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RESEARCH ARTICLE

Self organising cloud cells: a resource efficient network densification strategy†

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ABSTRACT

Network densification is envisioned as the key enabler for 2020 vision that requires cellular systems to grow in capacity by hundreds of times to cope with unprecedented traffic growth trends being witnessed since advent of broadband on the move. However, increased energy consumption and complex mobility management associated with network densifications remain as the two main challenges to be addressed before further network densification can be exploited on a wide scale. In the wake of these challenges, this paper proposes and evaluates a novel dense network deployment strategy for increasing the capacity of future cellular systems without sacrificing energy efficiency and compromising mobility performance. Our deployment architecture consists of smart small cells, called cloud nodes, which provide data coverage to individual users on a demand bases while taking into account the spatial and temporal dynamics of user mobility and traffic. The decision to activate the cloud nodes, such that certain performance objectives at system level are targeted, is carried out by the overlaying macrocell based on a fuzzy-logic framework. We also compare the proposed architecture with conventional macrocell only deployment and pure microcell-based dense deployment in terms of blocking probability, handover probability and energy efficiency and discuss and quantify the trade-offs therein. © 2014 The Authors. *Transactions on Emerging Telecommunications Technologies* published by John Wiley & Sons, Ltd.

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1. INTRODUCTION

In recent years, there has been a tremendous increase in the number of mobile handsets, in particular smartphones, supporting a wide range of applications, such as image and video transfer, cloud services and cloud storage. Consequently, the average smartphone usage rate has nearly tripled in 2011 alone, and the overall amount of mobile data traffic demand grew by 2.3 times [1] in the same period. Furthermore, the amount of mobile data traffic is expected to increase dramatically in the coming years; recent forecasts are expecting the data traffic to increase by more than 500 times in the next 10 years [2, 3]. If the current traffic demand growth rate is maintained, current cellular system capacity will not be able to cope with it. Therefore, future cellular systems have to be designed to contain the expected traffic growth. The increase of traffic demand leads to the need for further densification of the network, especially in areas where traffic demand is the highest (hotspot areas). Although further densification provides means to overcome this increase of traffic, it proposes several challenges that need to be addressed, such as increased signalling level due to the increased handover events and dramatic increase in the power consumption.

Moreover, traffic load varies from time to time such as the typical night-day behaviour of users and their daily swarming to offices and back to residential areas [4]. While traffic varies, the power consumption of the radio access network does not effectively scale with it. In mobile networks, 10% of the overall power consumption corresponds to the cellular users, whereas 90% is incurred by the operator network [5]. The mobile network access part consumes a huge amount of energy in the base station (BS) operation. As network densification is envisioned as a key

source to accommodate the gigantic capacities expected from future cellular networks, the high energy consumption and mobility-related overheads are emerging as even bigger challenges.

As a back drop of these challenges, in this paper, we present a novel network densification strategy that exploits the notion of demand-based cloud-cell coverage to minimise the energy consumption and the handover-related overheads while maintaining quality of service (QoS) thresholds, for example, in terms of blocking probabilities. The proposed solution has the ability to self-organise the network deployment in order to gain the potential resource efficiency that can be harnessed from the spatiotemporal dynamics of user traffic, which are inherent to any cellular system.

The remainder of this paper is organised as follows: Section 2 presents related work. Section 3 explains our proposed alternative deployment strategy. Section 4 describes the proposed dynamic network optimisation framework, and Section 6 provides the simulation results. Finally, Section 7 concludes the work.

2. RELATED WORK

This section presents the state of the art in the deployment strategies that aim to achieve an energy-efficient deployment for the radio access parts of a cellular system. We focus mainly on two approaches, the heterogeneous deployment and a network management approach for their relevance to this work. The heterogeneous deployment aims to offload traffic from the macrocell to small cells deployed in the area of the overlay network. On the other hand, the network management approach adopts a self-organising methodology to manipulate the active node deployment by switching on/off the nodes with the aim of saving energy.

It is widely believed that using a mixed topology of macro with femto or microcells could lower the energy consumption for a targeted achievable capacity, thereby providing a heterogeneous deployment approach. It is well known that radio signals are subject to various channel attenuations. One of the major losses is building propagation loss: the indoor users suffer, compared with outdoor users, because of in-building penetration loss. This implies that the radio links that are subject to high losses are the most expensive in terms of macrocell resources. Therefore, by deploying femtocells, macrocell resources such as capacity and energy can be saved. Such offloading benefits of femtocells are discussed in [6]. Moreover, an advantage of deploying micro BS is their ability to scale their power consumption to their activity level [7]. By exploiting such scaling, the deployment of microcells with macrocells gives the advantage of having a larger power saving compared with normal macro deployment to achieve a targeted spectrum efficiency and higher throughput [8–10].

On the other hand, in order to cope with growing network density, the replacement of human-driven (half-manual) network management solutions with techniques providing self-organising networks is also being considered [11, 12]. Such solutions for retaining resource efficiency fall under the category of network-management-based solutions. A promising approach of reducing the overall energy consumption of mobile networks in this category is to reduce the number of active network elements. This approach involves dynamically switching BS OFF, thereby achieving a dynamic deployment architecture. When BS is switched OFF, radio coverage and service quality must still be guaranteed (QoS) by neighbouring BS or other means [13–15]. As the traffic load varies during a day, adaptively setting the bandwidth utilisation according to this variation of traffic, thereby making the power amplifier operate closer to its most efficient operational point to achieve a more effective operation, is an alternative energy saving scheme that does not require switching off/on of nodes and thus avoids associated problems [16]. Around 29% energy saving is expected when bandwidth adaptation is adopted, and this can be much greater for areas with reduced load demand [16].

To summarise, to the best of our knowledge, most of the heterogeneous deployment-based approaches and network-management-based approaches in the literature generally consider the energy efficiency problem by optimising the system in its high-demand or low-demand regions and neglecting the other, both in time and space. These approaches also compromise on QoS in some aspects. On the other hand, our proposed deployment framework provides a generic self-organising solution that can optimise radio and energy-wise resource efficiency in future cellular systems both in high-demand and low-demand regions, without compromising on the QoS criteria. In the next section, we describe the core idea behind our proposed framework.

