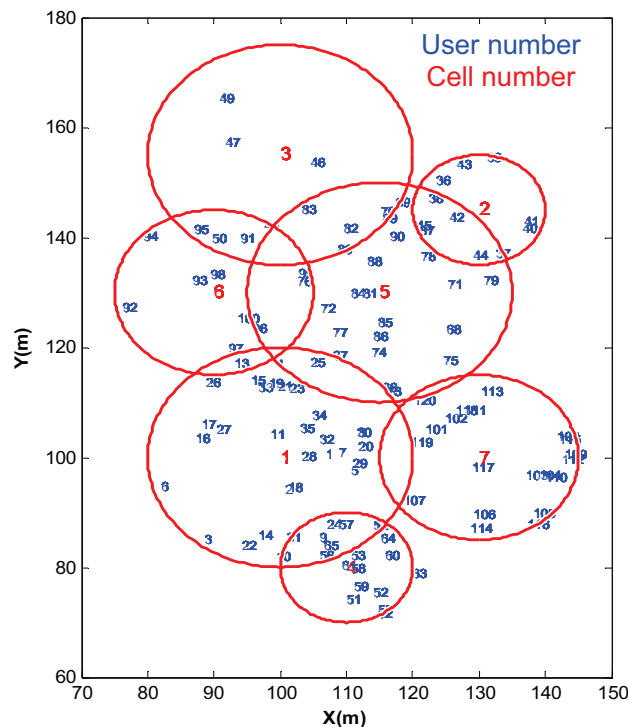
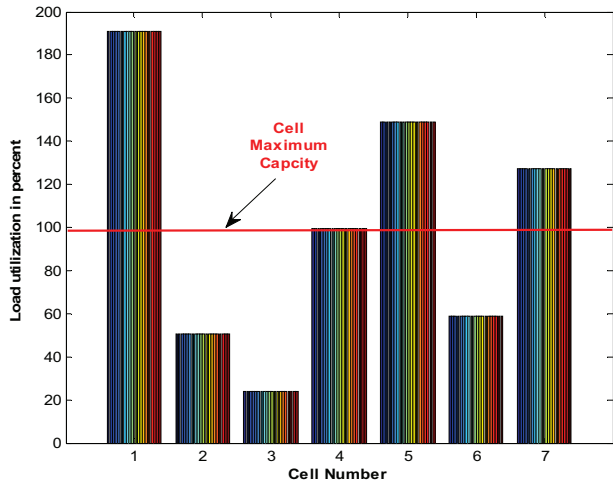
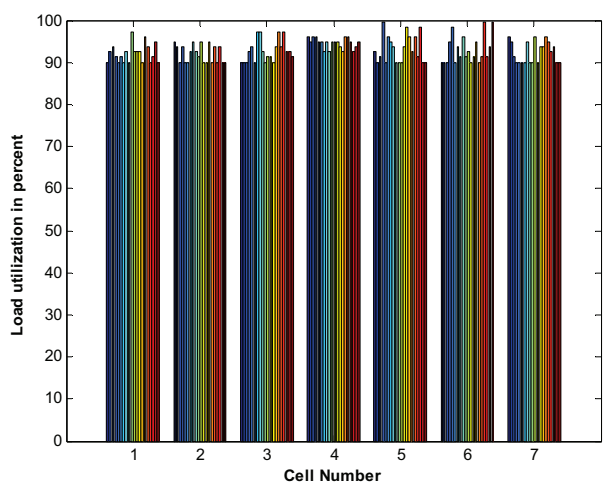


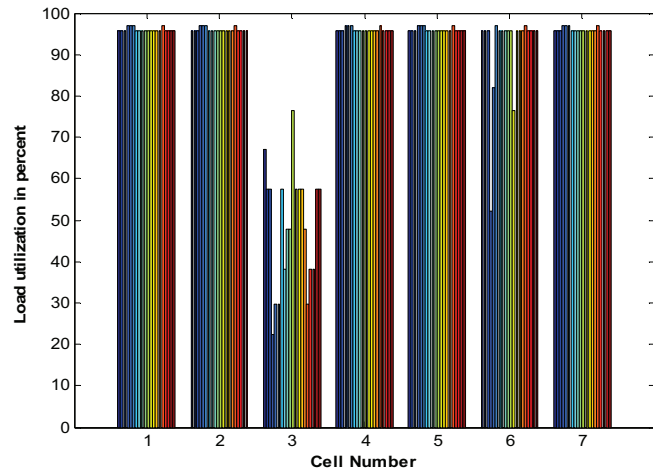
Fig. 3 Network example with 7 cells and 120 users



(a) No MLB



(b) After MLB-KO



(c) With an example of CRE (9dB) and ABS (20%)

Fig. 4 Load distribution for the seven cell scenario

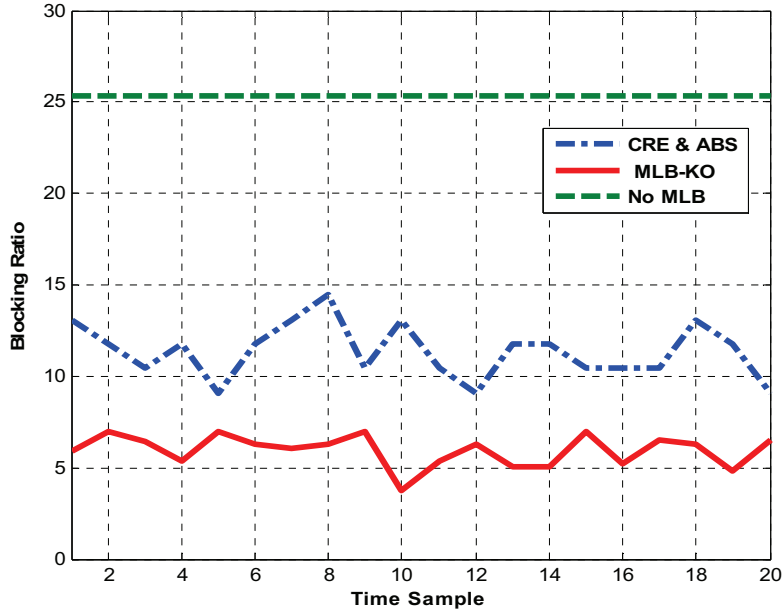


Fig. 5 Dynamic variation of the Blocking Ratio for the seven cell scenario (CRE: 9dB, ABS: 20%)

TABLE III. COMPARISON OF BLOCKING RATIOS FOR THE DIFFERENT TECHNIQUES

Technique	Average BR (%)	Improvement factor of MLB-KO
No MLB	26.06	4.22 x
CRE= 6 dB	14.78	2.39 x
CRE= 9 dB	12.31	1.99 x
CRE= 12 dB	9.55	1.54 x
MLB-KO	6.17	-

#### 4. Conclusions

A new approach for user association and Mobility Load Balancing (MLB) in dense small cells based on Knapsack Optimisation (KO) was presented. Example simulation scenarios targeting dense clusters of small cells deployments show that the MLB-KO technique is capable of achieving more than four times improvement in blocking ratios compared with the case where no MLB strategy is deployed in a network or a cluster of small cells. Moreover, MLB-KO always outperforms eICIC techniques relying on CRE and ABS for different bias values. The generality of the technique makes it suitable to support multi-tenancy and the vision for Small Cells as a Service (SCaaS) as advocated by the SESAME project. The future work aims at evaluating the signaling overheads for this new technique in different scenarios.

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