Knapsack Optimisation for Mobility Load Balancing in Dense Small Cell Deployments

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Abstract. We present a new approach for mobility load balancing (MLB) and user association in dense small cell scenarios. This Self Organizing Network (SON) approach relies on Knapsack Optimisation (KO) to evenly distribute users across participating cells subject to constraints. It is shown that the new technique referred to as (MLB-KO) achieves substantial improvements (better than three times reduction) in blocking ratios for the studied use cases.

Keywords: Small cells · Self-Organizing Networks (SON)
Mobility Load Balancing (MLB) · Knapsack Optimisation (KO)
Wireless network planning and optimisation
Cognitive networks · 5G

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

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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: Sect. 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 used MLB-KO approach. Section 3 presents examples of simulation use cases highlighting the effectiveness of the approach. Finally, Sect. 4 concludes the paper.

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.

For LTE 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:

$$\begin{aligned} \max C &= \sum_{j=1}^{m}\sum_{i=1}^{n} p_{ij}x_{ij} \\ \text{subject to } & \sum_{i=1}^{n} w_{ij}x_{ij} \le c_j, \quad j \in M = \{1,\ldots, m\} \\ & \sum_{j=1}^{m} x_{ij=1}, \qquad i \in N = \{1,\ldots, n\} \end{aligned} \tag{1}$$

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

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

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

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 σ^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.

$$SINR_{ij} \geq SINR_{threshold} \tag{3}$$

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 are presented in the following section.

3 Simulation Results and Discussion

We first consider a relatively simple case of a two small cell 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 5 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.

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.

$$BR = \frac{U_b}{U_t} \times 100\% \tag{4}$$

Figure 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

Table 1. Main simulation parameters for the two cell scenario

Parameter	Value
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 = 20 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 Log10 (distance in km)
Log normal shadowing mean value	4 dB

technique redistribute 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).

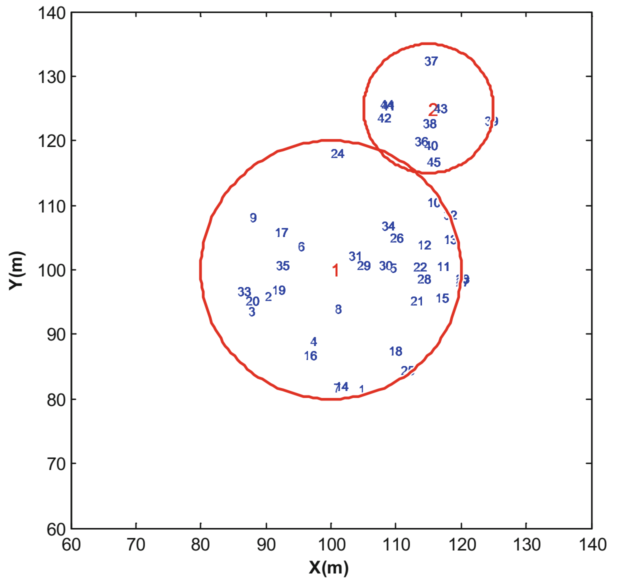
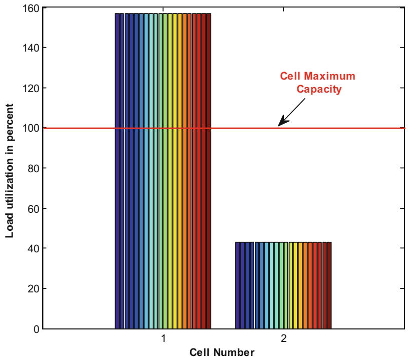
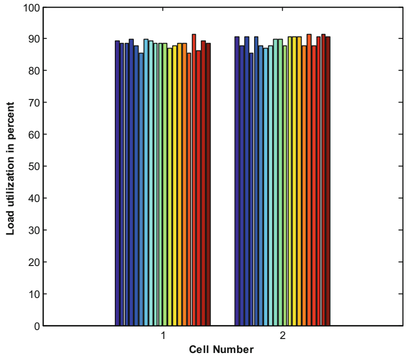


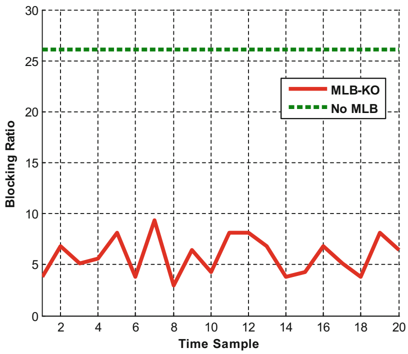
Fig. 1. Network topology example with two cells and 45 users



(a) No MLB



(b) After MLB-KO



(c) Blocking Ratio

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

Table 2. Main simulation parameters for the seven cell scenario

Parameter	Value
Number of cells	7 (randomly located)
Cell radius	Variable 10 to 20 m
Number and location of users	Variable 5 to 35 users per cell 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 Log10 (distance in km)
Log normal shadowing mean value	4 dB

