Leveraging Intelligence from Network CDR Data for Interference aware Energy Consumption Minimization

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Abstract—Cell densification is being perceived as the panacea for the imminent capacity crunch. However, high aggregated energy consumption and increased inter-cell interference (ICI) caused by densification, remain the two long-standing problems. We propose a novel network orchestration solution for simultaneously minimizing energy consumption and ICI in ultra-dense 5G networks. The proposed solution builds on a big data analysis of over 10 million CDRs from a real network that shows there exists strong spatio-temporal predictability in real network traffic patterns. Leveraging this we develop a novel scheme to pro-actively schedule radio resources and small cell sleep cycles yielding substantial energy savings and reduced ICI, without compromising the users QoS. This scheme is derived by formulating a joint Energy Consumption and ICI minimization problem and solving it through a combination of linear binary integer programming, and progressive analysis based heuristic algorithm. Evaluations using: 1) a HetNet deployment designed for Milan city where big data analytics are used on real CDRs data from the Telecom Italia network to model traffic patterns, 2) NS-3 based Monte-Carlo simulations with synthetic Poisson traffic show that, compared to full frequency reuse and always on approach, in best case, proposed scheme can reduce energy consumption in HetNets to 1/8th while providing same or better QoS.

Index Terms—5G, Heterogeneous Networks, Small Cells, Energy Efficiency, Inter-cell Interference, Resource Allocation, Binary Integer Linear Programming, CDRs, Big Data Analytics.

1 Introduction

1.1 Background

It is envisaged that network densification, a dominant theme in 5G, is going to play a key role in coping with the explosive mobile traffic growth. Co-channel small cells (SCs) i.e., SCs reusing the same spectrum as macro cells (MCs), are a preferred mode of densification since the spectrum is an expensive and scarce resource. However, reusing the spectrum amongst the MCs and SCs increases ICI which, if left un-managed, may significantly deteriorate overall network performance [1]. Besides the ICI problem, low energy efficiency (EE) is another major problem in HetNets. Although SCs have a relatively lower power consumption profile, one of the major concerns in the future dense deployments is the high aggregated energy consumption. As recently demonstrated through SC and MC power consumption models developed in Earth project [2], *always ON cells* based approach particulary increases energy inefficiency in the network when SCs are introduced. This is because, compared to MCs, the load independent power consumption (circuit power) component in SCs constitutes a much larger portion of over all power consumption. Therefore, a vision for an ultra-dense network cannot become a reality without addressing the two time-persistent challenges: higher ICI and higher aggregated overall energy consumption stemming from the classical always ON routine. In our study, we have proposed a pro-active approach that can simultaneously minimize the energy consumption as well as the ICI in emerging ultra-dense networks. This is in contrast to the state-of-the art, that is predominantly reactive rather than proactive. Specifically, the proposed work exploits deluge of largely untapped Call Data Records (CDRs) data to analyze and predict the spatio-temporal user activity behavior. This intelligence is then utilized to dynamically optimize the operational states of the SC (i.e., active, partially muted, or sleep mode), to divert and focus the right amount of resources, when and where needed, while simultaneously minimizing ICI and energy consumption. To the best of author's knowledge, this the first study to provide a detailed analysis of real CDR data and demonstrate its potential for developing a proactive energy saving mechanism.

Due to their importance, ICI mitigation and EE enhancement problems have been widely studied in the literature, initially targeting homogeneous MC only scenarios e.g., [1], [3]–[9]. However, the EE or ICI solution proposed for MCs cannot be directly used for HetNets because of underlying differences in the power consumption models of SC and MC and the interference dynamics. For example, one reason for this inapplicability is that the dominant interferes for a user in the MC only network are limited and usually not as strong as in the dense HetNet scenario, where a SC can be

very close to a MC user situated far from the serving MC.

Focusing on the HetNets scenarios, the authors in [10], [11] propose techniques to address SC-to-SC interference. Although SC-to-SC interference is a notable aspect in HetNets scenario, the degradation of performance for MC users due to the interference from SCs is more critical than the interference experienced by SC users; since there are fewer users served by SCs as compared to MC, SC served users are anyway allocated with more bandwidth resources. Hence, operators have a conflict between achieving commitments towards the MC users and maximizing network efficiency by relying heavily on SCs. To address this challenge, authors in [12]–[14] propose solutions to address interference caused by SCs to MC users.

Another line of ICI studies resorts to the spectrum partitioning between cell-center and cell-edge users for instance, as proposed by authors in [15]–[23]. However these approaches mitigate ICI by reducing overall capacity because of spectrum partitioning.

For joint ICI management and EE in HetNets, the studies in [24]–[29] focus on the improvement of EE through ICI mitigation rather than directly reducing the energy consumption by turning off the cells. Although ICI mitigation is a reasonable approach since it reduces the energy consumption for a given system throughput target, however, EE of the cellular systems can be further enhanced significantly through traffic-aware transmission strategies as proposed in [30]–[33], where under-utilized BSs are recommended to switch to sleep mode or can be turned off during off-peak time of traffic loads. The sleeping strategies proposed in these works are recognized as promising approaches to improve the EE of the cellular system. However, the sleep mode strategies proposed in [30]–[33], have not been considered in conjunction with aforementioned ICI-mitigation.

Studies in [34]–[36] on the other hand investigate EE in conjunction with ICI, albeit, for uplink transmission and therefore focus on UEs EE. In contrast to these studies, our work focuses on EE in the downlink which is the dominant energy consumption factor (and the main contributor to an operators running costs - OPEX) in cellular networks.

Furthermore, the above approaches for mitigating ICI and enhancing EE in HetNets, may not meet the ambitious 5G QoS and resource efficiency requirements because of their intrinsically reactive (reacting to the changes in traffic etc, after they have occurred) design approach. Contrary to prior studies, this paper provides a fundamentally different approach, i.e., a proactive approach, that builds on the lines of Big Data empowered Self Organizing Network (BSON) vision presented for 5G in [37] leveraging CDRs to simultaneously minimize energy consumption and ICI in emerging ultra-dense networks. Several studies have demonstrated the usefulness of using real-world CDRs data in the mobile network analysis and planning in comparison to analytical approaches [38], [39]. The authors in [38] have performed a spatio-temporal analysis of CDRs data collected from various base stations in China. It has been concluded that call arrival patterns vary over time and locations and Poisson distribution model over 1 hour interval is inaccurate and it has been pointed out that advance machine learning algorithms can help model the phenomena more precisely. Moreover in [39], the authors demonstrate that using real world CDR data for mobile network and planning can learn the insights that are not captured by smaller-scale or synthetic datasets. To the best of authors' knowledge, no other work has exploited real CDR traces in the scheduling small cell sleep cycles as we have done in this paper.

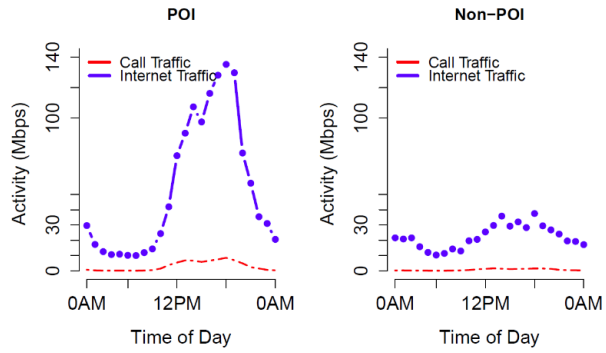


Fig. 1: Calling activity for POI versus Non-POI cells for 24 hours on 7th Dec 2013

1.2 Leveraging the Intelligence Extractable from CDRs for Designing Proactive ICI–EE Solution

Our study has analyzed large scale network data collected from Milan City [40], provided by Telecom Italia as part of their big data challenge [40]. We have performed large scale data processing and data analytics over 10 million real network CDRs and subsequently inferred a clear predictable pattern in the spatio temporal behaviour of the network traffic. Representative results from this analysis are illustrated in Figures 1-4. Fig. 1 shows the measurements