3. CLOUD COVERAGE: AN ALTERNATIVE TO CLASSIC STATIC DENSIFICATION APPROACH

In 3rd Generation Partnership Project (3GPP) LTE Release 10, network densification by deploying small cells has been an important subject to cover areas with high traffic growth. More recently, LTE Release 12 has also embarked on solutions containing small-cell enhancements. To achieve an optimal performance level and provide a cost-efficient and energy-efficient operation, small cells require further enhancements and may be required to complement and have the ability to communicate with existing macrocells' stations. However, network densification by means of deploying small cells proves to be a challenge, as small cell deployment creates and increases inter-cell and intra-cell handover that can affect connectivity, especially in existing high-mobility areas of the network [17]. Furthermore, network-wide deployment of small cells is difficult to operate and requires careful cell planning [3]. Therefore, solutions consisting of small cell deployment must overcome these challenges.

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For a given area to be covered, each cell size deployment provides a certain trade-off. When comparing large-cell (i.e. macrocells) and small-cell (i.e. micro, pico, femto and even WiFi nodes) deployment topologies, macrocells outperform smaller cells in terms of handover probability, which is expected because each smaller cell covers a fraction of the area; therefore, more handovers are expected and thus increased signalling is expected. On the other hand, from the point of view of blocking probability, small cells outperform macrocell deployment, which is one of the benefits of small-cell deployment [18]. In terms of power consumption, as the area of coverage increases, small-cell-deployment power consumption increases and surpasses the power consumption of macrocells for large coverage areas as the number of small cells increase to cover the area [19].

As each deployment topology has its weaknesses and advantages, considering which to deploy becomes a matter of perspective. For example, in a situation of low traffic demand and sparse user distribution, the deployment of a large cell is more efficient in terms of minimising handover and maximising operational/energy efficiency. On the other hand, in a situation of high traffic demand and/or dense user distribution, the availability of small cells is more beneficial because of the increase in the achievable capacity levels. Because traffic distributions and user demographics are far from being fixed in space or time, not even for duration of a day, none of the two deployment solutions discussed earlier may be optimal. To this end, in this paper, we propose a deployment strategy that is a hybrid of both. However, to overcome the drawback of traditional hybrid deployment, that is, increased power consumption and mobility management overheads, we propose to exploit the notion of cloud small cells to compliment the macrocells as compared with conventional small cells. Cloud small cells are smart small cells that underlay in the coverage area of the macrocell with high node density as shown in Figure 1. However, instead of being always on, these cells cooperate with their parent macrocell to become available on demand, that is, the coverage provided by these small cells can effectively follow the user and hence the name cloud cells and the term cloud coverage. The operation of the cloud cells can be controlled via the main macro station. The ability to have cooperative mechanisms between macrocells and small cells is already being envisioned in the 3GPP Release 12. Thus, when user equipments are in the coverage of the macrocell, the macro BS can evaluate the current situation in terms of traffic demand, current system performance level, target system performance level, criticality of user, energy tariffs at the time of day and many other similar factors to decide whether the activation of the respective cloud cells is needed or not. For example, if a certain part of the macrocell contains a large number of user equipments and the rest of the cell area has a low number of users with low traffic demand requests, the macrocell can offload the users in congested area by activating the respective cloud cells and handle the rest of the users on its own. This will consume less energy and will incur less handovers compared with a scenario where the total area is covered always by small cells. On the other side, it will create more capacity compared with a scenario where the total area is covered only by macrocells.

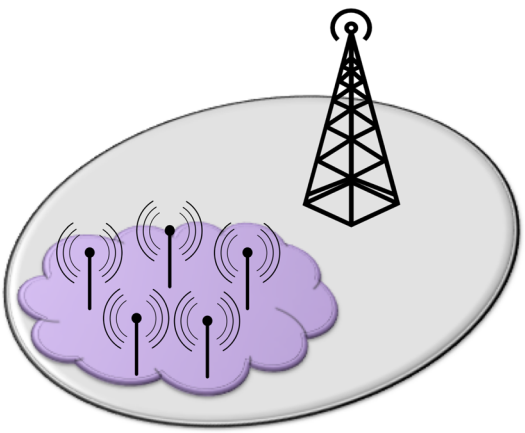

Figure 1. Cloud-cell architecture.

Our proposed dynamic approach enables the network topology to change based on current demand levels and performance expectations. Once new or different requirements arise, the proposed hybrid deployment topology can adapt with it. From the point of view of scalability, because cloud-cell coverage does not have to be continuous, initial deployment of cloud cells can be in the most affected parts of the network, to gradually add capacity. Further deployment can be based on capacity requirements by increasing the number of cloud cells in a given area. In the next section, we present the optimisation framework required to enable our cloud-cell-based deployment architecture.

4. DYNAMIC NETWORK OPTIMISATION FRAMEWORK

Self-organisation (SO) is not a new concept, it has been defined in several fields, such as computer science and biology [20]. The 3GPP aimed to provide a specification for agreed descriptions of use cases and solutions with emphasis on the interaction of self-optimisation, self-configuration and self-healing. A main document describing the concepts and requirements for self-organising networks in [21], self-establishment of eNodeBs in [22], self-optimisation in [23], self-healing in [24] and automatic neighbour management in [25, 26] is provided. The description in simple terms of those details of self-organising networks as in Release 9 and Release 10 can be found in [27, 28].

