Energy-Efficient User Association In Extremely Dense Small Cell Networks

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***Abstract*—Dense heterogeneous networks constitute the paradigm for the future networks. In fact, recent studies demonstrate that the data traffic demand increases exponentially and the traditional cellular networks are not able to provide enough capacity. For this reason operators and standardisation bodies are particularly eager to solve the problem, hence there is a lot of ongoing research on this direction. In this paper we focus on extremely dense networks, that could be found, e.g., in crowded public places or in offices. In such deployments, energy consumption must be kept proportional to the traffic dispatched, otherwise operational costs will render them unsustainable from an economic perspective. In this paper, we propose a network model for the estimation of the power consumption of an LTE dense network of small cells, which takes into account the backhaul network. Furthermore, we introduce a new mechanism for the association of the users to base stations, aiming at minimizing the energy consumption of the LTE access network. The achieved trade-off among capacity and power consumption is then evaluated by means of a classical association policy that connects each user to the base station which received signal is the strongest.**

I. Introduction

Mobile user data traffic demand is dramatically increasing in terms of total volumes and of bit-rate required by individual users. By 2015, nearly 1 billion people are expected to access the Internet exclusively through a mobile wireless device [1]. The traditional cellular and wireless networks are not able to support this data explosion, neither by a mere evolution of them, because the theoretical limits of transmission efficiency have been reached, nor allocating more bandwidth, because the spectrum is already scarce. Increasing the number of points of access is generally accepted as the only possible solution to face the increasing demand. One practical way forward is the deployment of femto-cells, one of the most interesting trends to emerge from this cellular (r)evolution [2], [3].

Femto-cells are small, inexpensive, low-power base stations, generally consumer deployed and connected to their own wired backhaul connection. In these respects, they resemble WiFi access points, but instead they utilize one or more commercial cellular standards and licensed spectrum. To a mobile station (MS), a femto-cell appears indistinguishable from a traditional base station. Based on recent studies, femto-cell deployments can be modeled realistically using a Poisson Point Process (PPP) [4], [5], which highlights a major difference with respect to the macro-cell base stations, whose deployment is carefully studied and planned using sophisticated tools and qualified personnel. This is one of the reasons why some important challenges arise in such dense networks.

A widely-discussed challenge for the femto-cells deployments is mitigating interference from nearby cells, which is more complex than in traditional cells due to two aspects: i) under closed access, unregistered mobiles cannot connect to a femtocell even if they are close by; ii) the signalling for coordinating cross-tier interference is difficult in both open and closed access (cells operating in open access mode means that all users of a given operator can access to them, in closed mode means that there is a Closed Subscriber Group (CSG) of users who can access to them) [6].

Furthermore, another important challenge is cell association: since a mobile terminal is expected to be in the range of many base stations, its assignment becomes more complex than in a traditional network, where Signal to Noise plus Interference (SINR) maximisation is commonly found as the best option. Opportunistic models of user association have been studied considering, as metrics, also the *biasing*, whereby users are actively pushed onto small cells, or the load of the evolved NodeBs (eNBs), which is often more important [7].

Finally, the last critical aspect is backhaul limitation: as the number of base stations increases exponentially, the backhaul network is not expected to experience the same growth (installation of a femto-cell is easier and much less expensive than upgrading the network connecting the dense wireless network to its core network or the Internet).

In such a complex scenario, this paper aims at studying the energy saving potential of a smart association of the mobile users to base stations in an Long Term Evolution (LTE) dense network. This is done by defining a network model that captures the essential features of such a network, including also the backhaul network devices into account, both as a capacity constraint and as a power consumer. The trade-off among power minimisation and overall capacity achieved by this policy, is evaluated by means of a traditional strategy, used in cellular networks, where the User Equipments (UEs) associate to the strongest eNBs in terms of Signal to Noise Ratio (SNR). Results were obtained via static simulation using a Monte Carlo method.

The remainder of this paper is structured as follows. Section II and Section III illustrates the proposed network model and the aforementioned association mechanism, respectively. Section IV reports the results obtained via simulation to quantify the performance gap in terms of energy consumption. In Section V we draw conclusions and discuss the future work.