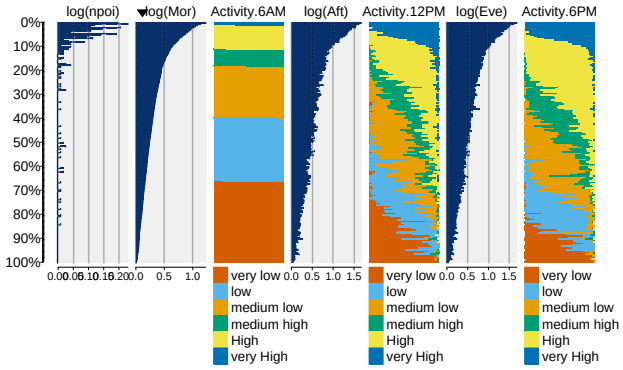


Fig. 2: Internet Activity level for non-POI (npoi) and POI cells

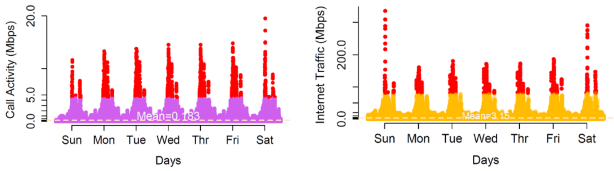
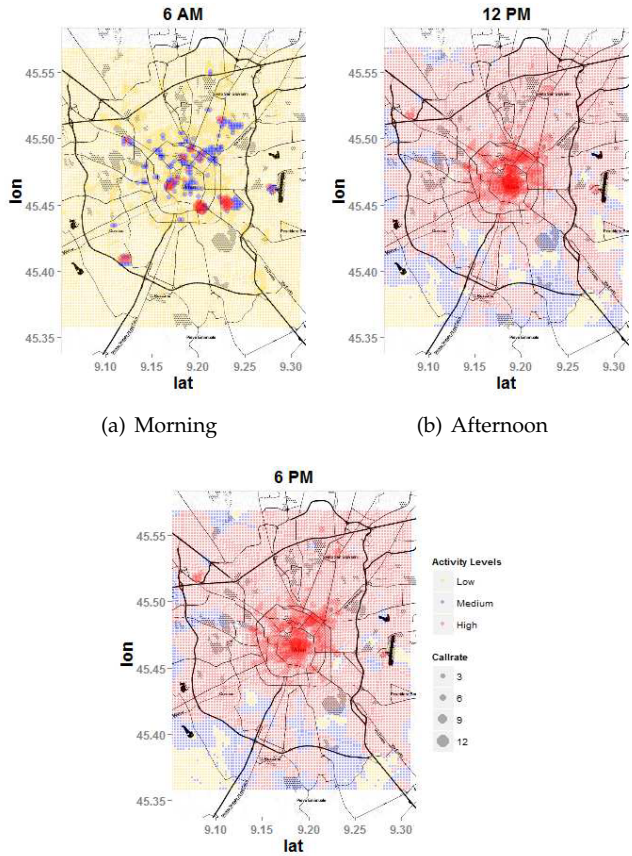


Fig. 3: Calling and Internet activity (week 1st Dec 2013- 7th Dec 2013)



(a) Morning (b) Afternoon

(c) Evening

Fig. 4: Activity level map for a) Morning b) Afternoon c) Evening

of the aggregate real traffic load over the course of one day for cells that contain a subset of popular destinations referred to as Point Of Interest (POI) versus cells that are in residential environment referred to as non-point of interest (non-POI) coverage cells. It is evident that calling activity has a pattern for both POI and non-POI. For both, traffic is relatively high between 8AM till 11PM. During the quite hours of the day (between midnight and 6am), both non-POI and POI cells have similar low activity levels. For the case of mobile data usage similar pattern can be observed in Fig. 2 that shows the activity levels for morning, midday and evening times. For the early morning case, majority of the cells are classified into the category of low and very low activity levels. Therefore, at certain extreme (low traffic) conditions, network utilization can become low and SCs deployed there can remain under-utilized either due to very limited existing load or may have to be muted when causing high interference to MC users.

Fig. 3 shows the calling and internet-usage activity pattern for the whole week that exhibits a distinct periodic predictive nature with internet activity relatively very high as compared to the calling activity. Similarly, the heat map of this activity level is shown in Fig. 4 wherein it is observed that the temporal variation of the traffic load has a strong relationship with time and the geographical location.

As inferred from our exploratory data analysis, the under-utilization of network at specific times, the clear periodicity in spatio temporal activity of the network provides us a clear opportunity to exploit it for energy savings as well as joint ICI mitigation. Building upon it, we subsequently devised a proactive sleep mode schedule strategy for SCs. A SC node, other than the active (i.e. fully operational) mode, can be in idle or sleep mode. Since generally there are fewer users served by SCs, many SCs are not utilized most of the time and the idle mode energy gets wasted; switching the node to sleep mode can significantly reduce the energy consumption. Considering the expected heavy deployment of SCs in the near future and the dynamic traffic demands, sleep modes pose a very promising solution to overcome the wastage of energy in case of low SC utilization.

While it is well-known and intuitive fact that traffic becomes heavy during day and light during night, following questions remain to be investigated:

1) Can CDR data, (instead of load indicators at base station level as other studies have used) be mined to extract meaningful traffic pattern?
2) If a minable traffic pattern exists in CDR data, what machine learning techniques can produce accurate traffic prediction models?
3) What is the accuracy of such prediction model?
4) Do factors such as presence of POI affect the traffic pattern?

Several studies on energy efficiency exist that refer to existence of day and night pattern in qualitative sense using it as a motivation to propose an ON/OFF schemes. However, this study for the first time provides a comprehensive quantitative analysis of the real CDR data. We mine traffic pattern using real data to propose and analyze a proactive, (not cyclic or reactive) ON/OFF scheme. Furthermore, we comprehensively analyze the performance of that scheme using a heterogeneous deployment model that takes into account the specific traffic pattern observed in the area where the real data was collected. This is done by placing small cells at points that were determined to be POI as outcome of the CDR data analysis. Therefore, another contribution of this work is the analysis of effect of POIs on the traffic pattern. The presence of POIs changes the periodicity pattern of the mobile network traffic and our results provides new insight on how the presence of POIs effects the energy saving potential.

1.3 Contributions and Paper Organization

The contributions and organization of paper can be summarised as follows:

1) Using a realistic HetNet system model, we mathematically formulate the joint optimization problem for minimizing the ICI and energy consumption for the predicted traffic scenario (Section 2).
2) We propose an algorithm that exploits the base station sleep-mode mechanism in conjunction with the resource allocation as the optimization control variables. We then propose a heuristic low complexity solution to solve this NP-hard problem. Our proposed energy consumption aware (ECA) resource allocation scheme addresses the limitation of fixed time-based sleep scheduling mechanism [41] that fails to adapt to

dynamic and unusual activity, since they are manually configured for a statistical traffic cycle, usually during few hours of night when user traffic is very low (Section 3).

3) We leverage the results of our big data analysis on Milan CDRs data to propose a HetNet deployment scenario and evaluate the performance of the proposed ECA scheme in the proposed HetNet deployment scenario, where traffic generation pattern is derived from the real data. The results indicate that with ECA the energy consumption could be reduced to $1/8^{th}$ in a dense heterogeneous network deployed in a typical urban city (Section 4).
4) We further compare the proposed ECA solution with the frequency reuse-1 scheme, through system level simulations in NS-3. Our deterministic-load based simulation results clearly indicate that nearly all MC users were protected from neighboring SC interference in comparison to Reuse-1 case wherein 20% users face outage. Moreover, during low traffic conditions, up to 23% saving in the total network power consumption can be achieved using ECA by putting under-utilized SCs in sleep mode (Section 5).
5) We compare the complexity analysis in terms of number of iterations between the state-of-the-art and ECA scheme that highlights the lower complexity and therefore, higher the practicality of the ECA scheme (Section 5).

2 System Model & Problem Formulation

We consider a system of $M+1$ cells, as depicted in Fig. 5, comprising one MC (identified as cell 0) and M SCs within the MC area. The set of SCs is defined as $\mathcal{M} = \{1, \ldots, M\}$. We assume that there are K active users in the system. We consider that each user can have only one serving node, but each cell can support multiple users; thus, $K \triangleq |\mathcal{K}| = |\mathcal{K}_0 \cup \mathcal{K}_1 \cdots \cup \mathcal{K}_M|$, where $\mathcal{K}$ denotes the set of all users in the system and $\mathcal{K}_m$ denotes the set of users served by cell m.

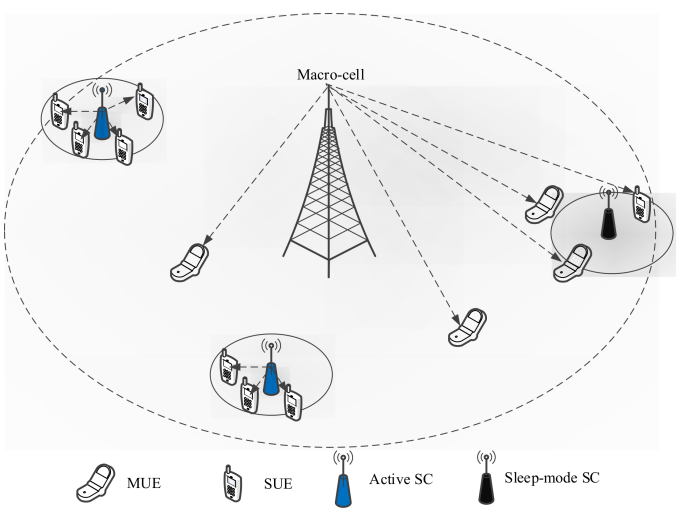


Fig. 5: System Model.