The self-organising framework proposed in this paper is applicable for short-term to large-term dynamics of cellular systems [11], that is, the density of active cloud cells can change in a time scale of seconds to days in response to the cellular ecosystem dynamics, such as mobility, temporary hotspots or shadowing. The framework maximises the overall performance of the system while considering

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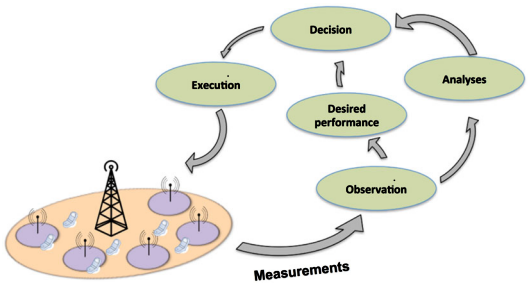

Figure 2. Self-organisation cloud coverage for future cellular systems.

the needs of individual users in the macro BS coverage. The framework is based on SO to exploit the benefits of small-cell deployment whilst not losing the benefits provided by macro station-based deployment by dynamically adapting node density with user associations. It aims to maximise performance levels in terms of the desired key performance indicators (KPIs). As there are several performance indicators to measure a cellular system performance, the framework does not adopt a simple maximum or minimise the problem but is modelled as a generic multiple-objective problem involving several criteria such that other criteria can be included to tailor the optimisation objective according to the operator's specific policy requirements. However, in the scope of this paper, we have focused our performance evaluation study on the main KPIs, namely, achievable capacity, blocking probability, handover probability and energy consumption.

Each BS (i.e. macro station) is responsible for forming a decision on which of the cloud nodes are active and if its services to users are required or not. On the other hand, cloud nodes are responsible for serving the users in their small coverage area if they are activated. Therefore, from the perspective of cloud nodes, it is considered to be a centralised approach. On the other hand, from the perspective of the network as a whole, it is a decentralised approach as the decision is carried out on a cell basis. The centralised approach benefits from an overall picture of the cell status, and thus, the macrostation can manage the performance level with the knowledge of the impact of activating each node would have. On the other hand, the decentralisation in terms of the network benefits the network in terms of the simplicity it provides and its suitability for cellular deployments in a wide scenario. The most attractive feature of the proposed cloud-cell approach is its SO capability, regardless of the functional architecture framework (centralised or decentralised).

Figure 2 illustrates the main SO concepts included in the proposed cloud-coverage approach. The *Observation* and *Analysis* stages are used to detect if the current deployment is insufficient and then automatically *riger* issues a request to find an alternative deployment approach. KPIs are used to monitor the current status of the network and to form appropriate decisions to be made. KPIs can be average blocking probability, power consumption and so on. Based on the KPIs, the algorithm is executed in order to make a decision for a new cloud-node activation. Finally, the Execution stage is responsible for enforcing the new architecture to be deployed.

5. DYNAMIC CLOUD COVERAGE EXECUTION

The dynamic cloud executioner (DCE) is located at each main BS (i.e. at each macrocell). The DCE objectives are as follows: (i) to collect the necessary metrics to determine the status of the KPIs and (ii) to provide a decision and enforce it.

5.1. Decision-making for self-organising cloud coverage

We consider a heterogeneous network comprising different BS types that offer different cell coverage. To save energy, some of the network elements are switched off, and others are switched on to compensate and ensure QoS and coverage. To decide which network elements are active and which are not is considered to be a multiple-objective decision-making (MODM) problem involving different network criteria and requirements. The conventional multiple-attribute decision-making methods lack the ability to make an efficient decision when imprecision or ambiguity is introduced to the data. Therefore, the use of fuzzy logic provides the ability to deal with imprecise data and also to evaluate multiple criteria simultaneously to provide a robust mathematical framework and can thereby be used to model nonlinear functions with arbitrary complexity. As network criteria and requirements are changing with time in which can cause the decision on which network element are active to fluctuate between two decision causing extra power consumption, loss of service, increased signalling and, in the long-term, can lead to hardware failure. Whereas fuzzy logic has the ability to deal with this fluctuations more efficiently because of the presence of the fuzzifier especially in areas where a simple true/false statement is insufficient. We adopt the weighted fuzzy-logic approach for MODM where the KPIs are used to generate a decision on which cloud cell should be activated. Building on this feature of fuzzy logic, in our decision-making framework, we consider each user individually and obtain a decision that benefits the users based on their geographic distribution and requirement. Fuzzy logic provides the ability to compare, study and evaluate multiple objectives simultaneously to provide a robust mathematical framework for decision-making therefore moving from a binary decision to MODM, making it the most suitable choice.

The block diagram of the proposed weighted fuzzy-logic system is presented in Figure 3, where the system KPIs are first normalised based on the desired achievable performance of each KPI, for example, if we would like the maximum acceptable blocking probability to be '0.001', then the blocking probability KPI would be scaled from '0'

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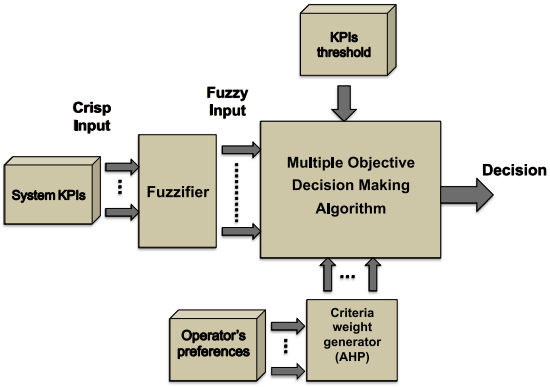

Figure 3. Block diagram of weighted fuzzy logic for cloud coverage.

to '1' based on the threshold of '0.001'. Then the fuzzifier would convert the crisp KPIs to fuzzy sets. The membership functions would be set in a way to have larger membership values for the desired outcome.

Assuming that n KPIs are to be evaluated, each KPI is input to the fuzzifier, generating fuzzy sets $C_1, C_2, \ldots, C_n$. Important values are assigned for each KPI using an analytic hierarchy process (AHP). The final weights w are derived using an eigenvector method. The weightings are then applied to each KPI for decision-making. The summation of each fuzzy KPI multiplied with its correspondent weight provides a preference value $\mathcal{F}$ for the given architecture to be adopted. If we assume that we have N $(n = 1, 2, \ldots N)$ KPIs and M $(m = 1, 2, \ldots M)$ possible decisions to adopt a network architecture to be made, then

$$\mathcal{F}(m) = \sum_{i=1}^{N} \omega_m^i x_n^i \tag{1}$$

such that

$$\begin{aligned} \mathcal{F}(1) &= \omega_1^1 x_1^1 + \omega_1^2 x_1^2 + \ldots + \omega_1^N x_1^N \\ \mathcal{F}(2) &= \omega_2^1 x_2^1 + \omega_2^2 x_2^2 + \ldots + \omega_2^N x_2^N \\ &\vdots \\ \mathcal{F}(M) &= \omega_M^1 x_M^1 + \omega_M^2 x_M^2 + \ldots + \omega_M^N x_M^N \end{aligned} \tag{2}$$