II. Network model

In this section we describe the proposed model of a dense LTE network, whose eNBs are connected to the core network of the mobile operator via a hierarchical (switched) backhaul network. The network consists of U UEs, B eNBs, and S switches. Each switch s has a limited total capacity of traffic it can handle simultaneously, equal to C_s^{tot}, and its ports have maximum transmission rate equal to C_s^{port}. As in [4], we assume that UEs and eNBs are distributed over a finite flat surface using a Poisson Point Process distribution. An example network is illustrated in the reference diagram in Fig. 1. In

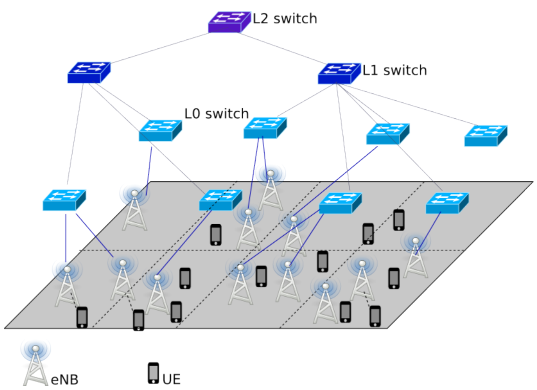


Fig. 1. Example of LTE dense network, with backhaul.

order to keep low the complexity of the presented dense access network, we propose to set the transmission power P_{TX} to the same value for all the eNBs. P_{TX} is chosen such that every UE experiences a minimum SNR ($SNR_{\min}$) from at least one eNB, when all the others are not active, subject to a maximum value $P_{TX}^{\max}$. In practice:

$$\begin{aligned} P_{TX} = \min[P_{TX}^{\max}, SNR_{\min} + \\ + \max_{i \in U}(\min_{k \in B}(L(k,i) + L_{NS}(k,i) + \mathcal{N})], \end{aligned} \quad (1)$$

where $L(k,i)$ and $L_{NS}(k,i)$ are respectively the path loss for femto-cells ($L(k,i) = 37 + 30\ log(d(k,i))$, $d(k,i)$ distance UE i - eNB k), [8], and the log-normal shadowing in decibels, while $\mathcal{N}$ is the thermal noise.

We call *association* the process by which every UE is assigned to at most one eNB, based on the static positions of all UEs and eNBs and on the capacity and the interconnections of the switches. When the association phase ends, we assume that the maximum Modulation and Coding Scheme (MCS) supported, based on its Signal to Interference plus Noise Ratio (SINR), is assigned to each UE i associated to eNB j. We compute such SINR ($SINR_i(j)$) as:

$$SINR_i(j) = \frac{P_{RX}(j,i)}{\mathcal{N} + \sum_{k=1, k \neq j, k \notin \mathcal{I}}^{B} P_{RX}(k,i)}, \quad (2)$$

where $P_{RX}(j,i)$ is the power received by UE i from eNB k, considering both propagation and fading, while $\mathcal{I}$ is the set of eNB to which no UE is assigned to. Finally, we assume that the throughput of UE i can be computed as follows. Once all the associations are performed and the actual SINR_i is computed, (2), the efficiency of user i, η_i, is obtained through:

$$\eta_i = \log_2\left(1 + \frac{\text{SINR}_i}{\Gamma}\right) \quad (3)$$

where Γ is a parameter that depends on the BER target. Supposing UE i the only user associated to eNB j, the throughput of i can be obtained from table in [9], based on the related η_i. When instead UE i shares the access through eNB j with other UEs, we assume it receives a portion of the total capacity that is proportional to its maximum throughput (or its η). For instance, if $\eta_1/\eta_2 = 2$ then the physical resources assigned to UE1 will be twice as much as those assigned to UE2. Furthermore, if the eNB total capacity is limited by the backhaul network of switches, the throughput of each of its UEs is reduced proportionally to its η.