The total system bandwidth is divided in N resource blocks (RBs) and each RB can be allocated to only one user in each cell. MC can allocate all the available RBs to its associated macro-users (MUE). Moreover, MUEs are assumed to have minimum data rate requirements. On the other hand, SCc reuse the same resources to serve their small cell-users (SUE) based on a resource allocation policy. We consider a central entity residing at the MC which is able to collect relevant information to make resource allocation decisions and guide SCs on the resource allocation policy to be adopted.

We define binary indicator variables $\phi_{k,m,n} \in \{0,1\}$, where $\phi_{k,m,n} = 1$ when SC m serves its kth assigned user using the nth RB; otherwise, the RB allocation parameters take the zero value. Thus, we can define the vector containing all RB allocation parameters $\boldsymbol{\phi} = [\phi_{1,1,1} \ldots \phi_{K,M,N}]$, which characterizes the SCs' *RB allocation policy*. We also define the binary cell ON/OFF state indicator $\psi_m \in \{0,1\}$, where $\psi_m = 1$ indicates the active state of cell m; otherwise, in OFF state it take the zero value. Moreover, transmit power of the mth SC in the nth RB is denoted by $p_{m,n} \leq P_{\max}$, where $P_{\max}$ is the maximum allowed transmission power of any small cell. Vector $\mathbf{p} = [p_{1,1} \ldots p_{M,N}]$ characterizes the SC *power allocation policy*.

2.1 User SINR and Rate Modelling

The SINR of the uth MUE at RB n in cell 0 (macrocell) can be given by:

$$\gamma_{u,0,n} = \frac{p_{0,n}\Gamma^0_{u,0,n}}{\sum_{m=1}^{M}\left(\sum_{k\in\mathcal{K}_m}\phi_{k,m,n}\right)p_{m,n}\Gamma^m_{u,0,n} + N_0 B}, \quad (1)$$

where $p_{0,n}$ denotes the transmit power of macrocell at RB n, $\Gamma^i_{k,m,n}$ is the channel gain between cell i and user k being served at cell m in RB n, N_0 is the noise power spectral density and B is the bandwidth of each RB.

Similarly, the SINR of SUE k in cell m at RB n can be given by:

$$\gamma_{k,m,n} = \frac{p_{m,n}\Gamma^m_{k,m,n}}{p_{0,n}\Gamma^0_{k,m,n} + \sum_{\substack{i=1\\ i\neq m}}^{M}\left(\sum_{l\in\mathcal{K}_i}\phi_{l,i,n}\right)p_{i,n}\Gamma^i_{k,m,n} + N_0 B}. \quad (2)$$

The rate (in bit/sec) of each user (SUE or MUE) can be expressed by the Shannon-Hartley theorem as follows:

$$R_{k,m,n} = B \ \log_2\left(1+\gamma_{k,m,n}\right). \quad (3)$$

It should be noted that although (3) does not provide a practically achievable rate, it serves as a good estimate of a performance indicator for comparison purposes.

2.2 Maximum Interference Allowance

Given the set of RBs (N_k RBs) allocated to k^{th} MUE in m^{th} macro cell by the scheduling scheme employed in the system (e.g., Round Robbin, Proportional Fair etc.,), minimum overall data rate demand for that MUE ($R^{req}_{k,m}$) can be translated into a minimum data rate demand at each of the RBs allocated to that MUE ($\frac{R^{req}_{k,m}}{N_k}$). This further can

be translated into a specific minimum required $\gamma_{u,0,n}^{req}$ SINR value [42] as:

$$R_{k,m,n}^{req} = BR(r).[1 - BLER(r, \gamma_{u,0,n}^{req})] \tag{4}$$

where BR is the theoretical bit rate for any modulation and coding scheme (MCS) r when there are no errors. BLER denotes the block error rate suffered by this user on RB n which is a function of the realized SINR and the MCS used. Having identified the minimum SINR value and considering (1) we can find the maximum interference power $\Omega_{u,n}^{\max}$ that MUE u can tolerate in RB n from all SCs to obtain this rate threshold:

$$\Omega_{u,n}^{\max} = \frac{p_{0,n}\Gamma_{u,0,n}^{0}}{\gamma_{u,0,n}^{\text{req}}} - N_0 B. \tag{5}$$

If the potential channel gain from any SC m to the MUE is denoted as $\Gamma_{0,u,n}^{m}$, the total interference caused to it by all SCs in each RB can be given by:

$$\begin{aligned}\Omega_n^{\text{sum}} &= \sum_{m=1}^{M}\left(\sum_{k\in\mathcal{K}_m}\phi_{k,m,n}\right)p_{m,n}\Gamma_{u,0,n}^{m} \\ &= \sum_{m=1}^{M}\left(\sum_{k\in\mathcal{K}_m}\phi_{k,m,n}\right)\omega_{u,0,n}^{m},\end{aligned} \tag{6}$$

where $\omega_{u,0,n}^{m} \triangleq p_{m,n}\Gamma_{u,0,n}^{m}$ can be interpreted as the interference that is caused to user u in cell 0 (MC) on RB n from SC m.

2.3 Network Power Optimisation

The total instantaneous power of a cell can be given by the sum of the circuit power and the transmit power as:

$$P_m^{\text{total}} = \psi_m(P_m^{\text{circuit}} + \Delta_m.P_m^{\text{transmit}}) \tag{7}$$

where P_m^{circuit} is the constant circuit power which is drawn if transmit node m is active and is significantly reduced if the node goes into sleep mode. P_m^{transmit} is the node's transmit power and Δ_m denotes the slope of load dependent power consumption of cell m [2].

The general network power optimisation problem comprising the objective function and the imposed constraints can be formulated as follows:

$$\min_{\mathbf{p},\boldsymbol{\phi},\boldsymbol{\psi}} \sum_{m=0}^{M} P_m^{total} \tag{8}$$

subject to:

$$\phi_{k,m,n} \in \{0,1\}, \forall k \in \mathcal{K}\setminus\mathcal{K}_0, m \in \mathcal{M}, n; \tag{9a}$$

$$\sum_{k\in\mathcal{K}_m}\phi_{k,m,n} \in \{0,1\}, \forall m \in \mathcal{M}, n; \tag{9b}$$

$$\Omega_n^{\text{sum}} \le \Omega_n^{\max}, \quad \forall n; \tag{9c}$$

$$\psi_m \in \{0,1\}, m \in \mathcal{M}, n; \tag{9d}$$

$$\psi_0 = 1; \tag{9e}$$

$$R_{k,m} \ge R_{k,m}^{min}, \forall m \ne 0; \tag{9f}$$

$$\sum_{n=1}^{N}\left(\sum_{k\in\mathcal{K}_m}\phi_{k,m,n}\right)p_{m,n} \le P_{\max}, \forall m \in \mathcal{M}; \tag{9g}$$

$$p_{m,n} \ge 0, \forall m \in \mathcal{M}, n. \tag{9h}$$

Constraint (9b) indicates that RBs are exclusively allocated to one user within a cell to avoid intra-cell interference; constraint (9c) denotes the total maximum interference that a MUE served by MC on RB n can tolerate from all SCs in the MC area in order to satisfy its minimum rate needs; constraint (9d) indicates the ON/OFF state of the cells and constraint (9e) makes sure that the MC is always in active state. This constraint ensures coverage reliability. In case when some SCs are switched OFF by our proposed proactive sleeping pattern solution, Always ON macro cells are expected to ensure that minimum coverage threshold is met all the time. Constraint (9f) is the minimum required rate constraint for each user; finally, constraints (9g)-(9h) stand for the maximum and minimum transmission power constraints at each SC node.

2.4 Energy Efficiency Performance Metrics

Before the proposed algorithm is discussed, it is important to define the EE performance metrics. EE is simply calculated as the total number of bits transferred, divided by the total amount of energy consumed.

$$EE = \frac{\text{Total data transferred}}{\text{Total energy consumed}} \qquad (bit/Joules) \tag{10}$$

This can also be expressed as Energy Consumption Ratio (ECR), i.e., the amount of energy consumed to transmit one bit [43], [44].

$$ECR = \frac{P}{D} \quad \left(\frac{Watt}{bit/sec}\right) \tag{11}$$

Where, $D = \frac{B}{T}$ is the data rate in bits per second and P is the power in Watts required to deliver B bits over time T. Furthermore, energy efficiency between two systems can also be expressed by Energy Consumption Gain (ECG), which is a ratio of ECR for two systems [43], [44].

$$ECG = \frac{ECR_a}{ECR_b} \tag{12}$$

Energy savings on the other hand are expressed as Energy Reduction Gain (ERG) [43], [44].

$$ERG = \left(\frac{ECR_a - ECR_b}{ECR_a}\right) \times 100\% \tag{13}$$

For comparison of two schemes where the coverage area does not remain same, Area Power Consumption [45] metric is helpful in accessing the power consumption of the network relative to its size. It is the average power consumed in a given area divided by the area. This metric is measured in Watts per square Kilometre.

$$P_{Area} = \frac{P_{av}}{A_c} \tag{14}$$

where P_{av} is the average power consumed and A_c is the coverage area.