where x is the output of the fuzzifier of each KPI and ω is the corresponding weight from the outcome of the AHP. At this point, if the membership functions were designed to give greater values for the desired outcome, the decision becomes the largest value of the decision function given in Equation (3). As the algorithm operates in the short term, several challenges arise. The decision on which architecture to be adopted depends on several criteria (KPIs); therefore, we aim to minimise the effects of maximising a given KPIs negative impact on the other KPIs that might occur, as maximising throughput can cause an increase in handover occurrence. As cloud nodes are activated and deactivated dynamically, they impose several types of handover that should be considered, that is, intra-cell and inter-cell handover for both cloud nodes and macrocell.

Therefore, if we have J number of small cells (cloud nodes) deployed in the area of a macro station where each cell has one of two possibilities: for macrocells, it is either active (i.e. has active transmission), denoted by '1', or in sleep mode, denoted by '0'. On the other hand, the small cells (cloud nodes) are active, denoted by '1', or in available mode, denoted by '0', because the small cells are not required to provide service only awaiting activation by the macrocell in its domain (i.e. in a mode consuming less energy since only signalling is required). Therefore, the solution space is 2^{1+J}, as we also consider the use of the overlay macrocell to serve the traffic, such that $\{I_{BS}, I_1, I_2, \ldots, I_J\}$ where $I \in \{0, 1\}$.

5.2. Metrics collection and KPIs estimation

The DCE collects the necessary metrics to determine the status of each KPI to be able to generate a decision. The required information can be retrieved via an uplink control channel in which users transmit their normal measurement report messages. In this paper, the three main KPIs considered are probability of blocking, indicating users' satisfaction; handover probability, indicating connectivity and mobility and power consumption, indicating the level of consumed power per cell area.

5.2.1. Blocking probability.

The DCE determines the blocking probability of the cell through the channel quality indicator of each single user, which represents the SNIR:

$$\gamma_u = \frac{P_{\mathrm{rx}}(u,i)}{\sum_{j \neq i} P_{\mathrm{rx}}(u,j) + n_0} = \frac{P_{\mathrm{tx}}(i) PL_{u,i} S_{u,i} F_{u,i}}{\sum_{j \neq i} (P_{\mathrm{tx}}(j) PL_{u,j} S_{u,j} F_{u,j}) + n_0} \tag{3}$$

where γ_u represents the signal-to-interference-plus-noise ratio (SINR) of the uth user, index i denotes the serving cell with j representing the interfering cells. $P(i)$ represents the transmitted signal power including transmitter and receiver antenna gains, and $S_{u,i}$ and $F_{u,i}$ denotes shadowing (large-scale fading) and fast frequency-selective fading, respectively. PL denotes the inverse of the path loss. Lastly, n_0 represents the total thermal noise.

From the SINR, the transmission bit rate can be obtained using the adaptive modulation and coding scheme. Several approaches to performing the mapping are available throughout the literature. Goldsmith and Chua [29] provide an analytic formula for a target bit error rate (BER) and for a Rayleigh fading channel:

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Table I. Adaptive modulation and coding.

SINR threshold (dB)	Modulation m (bits/s/Hz)	Coding rate r	Spectral efficiency (bits/s/Hz)
< 0.9	–	–	0
⩾ 0.9	2 (QPSK)	1/3	0.66
⩾ 2.1	2 (QPSK)	1/2	1
⩾ 3.8	2 (QPSK)	2/3	1.33
⩾ 7.7	4 (16QAM)	1/2	2
⩾ 9.8	4 (16QAM)	2/3	2.66
⩾ 12.6	4 (16QAM)	5/6	3.33
⩾ 15	6 (64QAM)	2/3	4
⩾ 18.2	6 (64QAM)	5/6	5

$$\xi_u = \log_2\left(1 + \frac{-1.5\gamma_u}{\ln(5BER)}\right) \tag{4}$$

where ξ_u denotes the spectral efficiency in bits/s/Hz of the uth user, BER<(1/5)exp(-1.5) $\approx$ 4.46% and γ_u < 30 dB.

Moreover, Schoenen *et al*. [30] propose a table-based alternative that is in line with 3GPP LTE systems given in Table I.

From the achievable spectral efficiency, we are able to calculate the throughput of a user as follows:

$$th_u(t) = \frac{B_w \xi(t)}{U_i} \tag{5}$$

where B_w denotes the cell bandwidth, $\xi(t)$ denotes the estimated channel spectral efficiency and U_i is the total number of users in the ith cell that the user terminal is connected with.

To obtain each user blocking probability, we adopt an MMPP/M/l/D-PS queue (a single-server processor sharing queue, with MMPP arrival process, Markovian service time) traffic model. User service rate is exponentially distributed with a mean value of $\mu_u = 1/\Gamma$, where Γ is the mean value of the service time. The amount of information transferred in each data connection is exponentially distributed with mean value R. Therefore, the data connection service time is exponentially distributed with mean value $\mu_d = th_u/R$, where th_u is the user throughput. The steady-state probability is defined as $w(u,d)$, where u and d are the number of users and data connections, respectively, with a maximum of U users that can be admitted and a maximum of D data connections. The blocking probability is the probability of having a new user or a data connection that is unable to be admitted for service. The MMPP is characterised by the infinitesimal generator matrix $\mathbf{Q}_{(U+1)(D+1)\times(U+1)(D+1)}$:

$$\mathbf{Q} = \begin{bmatrix} \mathbf{Q}_u - \Lambda & \Lambda & & \\ \mu_d\mathbf{I} & \mathbf{Q}_u - \Lambda - \mu_d\mathbf{I} & \Lambda & \\ & & \cdots & \\ & & \mu_d\mathbf{I} & \mathbf{Q}_u - \mu_d\mathbf{I} \end{bmatrix} \tag{6}$$

where $\mathbf{I}$ is the identity matrix,

$$\Lambda = \begin{bmatrix} 0 & & & & \\ & \mu_d & & & \\ & & 2\mu_d & & \\ & & & \ddots & \\ & & & & U\mu_d \end{bmatrix} \tag{7}$$

and

$$\mathbf{Q}_u = \begin{bmatrix} -\lambda_u & \lambda_u & & & \\ \mu_u & -(\lambda_u + \mu_u) & \lambda_u & & \\ & \ddots & \ddots & \ddots & \\ & & \mu_u & -(\lambda_u + \mu_u) & \lambda_u \\ & & & -\mu_u & \mu_u \end{bmatrix} \tag{8}$$