When computing the power consumption of the elements of the LTE access network, we assume that each eNBs to which no UE is associated with, enters an idle mode from which it can be easily brought back to full functionality [10]. Then, according to the model in [11], the power consumption of each eNBs $P_{in_{eNB_j}}$ is assumed to be:

$$P_{in_{eNB_j}} = \begin{cases} N_{TX}(P_0 + \Delta p \cdot P_{TX}), & \text{if } 0 < P_{TX} \leq P_{\max_{eNB}} \\ N_{TX} \cdot P_{idle}, & \text{if} P_{TX} = 0 \end{cases} \quad (4)$$

where N_{TX} is the transmit/receive antennas per site, $P_{\max_{eNB}}$ is the maximum RF output power per transmit antenna, P_0 is power consumption at the zero RF output power (assumed to be 1% of $P_{\max_{eNB}}$), P_{TX} is computed as shown in (1), Δp is the slope of the load dependent power consumption, while P_{idle} indicates the power consumption of an eNB when no UEs are associated with it.

According to [12], we assume that the power consumption of each switch l $P_{in_{sw_l}}$ can be computed as follows:

$$P_{in_{sw_l}} = \alpha \cdot P_{\max_{sw}} + (1-\alpha) \cdot \frac{Ag_{switch}}{Ag_{\max}} \cdot P_{\max_{sw}} \quad (5)$$

where $P_{\max_{sw}}$ is the maximum power consumption of the switch, $Ag_{\max}$ is the maximum amount of traffic a switch can handle and α is a weighting parameter $\alpha \in [0,1]$. α represents the percentage of traffic dependent power consumption of the switches. We assume that the switches of the access network are moderately power efficient, i.e., we set $\alpha = 0.5$.

III. The Min-Energy association algorithm

In this section we introduce the main contribution of the paper, i.e., an association algorithm that trie to maximise the energy saving of the LTE access network, namely the *Min-Energy* association algorithm. Basically, the studied approach is based on a careful connection of the UEs to the eNBs, so that *i*) the set of eNBs where at least an user is attached to is the smallest possible *ii*) the set of active eNBs is connected to the least number of switches possible, *iii*) the set of active switches is loaded up to its capacity limit. The ultimate goal of this approach is to switch off as many eNBs and switches as possible, while keeping their utilization to the highest level.

A detailed description of the proposed *Min-Energy* algorithm is in Algorithm 1. In the initialisation phase, we set a maximum number of UEs per eNB equal to L_{TOT} and we decide an arbitrary order for processing the UEs. Then the association phase follows. For each UE i is considered the set of already active eNBs with less than L_{TOT} UEs associated. For all the selected eNBs, the correspondent $SNR_i(j) = P_{RX}(j,i)/\mathcal{N}$ is computed. Among all SNR_i computed, the maximum value SNR_i^{MAX} is compared to the threshold $SNR_{\min}$ we used to set the P_{TX} of the eNBs. If $SNR_i^{MAX} \geq SNR_{\min}$, the SNR-best eNBs is associated to UE$_i$. In case it is not possible to find an association for UE$_i$, the set of eNBs inactive, but connected to a switch already receiving the traffic from another eNB, is analysed.

If also in this case it is not possible to find any eNB which $SNR_i(j) \geq SNR_{\min}$, then UE$_i$ is associated to the inactive eNB having the best SNR_i. Although interference effects are not taken into account in the association phase, the algorithm presents a very low-complexity, crucial when dealing with dense scenarios. Indeed, considering that the *Min-Energy* algorithm analyses the possibility of connecting each UE to the eNBs at most one time, the overall complexity is just $\mathcal{O}(U \cdot B)$.

IV. Performance evaluation

In this section we analyse the performance of the proposed association algorithm in several network conditions. Furthermore, we benchmark the throughput and power consumption achieved by means of the *Min-Energy* association policy against a simple algorithm that associates each UE i to the eNB j whose received power is the strongest. We name this association policy *Max-Capacity*. In order to have a fair comparison, both the P_{TX} setting, both the power consumption computation are performed as for the the *Min-Energy* association.

The numerical analysis assumptions are reported first in Section IV-A. Then, in Section IV-B, we discuss the obtained results .