3 Energy Consumption Aware Heuristic Resource Allocation Scheme (ECA)

The formulated combinatorial optimisation problem in (8) contains both continuous ($\mathbf{p}$) and binary ($\boldsymbol{\phi}$,$\boldsymbol{\psi}$) decision variables. The problem in (8) can be identified as a mixed integer non-linear programming problem since the constraint (9f) i.e., $R_{k,m}$ is non-linear in p considering equations (3) and (2). The problem is similar to the classical 0/1 knapsack problem since the user can be scheduled at only one cell at any given time which is known to be NP-hard (similar to the one in [46]). Finding the optimal solution to these non-convex problems in real network with dynamically changing network conditions requires computationally complex exhaustive search, rendering its implementation in practical systems impossible. It becomes even harder when QoS constraints are added on top (as is the case here with the minimum MUE rate constraints). Consequently, the complexity is expected to grow exponentially with the number of cells. Considering that SCs allocate power to RBs according to some predefined power levels, vector $\mathbf{p}$ can instead contain integer variables. This of course renders the optimisation problem even harder to solve.

To address the complexity issues we devise a low complexity heuristic solution. The proposed Energy Consumption Aware Resource Allocation Scheme (ECA) heuristically tries to achieve the objective in (8). Although the proposed scheme is a sub-optimal solution to problem in (8), the aim behind this solution is to keep the computational complexity very low to allow its implementation in practical network. The flow diagram of the proposed ECA algorithm is presented in Fig. 6, followed by the pseudocode. In the first step, the ECA scheme solves the RB allocation problem using linear binary integer programming. To this end, we assume all SCc are ON i.e., $\psi_m = 1, \forall m$ with maximum transmit power and equal power allocation across RBs, i.e., $p_{m,n} = P_{max}/N$ for any SC m. With this consideration, the network power minimization problem is transformed into a pure binary linear optimisation problem which can be written as follows:

$$\min_{\boldsymbol{\phi}} \sum_{m=0}^{M} P_m^{total} \tag{15}$$

subject to:

$$\phi_{k,m,n} \in \{0,1\}, \forall k \in \mathcal{K} \setminus \mathcal{K}_0, m \in \mathcal{M}, n; \tag{16a}$$

$$\sum_{k \in \mathcal{K}_m} \phi_{k,m,n} \in \{0,1\}, \forall m \in \mathcal{M}, n; \tag{16b}$$

$$\Omega_n^{\text{sum}} \leq \Omega_n^{\max}, \quad \forall n; \tag{16c}$$

$$R_{k,m} \geq R_{k,m}^{min}, \forall m \neq 0; \tag{16d}$$

The objective is to guide the SCs with their respective muting parameter in $\boldsymbol{\phi_n}$, in order to satisfy the maximum interference tolerance threshold for the MUEs. This results in significant reduction of the optimisation problem search space by considering only RB allocation. This reduces the complexity and convergence time of the problem; hence, it can be easily solved after multiple or even every transmission time interval (TTI) e.g. in LTE networks. Once the SCs are guided with their muting parameter, the algorithm analyses the possibility of switching off under-utilized SCs. For this, the MC checks if it has sufficient free resources to accommodate small cell users without hurting its own users. If that is the case, the under-utilized SCs are switched to sleep mode. We simplify this process by comparing the number of available RBs (RB_0^{Avail}) at the MC (the RBs which are not being used to serve MUEs) with a minimum threshold number of RBs (RB_0^{Thres}). Now, based on the reported activity of the SCs, the ON/OFF state problem is solved in a progressive manner considering the SCs with lowest utilization at first. Here we consider that a SC may result in a low utilization if it has very low load (serving few users with low average data rate requirement/constraint) or if it has a very high RB muting factor (causing high interference to MC users). The ON/OFF state solution is passed to the SCs (SC State Array $\boldsymbol{\psi}$), and the MC continuously monitors its performance over a longer time interval e.g. minutes. If a congestion ($C_0 = 1$) occurs i.e., number of resource blocks required for all of the MC users previously associated with any m^{th} sleeping SC i.e., $\sum_k RB_{k,m}^{Req}$ exceeds number of available RBs (RB_0^{Avail}) then it starts activating sleeping SCs prioritizing the ones whose users, that were handed over to the MC, have hefty average data-rate requirements.

It is necessary to highlight here that for the sake of conciseness, this work does not address the macro-to-macro cell interference that becomes particularly easy to manage due to presence of X2 interface. The rationale behind this simplification is that focus of this paper is to study how much energy can be saved by proactively switching ON/OFF small cells, given that the macro to macro interference problem is already solved using one of the existing methods in literature.

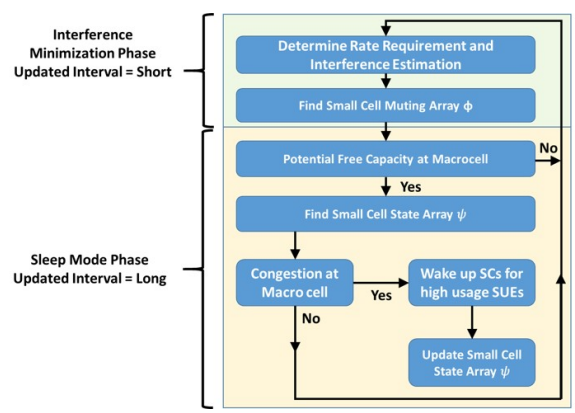


Fig. 6: Flow Diagram for ECA Scheme

3.1 Practical Implementation of ECA in a Real Network

In this section, we present a high-level description of the implementation aspects of the ECA algorithm in real SON enabled LTE HetNets comprising macro and small cells.

- The centralized SON engine can apply Big Data analytics on the past CDRs to analyze the spatio-temporal traffic pattern and forecasts the required data rates of the macro and small cell users in each of the cells. State of the art Big Data analytics tools from Hadoop ecosystem like Apache Spark and Apache Mahout can be leveraged to achieve this objective.

Algorithm 1 Energy Consumption Aware Resource Allocation (ECA)

for $n = 1 \rightarrow N$
  Initialise : $\vec{\phi}_n = \vec{0}$
  Calculate : $\Omega_n^{\max}$,$\omega_{u,0,n}^m$,$R_{k,m,n}$ as in eq. 3, 5 and 6
  $\vec{\phi}_n$= *bintprog* ($\vec{R}_n$, $\vec{\omega}_{u,0,n}$, $\Omega_n^{\max}$)
end
Notify SCs with their respective $\phi_{m,n}$.

SC Sleep Mode Phase
Analyse Available n RBs at Macrocell
if $RB_0^{\text{Avail}} > RB_0^{\text{Thres}}$
  Sort SC utilisation $\vec{U}$ in Ascending order
  while $RB_0^{\text{Avail}} > RB_0^{\text{Thres}}$
    Send sleep mode activation message to SC on top of $\vec{U}$.
    Update RB_0^{Avail}, Remove top element from $\vec{U}$.
  end

SC Wake-up Phase
For every SC in sleep mode **do**:
if $\sum_k RB_{k,m}^{\text{Req}} > RB_0^{\text{Avail}}$ **OR** $C_0 = 1$
  Sort $\sum_k RB_{k,m}^{\text{Req}}$ in ascending order for all m
  while $\sum_k RB_{k,m}^{\text{Req}} > RB_0^{\text{Avail}}$ **OR** $C_0 = 1$
    Send wake-up message to SC on top of the list
    Update RB_0^{Avail}
  end
end

- Minimization of Drive Test (MDT) reports recently standardised by 3GPP [47] and CQI reports collected at SON engine can be utilized to determine the user channel gain on specific RBs. On the basis of these reports (3) and (4) can be used to estimate the maximum interference that MUE can tolerate on a certain RB. The MDT reports of the UEs also contain information relevant to their neighboring cells such as the neighboring cells reference signal received quality along with the physical cell ID of the neighboring cell. These respective MUE reports can be used by the SON engine to estimate the top neighboring interfering small cells; then, this information can be used to estimate the total interference caused to it by all small cells in each RB and formulate the optimisation constraint (16c).
- Finally, the optimisation process of the suboptimal problem in (15) is performed at the SON engine using ECA algorithm. The optimisation function returns the muting matrix for the small cells which is passed to the small cells. Furthermore, the sleep mode phase is utilized to determine and pass on the state array (ON/OFF) to the small cells. Moreover, in order to avoid introducing unnecessary control overheads into the network, muting and state array can only be forwarded subject to change in the optimisation parameters. In that case, small cells can continue to use the last updated muting and state array matrix until a new update is passed by the SON engine.