The steady probability is defined as the stationary vector $\pi = (\pi_0, \pi_1, \pi_2, \ldots, \pi_{D+1})$, where $\pi_d = (\pi_{d,0}, \pi_{d,1}, \pi_{d,2}, \ldots, \pi_{d,U})$ and $\pi_{d,u} = w(u,d)$ and satisfies the following:

$$\pi\mathbf{Q} = 0, \pi e = 1 \tag{9}$$

From the steady-state probability, we can calculate the blocking probability as follows [31]:

$$p_b = \frac{\sum_{d=0}^{D} \pi_{d,U}\lambda_u + \sum_{u=0}^{U} \lambda_{D,u} u \lambda_d}{\sum_{u=0}^{U}\sum_{d=0}^{D} \pi_{d,u}(u\lambda_d + \lambda_u)} \tag{10}$$

5.2.2. Handover probability.

As cloud nodes are activated and deactivated dynamically, they impose several types of handover that should be considered:

- Inter$_{B\text{-}B}$ handover: represents a user terminal handing over from a BS → to a neighbouring BS.
- Inter$_{C\text{-}B}$ handover: represents a user terminal handing over from a cloud cell → to a neighbouring BS.
- Intra$_{B\text{-}C}$ handover: represents a user terminal handing over from the parent BS → to a cloud cell with in its area.
- Intra$_{C\text{-}B}$ handover: represents a user terminal handing over from a cloud cell → to the parent BS.
- Intra$_{C\text{-}C}$ handover: represents a user terminal handing over from a cloud cell → to another cloud cell.

We consider the scenario of a mobile terminal located at point X (show in Figure 4) handing off from an old BS to a future BS. We assume that cells are in a hexagonal shape, where the borders of the BS are defined by the threshold value of the received signal strength that would initiate the handover process. Initially, the mobile terminal would be served by the old BS and is moving with a velocity of v, which is uniformly distributed in $[v_{\min}; v_{\max}]$. We assume

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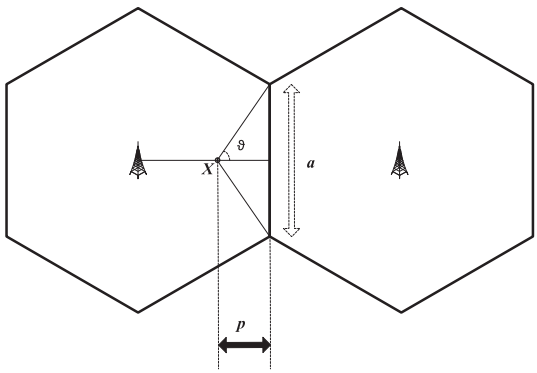

Figure 4. The assumed handover scenario of a mobile terminal [32].

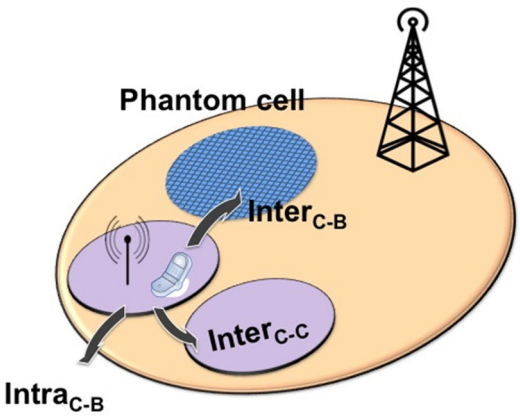

Figure 5. The use of phantom cell to estimate the handover probability.

that a mobile terminal can move in any direction with equal probability; hence, the pdf of the mobile terminal direction of motion θ is [32]:

$$f_\theta = \frac{1}{2\pi} - \pi < \theta < \pi \tag{11}$$

We also assume that the speed and direction of motion of a mobile terminal from point X until it goes out of coverage remain constant, because the distance from point X to the cell boundary is assumed to be small given a dense network. At this point, the mobile terminal would handover when the direction of motion is between $\theta \in (-\vartheta, \vartheta)$ from Figure 4:

$$\vartheta = \arctan\left(\frac{a}{2p}\right) \tag{12}$$

where p is the distance between point X and the cell boundary and a is the hexagon side length. The time that the mobile terminal takes to move out of coverage when moving in the direction $\Theta \in (-\vartheta, \vartheta)$ is

$$t = \frac{p \sec \Theta}{v} \tag{13}$$

The probability of a mobile terminal handing off in a time less than τ is:

$$p_{ho} = \begin{cases} 1 & \tau > \frac{\sqrt{\frac{a^2}{4}+p^2}}{v} \\ \approx \frac{1}{\vartheta} \arccos\left(\frac{p}{v\tau}\right) & \frac{p}{v} < \tau < \frac{\sqrt{\frac{a^2}{4}+p^2}}{v} \\ 0 & \tau \leqslant \frac{p}{v} \end{cases} \tag{14}$$

On the other hand, $\text{Intra}_{C\text{-}B}$ and $\text{Intra}_{B\text{-}C}$ handover proposes a challenge to be estimated. To solve this, in terms of estimating the $\text{Intra}_{B\text{-}C}$ where the user is expected to hand over from the parent macrocell to the cloud node in its domain, we consider the user to be located at a phantom cell in its location, and therefore, we are able to estimate the handover probability of the user to the neighbouring cloud cell. On the other hand, to estimate the $\text{Intra}_{C\text{-}B}$, we consider that the user is handing over to a phantom cell located at the closest side of the cloud node to the user; thus, we are able to estimate the handover probability. The phantom cell would serve as a means to estimate the inter-handover probabilities as shown in Figure 5. At this point, averaging the overall handover probability would yield the estimated handover probability of a user terminal.