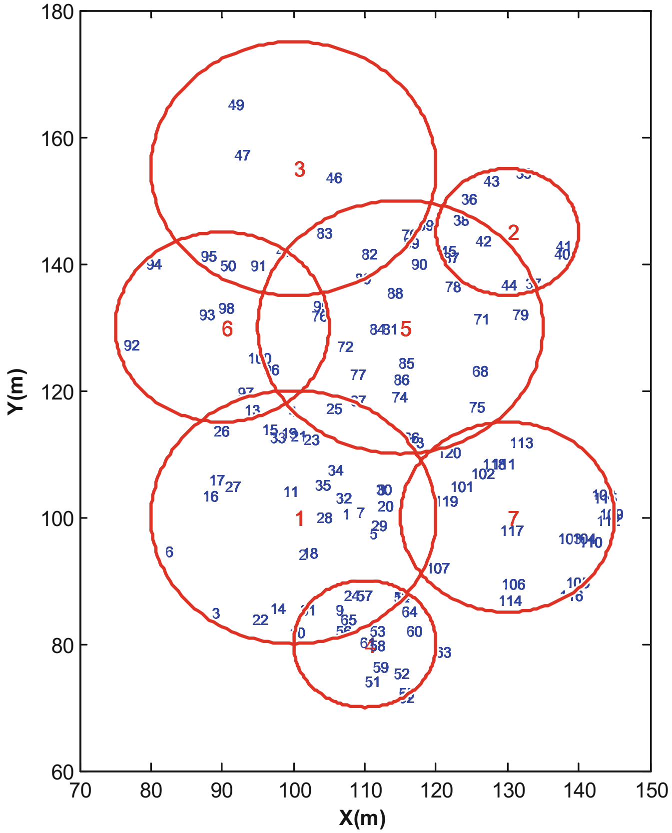
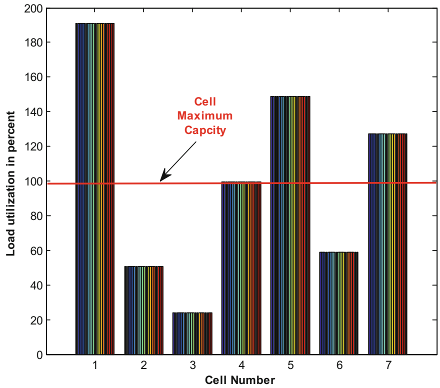
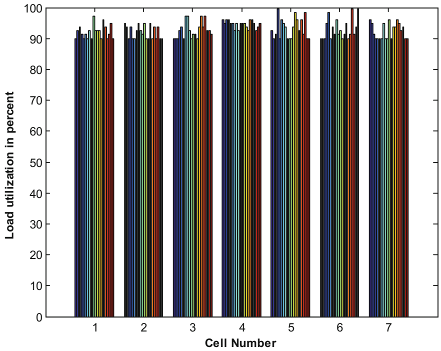


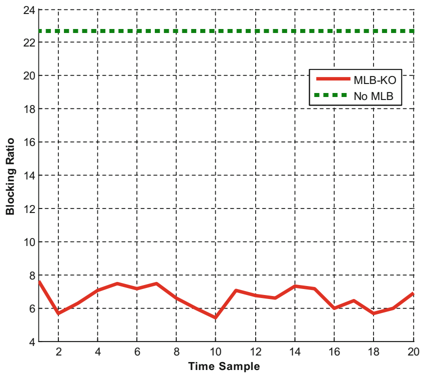
Fig. 3. Network topology example with seven cells and 120 users



(a) No MLB



(b) After MLB-KO



(c) Blocking Ratio

Fig. 4. Comparison of the blocking ratio before and after MLB-KO for the seven cell scenario

A more challenging use case is now considered with a seven small cell scenario and 120 users unevenly distributed as illustrated in Fig. 3. A summary of main simulation parameters is presented in Table 2.

Figure 4 shows the load distribution for each of the seven cells (a) before and after MLB-KO (b). Figure 4(c) shows the variation in BR resulting from path loss dynamics due to shadowing and users' speed with sampling time. It is concluded that the MLB-KO technique achieves approximately 3.5 times improvement in blocking ratio compared to the case where no MLB scheme is implemented for the studied seven cell scenario.

4 Conclusions

A new approach for user association and MLB in dense small cells based on Knapsack Optimisation was presented. Example simulation scenarios targeting dense small cells deployments show that the MLB-KO technique is capable of achieving three to 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. 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 comparing the performance of MLB-KO with enhanced Inter Cell Interference Cancellation (eICIC) techniques relying on Cell Range Expansion (CRE) and Almost Blank Subframes (ABS) and investigating signaling overheads.

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