4 Results and Analysis using Real Traffic Traces Derived from CDRs of Milan City

In this section we present our analysis based on a real networks traffic data to show there is sufficient predictability component that can be exploited for significant energy savings through the proposed scheme. Later in section 5, we utilize simulation based deterministic traffic models to show how the proposed scheme can enhance aggregate throughput and energy savings.

4.1 Introduction to CDR Data from City of Milan

The data used for this analysis comes from Telecom Italia's network, Italy, shared as part of their big data challenge 2015 [40]. In our study, a week's data (01st Dec 2013 to 07th Dec 2013) is used to analyze user activity trends in the metropolitan city of Milan. The data made public by Telecom Italia is in form of CDRs for calling and internet activity. We translated this data into traffic volumes by exploiting the big data eco-system, the details of which are omitted for brevity. As shown in Fig. 4, in the data shared by Telecom Italia, the city of Milan is divided into several smaller grids (10,000 square grids). For each grid, a CDR value corresponding to call and internet activity logged at 10 minutes interval, is made public.

4.2 Heuristic Methodology Augmenting Real Traffic Traces with Realistic Intuitive Topology

The available data lacks information about the real base station deployed within the city. Therefore to achieve the objectives of this analysis, without compromising the generality of its conclusions, we assume that the calling and internet activity belongs to a macro-cell and small-cell, respectively. From this point onward, we refer to them as macro-cell and small-cell activity levels. The macro-cell is assumed to cover an area of 225 square meters while each of the grid is assumed to have one small cell. The calling activity for each macro-cell (accumulated calling activity for 225 square grids) is translated into data activity according to the Voice over LTE (VoLTE) standard. Each call is assumed to be 3 minutes based on the average European calling statistics [48]. As for the VoLTE standard approximately 300 bits of data packet is required to be transmitted by the end interface every 20ms. This brings the data rate for each VoLTE call to 15Kbps. Based on these details we map the CDR based activity levels into data rates as shown in figures 1-3 earlier. It is observed that cells have a wide variation in the range of activity levels (some small-cells have high activity and some have very low activity). An obvious reason for this phenomenon is the number of POIs within each cell (the popularity of POIs also affects the activity levels of cells). To capture this aspect of cells with and without POIs, we consider two macro-cells as depicted in Fig. 7. The first macro-cell M1 has no POIs within its coverage area, where as the second macro-cell M2 has a number of POIs in its coverage as indicated by blue dots on the grid. In the discussion forward, we refer M1 and M2 as Non-POI and POI cells. The plot in Fig. 7 was constructed by plotting the geographical coordinates of most popular POIs in city of Milan as determined through information available on tripadvisor.com [49].

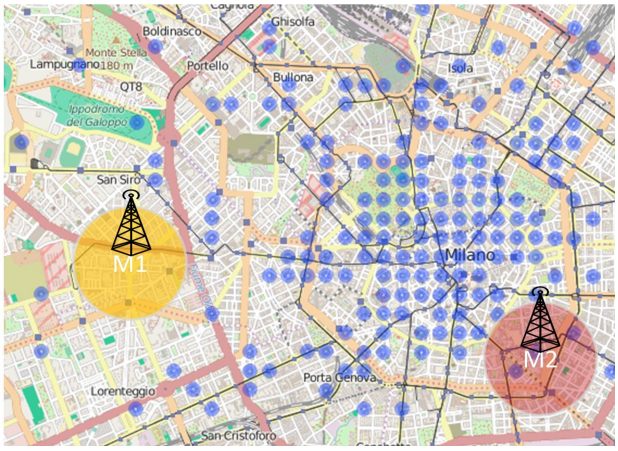


Fig. 7: Points of Interest (POIs) on City of Milan grid

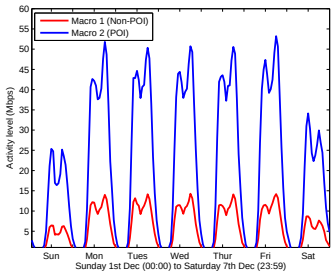


Fig. 8: Activity level for NON-POI (red) and POI (blue) macro-cells

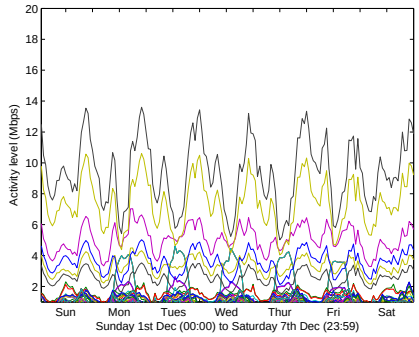


Fig. 9: Activity level for NON-POI small-cells

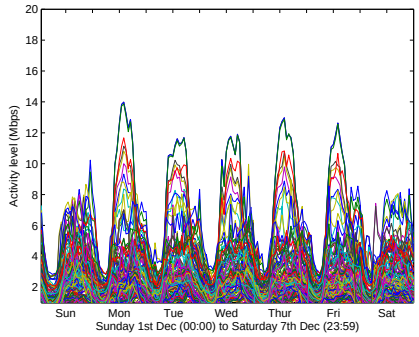


Fig. 10: Activity level for POI small-cells

4.3 Simulation Results for Application of ECA Algorithm on CDRs Data

In order to analyze the potential energy savings resulting from the application of ECA algorithm on real networks data, sleep mode phase of the ECA algorithm is leveraged in this section. Note that the interference estimation part of the ECA algorithm is not utilized in the algorithm evaluation since the big data available to us does not contain UE location and thus SINR information. Therefore, we estimated interference using average spectral efficiency. The objective of this study is to demonstrate that even with limited information that could be extracted by us from a real publically available data, a proactive and predictive instead of reactive or cyclic energy efficiency algorithm can be developed that can result into significant energy saving gain. Additional information when incorporated into the algorithm including user locations and SINR maps etc, can lead to even better performance in terms of interference aware energy efficiency.

The results and analysis are presented specific to non-POI and POI macro-cells and under-laying small-cells as visualized in Fig. 7. Fig. 8 shows the activity levels of non-POI and POI macro-cell from Sunday until Saturday, presented as data rates (Mbps). As previously deduced, activity levels are high for the POI cell as compared to the non-POI cell. Another interesting aspect to consider for these two considered macro-cells is that the activity levels during the week days are relatively higher as compared to weekends. Similar activity plots are presented for non-POI and POI small-cells in Figures 9-10. Since there are up-to 225 small cells, in the non-POI case, activity levels of most of the small-cells are below 1 Mbps, whereas in case of POI small-cells several small cells have an activity level higher as compared to non-POI cells.

To look into further details, graphs in Figures 11-12 are plotted to show the activity levels for a single day (hourly level) with the help of Box and Whisker plots. Each plot ranges from 9%ile to 91%ile of the values whereas the box expresses the lower and upper quartile (25% and 75%). Line dividing the box expresses the median and $'+'$ expresses the mean value. It can be observed that for 06:00 hrs and 18:00 hrs, the mean activity level for non-POI SCs is approximately 0.4 and 0.7 Mbps respectively. Similarly in case of POI SCs at 06:00 hrs and 18:00 hrs the mean activity levels are at 1.2 and 2.4 Mbps respectively. This traffic trend jointly motivates the use of ECA scheme for putting majority of the low activity small-cells into sleep-mode and serving their load with the macro-cell.

Utilizing these statistics, state of the art machine learning algorithms were employed to predict activity levels of the cells based on past activity levels. 70% of the data set was employed for training while remaining 30% for testing phase. The Support Vector Machine based regression outperformed all other techniques and was able to achieve 97% prediction accuracy. As discussed in section 1, unlike classical modelling approaches, our machine learning approach has been able to quite accurately predict the hourly traffic pattern (Figure 13) since it takes into account location metric as well. The predicted activity levels of each of the macro and small cells (1 Macro + 225 Small Cells) were translated

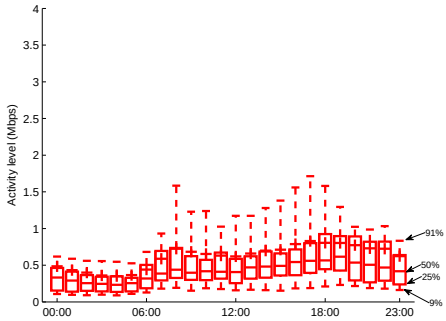


Fig. 11: Activity level for NON-POI small-cells for 24 hrs of a day. Each plot ranges from 9%ile to 91%ile of the values where as the box expresses the lower and upper quartile (25% and 75%). Line dividing the box expresses the median and $'+'$ expresses the mean value.