Therefore, if a user is allocated to a cloud node

$$p_{HC} = \text{mean}\,(\text{Intra}_{C\text{-}C}, \text{Inter}_{C\text{-}B}, \text{Intra}_{C\text{-}B}) \tag{15}$$

where $\text{Inter}_{C\text{-}B} = \text{Inter}_{C\text{-}phantom}$. On the other hand, if the user is allocated to the macro station

$$p_{HB} = \text{mean}(\text{Intra}_{B\text{-}C}, \text{Inter}_{B\text{-}B}) \tag{16}$$

where $\text{Inter}_{B\text{-}C} = \text{Intre}_{phantom\text{-}C}$.

5.2.3. Power consumption.

The power consumption of a BS is not constant but varies depending on the actual real-time traffic load. The main component power consumption that scales with traffic is the Power Amplifier (PA) Direct Current (DC) power consumption. This is due to the fact that, in an idle mode, the number of loaded subcarriers transmitted is reduced, and thus, the power is less and/or some subframes are free of data because of the reduced traffic load [33]. Moreover, the baseband processor power consumption scales with traffic due to the fact that when there are fewer users, there are fewer subcarriers to be processed. On the other hand, power consumption scaling in small BS is less significant, as the PA accounts for 30% or less of the total power consumption.

The relation between the output power $P_{\max}$ and the BS power consumption P_c is nearly linear, and the BS power model can be approximated as follows [34]:

$$P_c = \begin{cases} N_T P_0 + \Delta_P P_{\text{out}} 0 < P_{\text{out}} \leqslant P_{\max} \\ N_T P_{\text{sleep}} P_{\text{out}} = 0 \end{cases} \tag{17}$$

where P_0 is the power consumption at the minimum non-zero output power, P_{out} is the RF output power, Δ_P is the

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Table II. Parameters of the linear power model.

Base station type	N_{TRX}	$P_{\max}$ W	P_0 W	Δ_P	P_{sleep} W
Macro	6	20.0	130.0	4.7	75.0
Micro	2	6.3	56.0	2.6	39.0
Pico	2	0.13	6.8	4.0	4.3
Femto	2	0.05	4.8	8.0	2.9

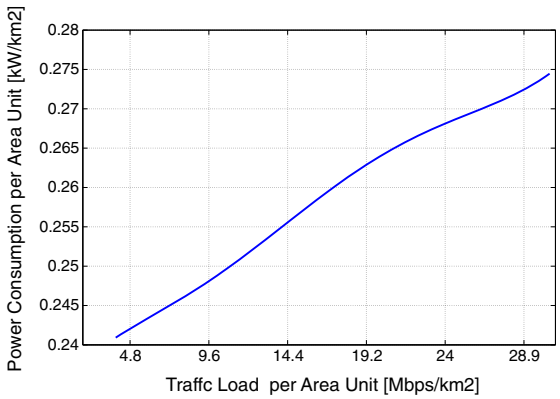

Figure 6. Macro base station traffic load versus power consumption [35].

slope of the load-dependent power consumption and N_T is the number of transceiver chains. The parameters of the linear power model for the considered BS types are listed in Table II. As the macro stations are most affected by the traffic load variation, it is important to represent this variation in the evaluation. Therefore, a system level simulation was conducted to derive the relation between the traffic load and the power consumption as shown in Figure 6. We considered a dense urban area in which the maximum traffic load at peak hours was assumed to be 30 mbs/km^2. From Figure 6, we are able to estimate the power consumption of a macrocell based on the instantaneous traffic load, as for a given traffic load, the macrocell would require a given power consumption.

6. EVALUATION AND DISCUSSION

System-level simulations were conducted to evaluate the performance of the proposed solution. The aim was to obtain performance improvement figures in terms of the achievable blocking probability and power consumption and to assess the impact on mobility in terms of handover probability. The performance indicators used were (i) average user blocking probability; (ii) average user handover probability (i.e. the probability of a user handing over, which reflects the possible mobility events occurring in a cell) and (iii) overall power consumption per cell. In order to model cloud-cell-based deployment architecture as proposed in this paper, seven microcells are placed inside the area of a macrocell to simulate a dense deployment. We compare our proposed cloud-cell-based deployment with conventional macrocell deployment and with only microcell-based dense deployment.

6.1. Simulation models and assumptions

Models and assumptions are aligned with 3GPP simulation case 1 [36]. Three-sector macrocells is simulated with wraparound with inter-site distance of 600 m. The link gain between the BS and a mobile is defined as the product of path loss, shadowing and fast fading effect assumption given in Table III in line with [37]. A series of snapshot simulations are performed. In each simulation run, user terminals are randomly positioned within the coverage area. The radio link between a user terminal and macrocell or cloud node is calculated based on the path loss model. A log-normal shadow fading with a zero-mean and standard deviation of 6 dB is assumed. The traffic model and mobility model parameters are presented in Table III where a typical urban model is given. A dense urban area in which the maximum traffic load at peak hours was assumed to

Table III. Main simulation parameters.