A. Methodology and assumptions

We consider the distribution of the L0 switches, the eNBs and the UEs, overlooking the positioning of the L1 switches (the number of L1 switches is calculated from the number of L0 switches), and L2 switches (fixed at 1). The number of the considered network elements vary according to the different scenario. L0 switches are distributed so that each switch has the same portion of rectangular area, which is, thus, equally divided for the number of L0 switches. The eNBs are randomly distributed in the area and connected to the related switch. Then the UEs are randomly distributed and attached to the eNB according to the specific algorithm. Once all the UEs are attached, the throughput is calculated as described in Section II. Several independent replications are executed (*runs*), from which mean values are estimated with a 95% confidence interval using a t-Student distribution.

// Initialisation phase;
$\mathcal{B}$:= set of eNBs;
$\mathcal{U}$:= set of UEs;
$\mathcal{F}(j)$:= function that returns the switch at which eNB j is connected;
foreach $j \in \mathcal{B}$ **do**
    // Set of UEs associated to eNB j;
    $\mathcal{A}(j) := \emptyset$;
    // Vector containing the switches status;
    $\mathcal{S}(\mathcal{F}(j)) := 0$;
// Association phase;
foreach $i \in \mathcal{U}$ **do**
    $k := 0$;
    $SNR_k := 0$;
    // Try association to a non-idle eNB;
    foreach $j \in \mathcal{B}$ **do**
        if $\|\mathcal{A}(j)\| > 0 \wedge \|\mathcal{A}(j)\| < L_{TOT}$ **then** continue;
        $SNR_j := P_{RX}(j,i)/\mathcal{N}$;
        if $SNR_j > \max(SNR_{\min}, SNR_k)$ **then**
            $k := j$;
            $SNR_k := SNR_j$;
    // If fails, try association to an idle eNB;
    // connected to an active switch;
    if $k = 0$ **then**
        foreach $j \in \mathcal{B}$ **do**
            if $\|\mathcal{A}(j)\| = 0 \wedge \mathcal{S}(\mathcal{F}(j)) = 1$ **then** continue;
            $SNR_j := P_{RX}(j,i)/\mathcal{N}$;
            if $SNR_j > \max(SNR_{\min}, SNR_k)$ **then**
                $k := j$;
                $SNR_k := SNR_j$;
    // If fails, associate to SNR-best eNB;
    if $k = 0$ **then**
        foreach $i \in \mathcal{B}$ **do**
            if $\mathcal{S}(\mathcal{F}(i)) = 0$ **then** continue;
            $SNR_i := P_{RX}(j,i)/\mathcal{N}$;
            if $SNR_j > SNR_k$ **then**
                $k := j$;
                $SNR_k := SNR_j$;
    $\mathcal{A}(k) := \mathcal{A}(k) \cup \{i\}$;
    $\mathcal{S}(\mathcal{F}(k)) := 1$;

Algorithm 1: Association algorithm *Min-Energy*.

B. Results

In this section the main results of the simulations are illustrated. Basically the tests are focused on the analysis of capacity in terms of UEs's average throughput (Mb/s) and on the eNBs network power consumption (Watt). The scope of the analysis is to highlight the gains introduced by a wise association of the UEs to the eNBs, while facing a limited reduction of the throughput if compared to traditional association techniques. We analysed two different scenarios with different the L0 capacity value and different $SNR_{\min}$ threshold to see the possible trade-off among power consump-

TABLE I
SIMULATION PARAMETERS AND VALUES

	Scenario 1	*Scenario 2*
$Ag_{\max}$- *L0 sw capacity*	100 MB/s	500 MB/s
$P_{\max sw}$	100 [W]	
$P_{\max_{eNB}}$	0.05 [W]	
N_{TX}	2	
P_0	4.8 [W]	
Δp	8.0	
P_{idle}	2.9 [W]	
L_{NS}	$\sigma_S = 8dB$	
$\mathcal{N}$, $\sigma^2 = K \cdot T \cdot B$	$\sigma^2 = -101dBm$	
Area	200x100	
L2 switch n.	1	
L1 switch n.	2	
L0 switch n.	10	
Max UEs per eNB	4	
eNBs number	100	
UEs number	25-400	
number of runs	100	
L2 switch capacity	1 Gb/s	
L1 switch capacity	1 Gb/s	
L1 switch ports n.	6	

tion and overall throughput. The simulation parameters for the two scenarios are reported in Table I. Fixed the number of eNBs and switches, we vary the number of UEs from a chosen minimum value up to the maximum number of UEs allowed, which is based on the total amount of eNBs in the scenario and on the maximum number of allowed UEs per eNB (L_{TOT}).