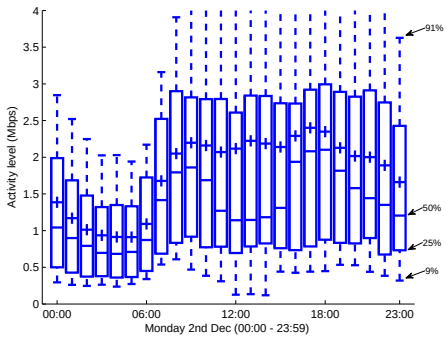


Fig. 12: Activity level for POI small-cells for 24 hrs of a day. Each plot ranges from 9%ile to 91%ile of the values where as the box expresses the lower and upper quartile (25% and 75%). Line dividing the box expresses the median and $'+'$ expresses the mean value.

to required number of PRBs using: $RB_m^{req} = R_m^{min}/w_B * S$ where w_B = 180 KHz is the bandwidth of one RB and S is the average spectral efficiency taken as 1.6 bps/Hz for LTE. A bandwidth of 20 MHz is considered wherein each cell has total of 100 RBs. Based on the availability of the potential free RBs at the macro cell, ECA algorithm off-loads small cell users to the macro cell and small cells are put to sleep mode. The performance of the proposed ECA algorithm is presented in terms of numbers of SCs put into sleep mode in Figures 14-15. Out of total of 225 small cells, ECA algorithms puts up-to 205 non-POI SCs in sleep mode while the traffic conditions are low for the small-cells as well

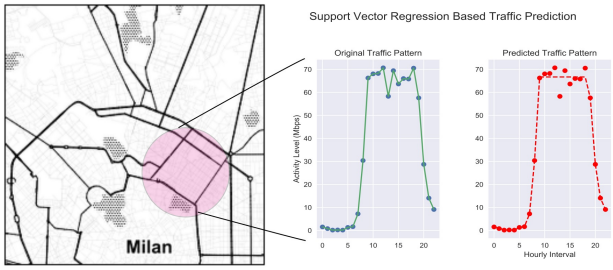


Fig. 13: Support Vector Regression based Traffic Prediction

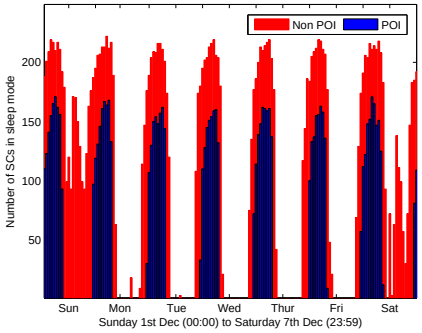


Fig. 14: Number of SCs put to sleep-mode for non-POI (red) and POI(blue) case for the whole week.

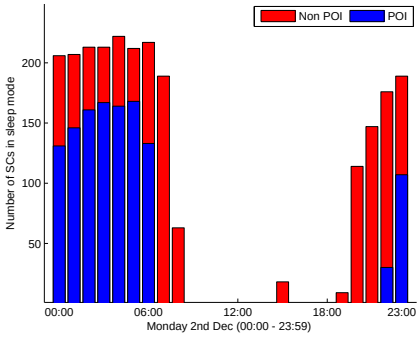


Fig. 15: Number of SCs put to sleep-mode for non-POI (red) and POI(blue) case for 24 hours.

as for the macro-cell. For the POI case up to 160 SCs can be put to sleep mode. However, generally there are far less SCs put into sleep-mode in case of POI SCs as compared to non-POI case. It can also be observed that during the peak hours of traffic load, no (a few in case of non-POI case) SCs are put to sleep mode. The energy savings possible by putting these the SCs in sleep mode are reflected in the later plots.

The EE performance of non-POI and POI cells is presented in Figures 16-17. It is interesting to observe that the EE performance of the non-POI case is significantly less than that in case of POI case. Such observed phenomenon can be explained by referring back to the definition of EE, i.e. the number of bits per Joule of energy (bits/Joule). Since the small-cells lie in the circuit power dominant regime (circuit power consumption is significantly higher as compared to transmit power consumption) and the circuit power being constant at all times. It is already established that the data traffic flow in non-POI cells is lower as compared to POI cells. So it can be deduced that the non-POI cells are under-utilized, whereas POI cells have higher utilization, hence better EE performance. Nevertheless, the important aspect to observe for these plots is that the EE performance before the ECA algorithm (solid black line) is improved with the application of ECA algorithm (red in case of non-POI and blue for POI). Also note that for the non-POI cells the EE performance is significantly improved as compared to the non-sleep-mode conventional case. This aspect of the performance analysis is further clarified through ERG (13) plots in Figures 18-19 for non-POI and POI cells respectively. For the non-POI case, up to 8 times ERG is achieved in certain

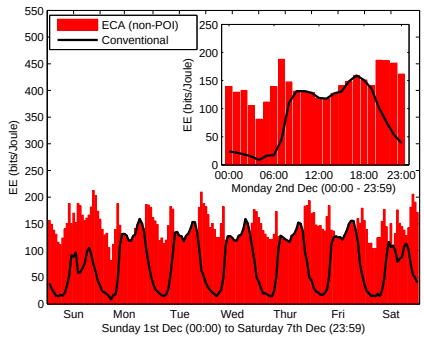


Fig. 16: EE (bits/Joule) performance for non-POI cells

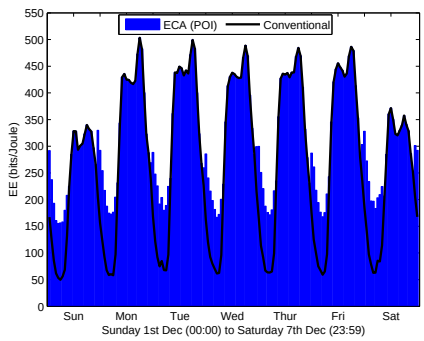


Fig. 17: EE (bits/Joule) performance for POI cells

off-peak traffic conditions, and the same results for the POI case reach a maximum of 2 times in off-peak conditions.

The traffic prediction accuracy will have crucial role in determining the holistic performance (Energy Reduction Gain) of the proposed Proactive Sleeping Cell solution that can be quantified as follows [50]:

$$ERG_{P-SON} = \alpha(ERG_c) + (1-\alpha)(ERG_{ic}) \tag{17}$$

where α is the prediction accuracy and ERG_c and ERG_{ic} are the Energy Reduction Gains for correct and incorrect predictions. While evaluation of ERG for different values of α is beyond the scope of this work, (17) can be employed for assessing the gain of Proactive Sleeping Cell Solution and the minimum accuracy needed to achieve any gain (refer to Fig. 3 in [50]). Inaccuracies in traffic prediction might lead to switching OFF some SCs in high traffic demand regions where they should not have been switched OFF. However, the proposed solution aims at switching the states

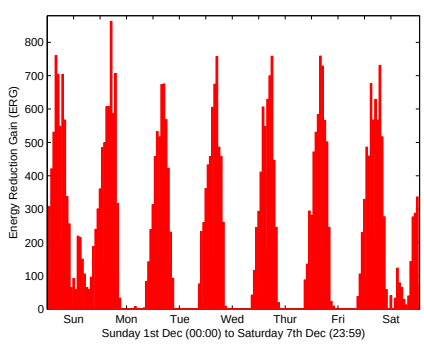


Fig. 18: Energy Reduction Gain (ERG) performance for non-POI case

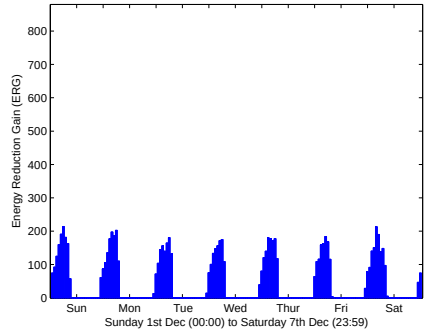


Fig. 19: Energy Reduction Gain (ERG) performance for POI case.

of SCs only while keeping the Macro cells ON all the time. Therefore, in case of inaccurate predictions, Always ON Macro cells will be there to offset the effect of inaccurate predictions.