Parameters	Values
Macrocell ISD	ISD = 600 m
Shadow fading	Log-normal 6 dB standard deviation
Path loss	PL = 131.1 + 41.8 log(d) (dB) d = distance in km
Cell structure	Hexagonal grid of 3-sector sites
Micro base station	$P_0 = 56.0\ W$
Micro base station	$\Delta_p = 2.6$
Micro base station	$P_{\max} = 6.3\ W$
Micro base station	$N_{TEX} = 3$
Channel bandwidths	10 MHz
Maximum users to be admitted	$U = 20$
Maximum data connections/user	$D = 10$
User data connections arriving rate	$\lambda_d = 12$ connection/s
User service time mean value	$T_h = 0.1017$ s
Information transferred mean value	$R = 2$ Mbits
Maximum cell load	30 Mbits/km^2
Blocking probability weight χ	$\omega_{(Pb,\chi)} = 0.35$
Handover probability weight χ	$\omega_{(Ph,\chi)} = 0.43$
Power consumption weight χ	$\omega_{(Pc,\chi)} = 0.22$
Blocking probability weight β	$\omega_{(Pb,\beta)} = 0.2$
Handover probability weight β	$\omega_{(Ph,\beta)} = 0.6$
Power consumption weight at β	$\omega_{(Pc,\beta)} = 0.2$
Blocking probability weight ζ	$\omega_{(Pb,\zeta)} = 0.6$
Handover probability weight ζ	$\omega_{(Ph,\zeta)} = 0.2$
Power consumption weight ζ	$\omega_{(Pc,\zeta)} = 0.2$
Measurement internal	τ 15 s
User terminal maximum speed	$v_{\max}$ 1.4 m/s
User terminal location	X random distribution in macrocell area

ISD, inter-site distance.

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be 30 mbs/km^2 in line with the average daily data traffic profile of Europe as given in [38] is considered, resulting in a maximum of 30 users to accommodate the traffic. Three scenarios of cloud cells were studied with three different preference values, generating different weights. The weights are set in a way to reflect various preferences, preferring a single KPI to others for simulation purposes. On the other hand, in practice, the weights would be generated from the operator preferences, which are at the AHP weight generator. The achievable spectral efficiency of a radio link was calculated using a table-based adaptive modulation and coding along the lines of 3GPP LTE system scheme [30].

6.2. Blocking and handover probability performance

In this section, we first compare blocking and handover performance of our proposed solution with the two alternative deployment approaches, that is, macro-based and micro-based deployments. The inter-site distance of the macrocell deployment is 600 m, and the relation between the two deployments is $D_{micro} = 2R_{macro}/3$ where the inter-site distance of the microcell deployment is then 133.3 m. Figures 7 and 8 represent the blocking and handover probability performance of several deployment strategies, thereby reflecting their ability to service current traffic demand and its ability to handle further requirements of traffic. As expected, the small-cell strategy achieves a better performance level but at the cost of much higher handover probability, reflecting a larger signalling demand and a greater occurrence of mobility events. Whereas for macrocell-based deployment, the trend is the opposite. On the other hand, as can be observed, the cloud-cell strategy merges the benefits of both and opens new regions for the system to operate in. Also by simply adapting the preferences in the AHP weight generator, the system can target a better cell mean handover or blocking probability, providing large flexibility in the operational region. Furthermore, the cloud-cell approach outperforms the dense micro deployment in terms of handover probability whilst maintaining a high level of blocking probability performance by intelligently allocating users to the most appropriate BS and having the ability to offload the most demanding users in terms of the expected handover probability (such as high velocity users) to the overlay macrocell to achieve a targeted goal. Because cloud coverage solution provides the ability to assign weights to the KPIs, it provides high flexibility in terms of which KPI gets the priority. As can be seen, using the β weight set provides higher performance levels in terms of mean user handover probability and using the weigh set ζ provides a much lower achievable blocking probability. Although ζ surpass the pure-micro deployment in terms of handover probability, it is due to the specific designed fuzzifier and can be avoided by either adopting the β or χ weights or adjusting the membership values in the fuzzifier.

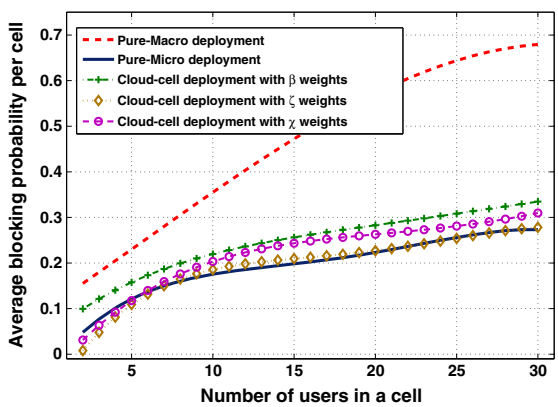

Figure 7. Blocking probability performance of several deployment strategies.

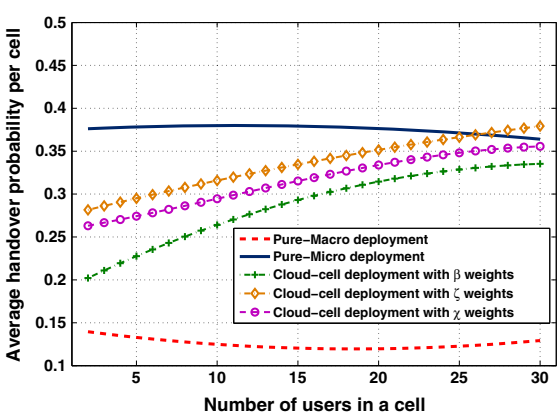

Figure 8. Handover probability performance of several deployment strategies.

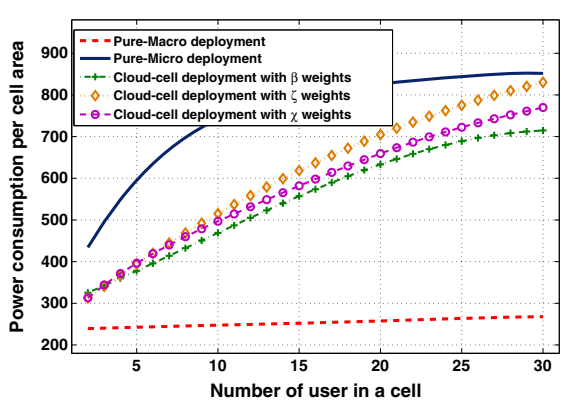

Figure 9. Cell power consumption of several deployment strategies.

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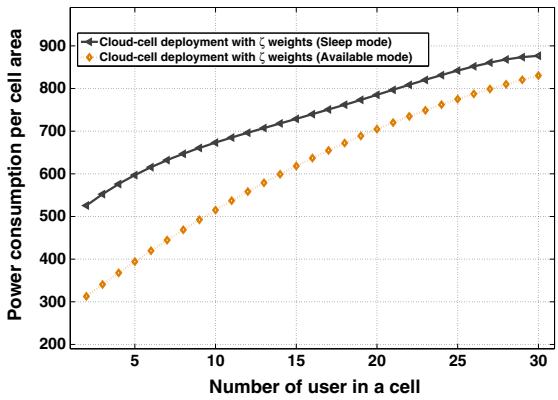

Figure 10. Cell power consumption (sleep vs. available).