In Fig. 2 the throughput achieved with the *Max-Capacity* association algorithm and the throughput obtained using the *Min-Energy* association are faced. In both cases, the results are shown for two different values of $SNR_{\min}$, when $Ag_{\max} = 100Mb/s$. Clearly, there is a loss of throughput when the *Min-Energy* algorithm is used and, on percentage, such loss is higher (around 30% with $SNR_{\min} = -7dB$) when the access network serves a number of UEs comparable to the one of the eNBs. In this conditions, the *Min-Energy* associates as UEs as possible to the same set of eNBs, i.e., under the same switches, while the *Max-Capacity* does not concentrate the UEs in the same geographical area. Therefore, the reason of the difference in throughput achieved is mainly due to the different interference condition they experience. When the number of UEs increases, i.e., the access network approaches saturation, the effects of interference decreases since in both cases almost all the eNBs are turned on.

From Fig. 2 is also possible to note that the choice of the $SNR_{\min}$ impacts less the performances as the number of UEs increases. Such behaviour is reasonable, since we assumed to use a scheduling of the physical resources of the eNBs to the UEs that is proportional to their efficiency. As the number of UE assigned to each eNB increases, the probability of having an UE experiencing good channel quality increases too, irrespective of the $SNR_{\min}$ chosen. Similar performances have been registered when the backhaul capacity increases to $500Mbit/s$ per switch. In Fig. 3 we show the distribution of the UEs throughput (range of throughput vs

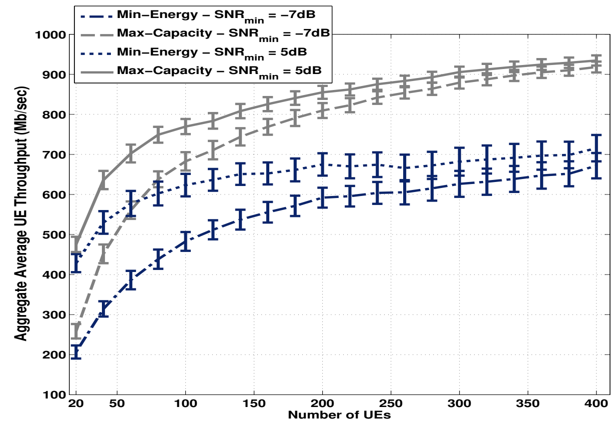


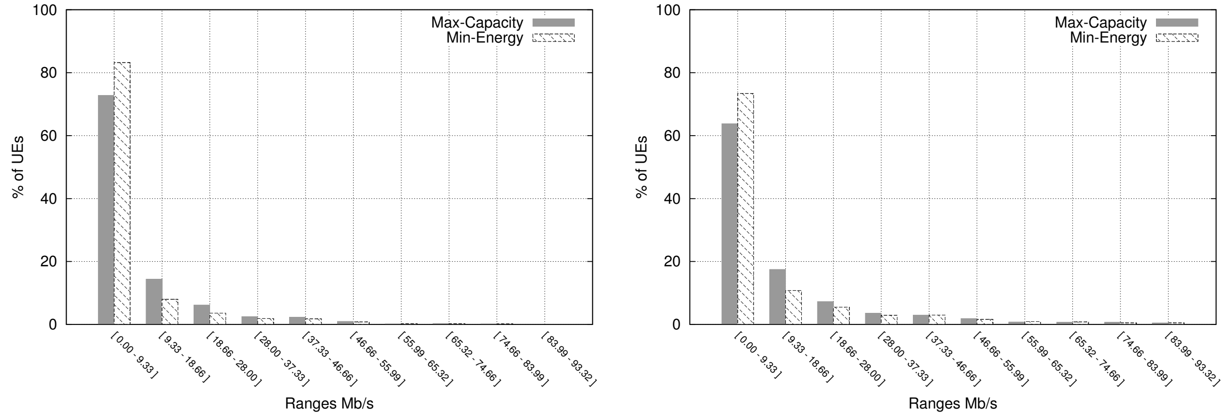
Fig. 2. UEs average throughput, $Ag_{\max} = 100Mb/s$, eNBs = 100.