Concept drift issues in this case i.e. variation in the underlying pattern of traffic over longer period of time that can make the learned model inaccurate, can be addressed by employing Adaptive Base Learning techniques in which the training is reduced and expanded to identify the impact of variation in learning window size. Training set is dynamically modified to include moistures of past and present data and prediction model is updated. Moreover, ensemble techniques can be leveraged for making sure that training data is diverse and unbiased. Weaker models are pruned and remaining models are combined based on some weighting criteria. Separate machine learning models trained for weekends/weekdays/holidays can be employed for further improvement of the prediction accuracies. Another possibly more promising method is to incorporate additional contextual data into the model that takes into account occurrence of events and festivals and awareness of point of interests to improve prediction accuracy.

5 Results and Analysis using Simulated Deterministic Traffic Model

In the aforementioned section, results pertaining to the sleep mode phase of the ECA algorithm were presented only since no information of the actual topology and user reported SINR was available. Therefore in this section we present results for our proposed ECA scheme using deterministic traffic model and simulated topology and compare the results in terms of power consumption and users data rate performance against the conventional schemes. Details of the simulation parameters are given in Table 1.

For the purpose of demonstrating the function of the proposed algorithm, we simulate a network with 15 SCs and a single macrocell. Number of users in the macrocell and SCs are generated using Poison arrival process for each snapshot. Simulations are performed for four normalised load conditions of the network (0.25, 0.50, 0.75 and 1). The value of λ for the Poison process is selected based on the load observed in the results presented in prior sections. We consider these four variations in network loads to analyse our algorithm at different times of the day [51]. Furthermore, it is assumed all MUE have minimum data rate

TABLE 1: LTE-Based Scenario - Simulation Parameters.

Parameter	Macro-cell	Small-cell
Number of nodes	1	15
Carrier frequency	2.1 GHz	
Bandwidth	10 MHz	
Node transmit power	43 dBm	23 dBm
Path loss model	$128.1 + 37.6 \log_{10}(d[\text{Km}])$	
UE Generation	Poison Arrival Process	
RB_0^{Thres}	15%	
Noise Figure at UE	9 dB	
Thermal noise density	-174 dBm/Hz	
Cell Radius	800m	50m
P^{circuit} [2]	120W	8.4W
$\Delta(7)$	3.2	4

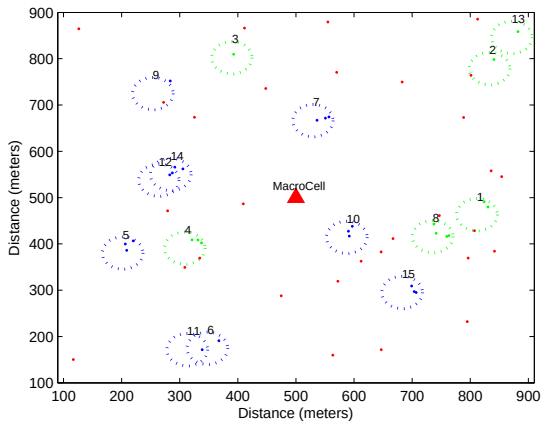


Fig. 20: Snapshot of the network with normalised load = 0.5. Red dots indicate the MUEs and blue dots indicate SUEs. Blue rings indicate the active SCs and green rings indicate SCs in sleep mode.

requirement of 250 kbps. Using Monte-Carlo simulations, 1000 snap shots are generated for each load case and results were averaged.

The operation of the ECA algorithm is depicted in Fig. 20 where a single snap shot is illustrated. The blue rings show the active SCs, whereas the green rings show the SCs which are switched to sleep mode and their SUEs are being served by the macrocell. If we consider for example SCs '2' and '13', both of them are switched to sleep mode and we can observe that they have a some MUEs (red dots) in their vicinity. The dominant interference to these MUEs causes muting of resources at the SCs. In return due the low utilisation of these SCs and the available capacity at the macrocell, the UEs of these SCs are handovered to the the macrocell and SCs '2' and '13' are switched to sleep mode. This will usually happen at the low load times of the day. Sleeping SCs might be awaken in case there is a congestion at the macrocell or in case of increase in network load. If for example all the SUEs have similar data rate requirements, then SC '4' would be awakened first, as it has more number of SUEs.

The Cumulative Distribution Function (CDF) for the data rates of MUEs is presented in Fig. 21. We compare the performance of our proposed ECA scheme with Reuse-1 scheme (where all nodes transmit at the same frequency resources). It is evident from the Fig. 21 that in case of Reuse-1 up to 20% of the users are in outage (below the required

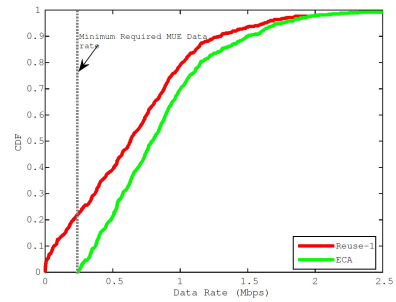


Fig. 21: CDF plot for MUE data rates

data rate mark, as indicated in the figure). This is due to the strong interference from the neighboring SCs serving their users on the same resources. However, in case of ECA scheme, this inter-tier interference is minimized and nearly all the users are safe guarded from outage. This is made possible by muting some of the SCs at certain RBs where the victim MUEs were being served. The proposed ECA scheme along with successfully safeguarding the victim MUEs present in the vicinity of SCs, also maximizes the energy efficiency of the network. The energy consumption comparison between ECA scheme and a conventional scheme with no sleep mode savings is presented in Fig. 22. This comparison is shown for the four different considered load states of the network. This comparison for different load conditions is shown with the help of bar graphs and the y-axis of Fig. 22 indicates the sum of total power consumption (circuit and load dependent transmit power) of all transmit nodes. The horizontal line in the middle of the plot indicates the constant circuit power of the macrocell given by equation (7) which is fixed for all cases. The remaining top portion of the bars indicates the sum of macrocells load dependent transmit power plus the circuit and transmit power of all the active SCs. The true potential of ECA scheme can be clearly seen for low to medium network load conditions. This is due to the fact that in low traffic conditions, the macrocell has unused capacity which can be successfully used to serve SUE of under-utilized SCs. The energy saving gains come from switching off the circuitry of the SCs but as a trade-off the load dependent transmit power of the macrocell is slightly increased. However, up to 23% saving in total network power consumption can be achieved using ECA in these traffic conditions.

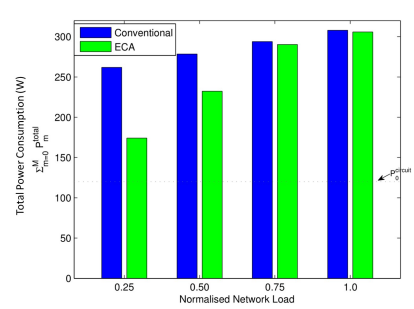


Fig. 22: Total power consumption for various network load conditions.

The time complexity of the optimal exhaustive search

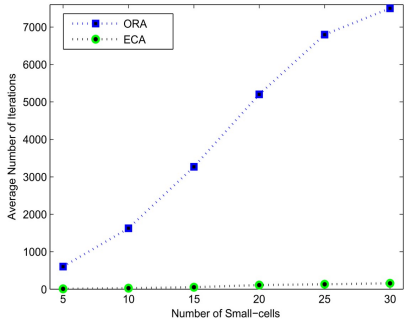


Fig. 23: Time Complexity performance of ECA scheme.

in our case shall be $O(2(KMN))$, which is exponential in nature. However, for the state of the art algorithms that either target interference or energy minimization problem such as ORA (Optimal Resource Allocation) scheme [52], the complexity is mainly dependent on solving the dual problem. The number of computations required to solve the RB allocation is $K(M+1)$ and N number of allocations are required to solve for all RBs. The complexity for each complete iteration is $O(NK(M+1))$. The total complexity of the sub-gradient method is polynomial in the number of dual variable and is $O(N+M)$. Therefore, the overall complexity of the ORA scheme is $O((N+M)2(NMK))$. The ECA scheme is solved by binary linear integer programming.

There are several linear programming relaxations applied to such algorithms, which make them very effective in practice but it is difficult to prove theoretical complexity bounds on the performance of such algorithms. A comparison in terms of number of iterations between the ORA and ECA scheme is presented in Fig. 23, emphasizing on the lower complexity, therefore, higher the practicality of the ECA scheme. The minimalistic complexity of the ECA algorithm makes it feasible to be applied to a practical LTE network and can be updated within every LTE frame.