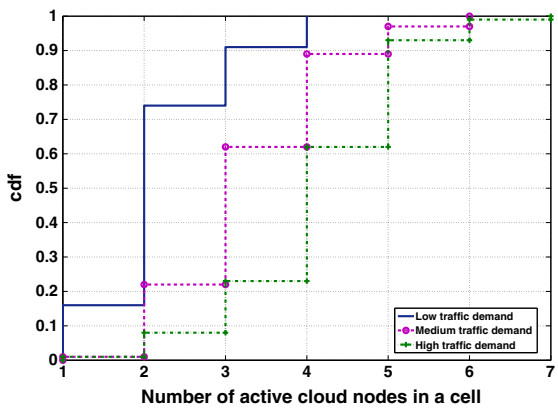

Figure 11. Cumulative distribution function (CDF) plot of the active cloud nodes in a cell for weight set χ.

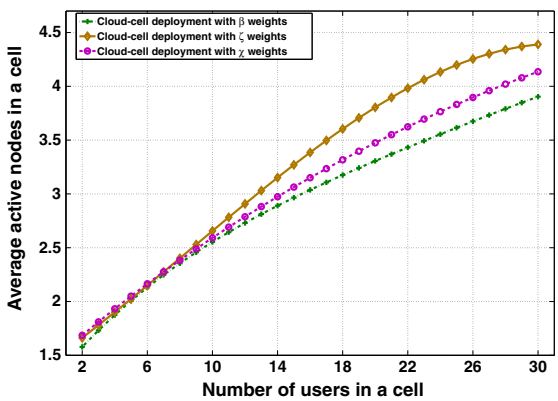

Figure 12. Mean active cloud nodes in a cell over traffic demand.

6.3. Power consumption performance

As seen previously a dense deployment provides a higher level of performance in comparison with a large deployment method at the expense of more mobility events. This makes a dense deployment more viable in areas where slow users are expected; on the other hand, when considering the power consumption values, it reveals a larger expense of using dense deployment. As seen in Figure 9, the impact on the network power consumption increases dramatically when adopting a pure dense deployment compared with large area deployment (i.e. macrocell deployment). On the contrary, the cloud-cell approach reduces this margin in terms of power consumption whilst maintaining a high level of performance, providing a way to increase system performance without a large impact on the network power consumption. Therefore, for further network densification, the cloud-cell approach provides much more benefits in terms of blocking, handover probabilities and power consumption.

As cloud nodes are not required to provide any services, only awaiting activation by the macrocell in its domain, they can achieve a lower power consumption in comparison with the conventional sleep mode (i.e. in a mode consuming less energy because only signalling is required). The available mode provides savings in both high-traffic and low-traffic periods in comparison with the conventional sleep mode. Figure 10 provides an idea of the amount of energy savings that can be achieved when deploying the proposed cloud-cell-based deployment architecture. This saving becomes highly important and is substantial when the density (number of cloud nodes) of deployment increases over time to further counter the annual increase in traffic.

6.4. Dynamics of the network

The dynamics of the network can be observed based on the changes of the environment, that is, user location, speed, traffic demand and so on in Figure 11. Therefore, the density of the cloud node changes based on current demand levels and performance expectations. Moreover, Figure 12 represents the mean active number of cloud nodes in a cell representing the adaptivity of the network based on the traffic demand changes. As can be observed, as traffic demand grows, the number of active nodes increases to contain this increase in demand, thereby aiming to provide higher level of performance. The activity of individual cloud nodes is managed by the parent macrocell, thereby becoming available on demand, taking into account the impact on each individual KPI.

7. CONCLUSIONS

In this paper, we presented an alternative deployment solution for densification of future cellular networks in order to meet the future traffic demands. This solution builds on a notion of cloud coverage provided by densely deployed self-organising small cells that can underlay the macrocells. The core idea of the proposed solutions is that,

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through a fuzzy-logic-based decision framework presented in the paper, the macrocells can control when to activate the cloud cells, while taking into account a number of factors of cellular ecosystems, for example, traffic and energy tariffs. We have evaluated the proposed framework through extensive simulations while using blocking probability, hand over probability and energy consumptions as KPIs of interest and compared it with both microcell-based and macrocell-based deployments. The key advantage of the proposed solution is that it combines the benefits of both macrocell-based and microcell-based deployments. However, unlike conventional heterogeneous network, these advantages are not gained at the cost of increased energy consumption or higher handover rates because of an underlying fuzzy-logic-based self-organising solution, which adapts the active deployment topology according to the spatial and temporal dynamics of traffic while targeting the desired KPIs as set by the operator. Although, only a specific number selected KPIs are considered in this paper, the proposed framework is expandable to number of other KPIs of interest for future work.

In cloud coverage, there is not a single radio access unit for a given user terminal, but several options are given on which the network would conduct its decision. Thereby, the coverage of a cell is considered to be cloud coverage as the coverage provided by these small cells can effectively follow the user. On the other hand, cloud radio access networks (C-RAN) proposes migrating the baseband units to the cloud for centralised processing, thereby separating it from the radio access units [39–41]. This approach provides several advantages as compared with the conventional RANs, as C-RAN allows for the ability of centralising the operation of baseband units and scalability in terms of the deployment of small cells as remote radio head. This migration of processing from the BS to a separated unit would provide several benefits for the proposed cloud coverage, as the cloud cell is required to generate a decision on which of the small nodes are active and which are not. This decision can be formulated at a separated unit as in C-RAN. Similarly to C-RAN, the BS of the parent radio access unit collects the necessary metrics to determine the status of the KPIs and would issue a request for a decision to be formulated, thereby separating the functionality of the DCE to take part at a cloud-processing unit. Also having this centralised processing unit provides an advantage in terms of flexibility of further deployment of cloud cells.

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