percentage of UEs) when using such capacity for the backhaul. The performances are shown for 80 UEs, where it can be noticed that the difference among the association policies for the aggregate throughput served by the network is higher. Both if we fix $SNR_{\min} = -7\ dB$ or $SNR_{\min} = 5\ dB$, the distribution of the UEs throughput is pretty close to the one we would achieve assigning the UEs to the eNB which signal received is the strongest. Indeed, the percentage of UEs that achieves less than 10 Mb/s increases of just the 8% and 11% when $SNR_{\min} = -7\ dB$ and $SNR_{\min} = 5\ dB$, respectively. We can conclude that the *per-user* perception of the service received is just slightly affected by the *Min-Energy* association policy, even if we analyse the system when the largest throughput loss is noticed at the network level.

In Fig. 4 we finally show the load dependent component of the power consumption for both the association techniques analysed. In order to compute the overall power consumed by the access network, we should add $P_{ON} = N_{eNB} \cdot N_{TX} P_{idle} + N_{sw} \cdot \alpha P_{\max_{sw}}$, where N_{eNB} and N_{sw} are the eNBs and the switches present. Such choice allow us to show the ability of the *Min-Energy* association technique to handle the real load of the access network, while leaving out of the scope of the paper the discussion on how reliably turn off idle elements of the network. Independently from the chosen $SNR_{\min}$ and the capacity of the backhaul, there is a considerable gain in term of energy saving. Basically, this occurs using *Min-Energy* algorithm as the eNBs and the switches are fully loaded. The maximum energy saving achieved is close to the 45% when the number of UEs and eNBs is close, while obviously decreases when the access network approaches the saturation.

V. CONCLUSION

In this paper we have defined a model for LTE dense networks of small cells that includes capacity constraints due to a limited backhaul capacity. We proposed an algorithm that take into account the minimisation of the power consumption of the network elements in the association procedure of the users to the base stations. We analysed the obtained results and compare them with the result obtained considering the traditional user association policy, used in cellular networks:



(a) $SNR_{\min} = -7dB$.

(b) $SNR_{\min} = 5dB$.

Fig. 3. UEs throughput distribution, $Ag_{\max} = 500Mb/s$, eNBs = 100, UEs = 80.

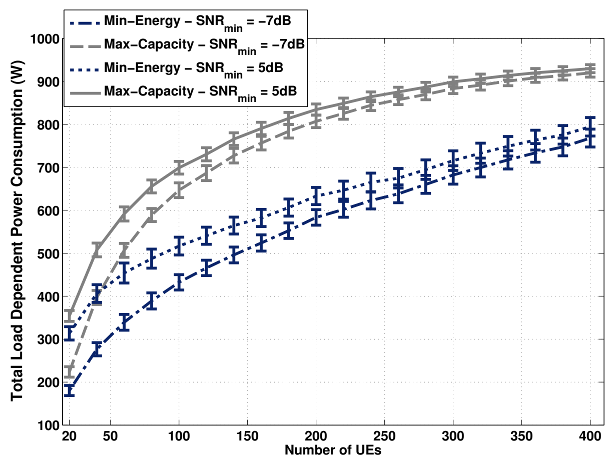


Fig. 4. eNB power consumption, $Ag_{\max} = 100Mb/s$, eNBs = 100.

thus, using a Monte Carlo analysis we have compared two very different user association policies.

Results have shown that there is a huge potential of energy that can be saved by a smart allocation of mobile to base stations. In practice this can be achieved by means of SON procedures continuously optimising network configuration based on change of conditions, which in dense networks can be hardly (if at all) predicted and optimised off-line.

These results can be improved with additional study. Currently we are working on the design of a user association policy that finds the best trade-off between capacity and energy consumption, taking into account both the downlink and the uplink, and it also determines the scheduling of LTE eNBs exploiting Almost Blank Sub-Frames (ABFS). Furthermore, we are positioning our activity within the main track of project CROWD which is working on a platform for fast optimisations in wireless dense and heterogeneous by means of a Software Defined Networking (SDN) approach.

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