6 Conclusions

In this paper, we have proposed a proactive energy efficient resource allocation solution that not only minimizes the overall network energy consumption but also incorporates the inter-tier interference mitigation solution in a LTE HetNets environment. In this study, we exploit the predictable nature of real traffic load to determine sleep schedule of small cells and formulated the mathematical optimisation problem. Furthermore, taking into account the computational complexity limitation of a practical network, we have proposed a heuristic energy efficient small cell centralized resource allocation algorithm. In order to demonstrate the scale of potential energy savings in a practical network, real CDR data from City of Milan was used. Large scale data processing and analysis was performed exploiting the big data ecosystem tools (Apache Spark) in order to analyze the activity patterns throughout the Milan City. The proposed ECA algorithm, by making use of sleep-mode in small cells shows a potential of significant energy savings especially in off-peak times of the day. Results showed that energy consumption could be reduced up to 8 times in the dense heterogeneous network within an urban city by incorporating our proposed energy consumption aware resource allocation algorithm. Moreover, our deterministic-load based simulation results clearly indicate that nearly all macro-cell served users were protected from neighboring small cell inter-tier interference in comparison to Reuse-1 case. In addition, during the low traffic condition, the proposed mechanism has shown to reduce a significant amount of network energy by switching the under-utilized cells to sleep mode.

Acknowledgement

This material is based upon work supported by the National Science Foundation under Grant Number 1619346 and Grant Number 1559483. The statements made herein are solely the responsibility of the authors.

References

[1] A. Saeed, A. Akbari, M. Dianati, and M. A. Imran, "Energy efficiency analysis for lte macro-femto hetnets," in *European Wireless 2013; 19th European Wireless Conference*, April 2013, pp. 1–5.

[2] G. Auer, O. Blume, V. Giannini, I. Godor, M. A. Imran, Y. Jading, E. Katranaras, A. Olsson, D. Sabella, P. Skillermark, and W. Wajda, "D2.3 v2: Energy efficiency analysis of the reference systems, areas of improvement and target breakdown," Tech. Rep. INFSOICT-247733 EARTH (Energy Aware Radio and NeTwork TecHnologies), 2012.

[3] D. Lopez-Perez, X. Chu, and J. Zhang, "Dynamic downlink frequency and power allocation in ofdma cellular networks," *IEEE Transactions on Communications*, vol. 60, no. 10, pp. 2904–2914, October 2012.

[4] C. Turyagyenda, T. O'Farrell, and W. Guo, "Long term evolution downlink packet scheduling using a novel proportional-fair-energy policy," in *2012 IEEE 75th Vehicular Technology Conference (VTC Spring)*, May 2012, pp. 1–6.

[5] L. Lei, D. Yuan, C. K. Ho, and S. Sun, "Optimal cell clustering and activation for energy saving in load-coupled wireless networks," *IEEE Transactions on Wireless Communications*, vol. 14, no. 11, pp. 6150–6163, Nov 2015.

[6] B. Maaz, K. Khawam, and S. Tohme, "Achieving spectral and energy efficiencies in multi-cell networks," in *2015 11th International Conference on Innovations in Information Technology (IIT)*, Nov 2015, pp. 98–103.

[7] E. Khaledian, N. Movahedinia, and M. Khayyambashi, "Spectral and energy efficiency in multi hop ofdma based networks," in *Telecommunications (IST), 2014 7th International Symposium on*, Sept 2014, pp. 123–128.

[8] J. Tang, D. K. C. So, E. Alsusa, K. A. Hamdi, and A. Shojaeifard, "Energy efficiency in multi-cell mimo broadcast channels with interference alignment," in *2014 IEEE Global Communications Conference*, Dec 2014, pp. 4036–4041.

[9] S. H. Ali and V. C. M. Leung, "Dynamic frequency allocation in fractional frequency reused ofdma networks," *IEEE Transactions on Wireless Communications*, vol. 8, no. 8, pp. 4286–4295, August 2009.

[10] J. Ling, D. Chizhik, and R. Valenzuela, "On resource allocation in dense femto-deployments," in *2009 IEEE International Conference on Microwaves, Communications, Antennas and Electronics Systems*, Nov 2009, pp. 1–6.

[11] F. Bernardo, R. Agust, J. Cordero, and C. Crespo, "Self-optimization of spectrum assignment and transmission power in ofdma femtocells," in *2010 Sixth Advanced International Conference on Telecommunications*, May 2010, pp. 404–409.

[12] A. Saeed, E. Katranaras, M. Dianati, and M. A. Imran, "Control and data channel resource allocation in macro-femto heterogeneous networks," in *2015 International Wireless Communications and Mobile Computing Conference (IWCMC)*, Aug 2015, pp. 1272–1276.

[13] J. D. Hobby and H. Claussen, "Deployment options for femtocells and their impact on existing macrocellular networks," *Bell Labs Technical Journal*, vol. 13, no. 4, pp. 145–160, 2009. [Online]. Available: http://dx.doi.org/10.1002/bltj.20341

[14] X. Chu, Y. Wu, D. Lopez-Perez, and X. Tao, "On providing downlink services in collocated spectrum-sharing macro and femto networks," *IEEE Transactions on Wireless Communications*, vol. 10, no. 12, pp. 4306–4315, December 2011.

[15] X. Chen, H. Xia, Z. Zeng, S. Wu, W. Zuo, and Y. Lu, "Energy-efficient heterogeneous networks for green communications by inter-layer interference coordination," in *2014 International Symposium on Wireless Personal Multimedia Communications (WPMC)*, Sept 2014, pp. 70–74.

[16] K. Davaslioglu, C. C. Coskun, and E. Ayanoglu, "Energy-efficient resource allocation for fractional frequency reuse in heterogeneous networks," *IEEE Transactions on Wireless Communications*, vol. 14, no. 10, pp. 5484–5497, Oct 2015.

[17] A. Y. Al-Zahrani and F. R. Yu, "An energy-efficient resource allocation and interference management scheme in green heterogeneous networks using game theory," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 7, pp. 5384–5396, July 2016.

[18] X. Shui, M. Zhao, P. Dong, and J. Kong, "A novel dynamic soft frequency reuse combined with power re-allocation in lte uplinks," in *2012 International Conference on Wireless Communications and Signal Processing (WCSP)*, Oct 2012, pp. 1–6.

[19] K. Wang, M. Zhao, and W. Zhou, "Graph-based dynamic frequency reuse in cloud-ran," in *2014 IEEE Wireless Communications and Networking Conference (WCNC)*, April 2014, pp. 105–110.

[20] X. Chen, H. Xia, Z. Zeng, S. Wu, and W. Zuo, "User partitioning based resource allocation and interference coordination in heterogeneous networks," in *2014 IEEE 25th Annual International Symposium on Personal, Indoor, and Mobile Radio Communication (PIMRC)*, Sept 2014, pp. 1104–1108.

[21] W. Li, W. Zheng, H. Zhang, T. Su, and X. Wen, "Energy-efficient resource allocation with interference mitigation for two-tier ofdma femtocell networks," in *2012 IEEE 23rd International Symposium on Personal, Indoor and Mobile Radio Communications - (PIMRC)*, Sept 2012, pp. 507–511.

[22] C. C. Coskun, K. Davaslioglu, and E. Ayanoglu, "An energy-efficient resource allocation algorithm with qos constraints for heterogeneous networks," in *2015 IEEE Global Communications Conference (GLOBECOM)*, Dec 2015, pp. 1–7.

[23] C. Yang, J. Li, and M. Guizani, "Cooperation for spectral and energy efficiency in ultra-dense small cell networks," *IEEE Wireless Communications*, vol. 23, no. 1, pp. 64–71, February 2016.

[24] C. Kosta, B. Hunt, A. U. Quddus, and R. Tafazolli, "Distributed energy-efficient inter-cell interference coordination (icic) in multi-cell hetnets," in *2013 IEEE 77th Vehicular Technology Conference (VTC Spring)*, June 2013, pp. 1–5.

[25] X. Sun and S. Wang, "Resource allocation scheme for energy saving in heterogeneous networks," *IEEE Transactions on Wireless Communications*, vol. 14, no. 8, pp. 4407–4416, Aug 2015.

[26] C. Yang, J. Li, A. Anpalagan, and M. Guizani, "Joint power coordination for spectral-and-energy efficiency in heterogeneous small cell networks: A bargaining game-theoretic perspective," *IEEE Transactions on Wireless Communications*, vol. 15, no. 2, pp. 1364–1376, Feb 2016.

[27] Y. Liu, C. S. Chen, and C. W. Sung, "Joint optimization on inter-cell interference management and user attachment in lte-a hetnets," in *2015 13th International Symposium on Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks (WiOpt)*, May 2015, pp. 62–69.

[28] R. Ramamonjison and V. K. Bhargava, "Energy allocation and cooperation for energy-efficient wireless two-tier networks," *IEEE Transactions on Wireless Communications*, vol. 15, no. 9, pp. 6434–6448, Sept 2016.

[29] H. Burchardt, S. Sinanovic, Z. Bharucha, and H. Haas, "Distributed and autonomous resource and power allocation for wireless networks," *IEEE Transactions on Communications*, vol. 61, no. 7, pp. 2758–2771, July 2013.

[30] R. Litjens and L. Jorguseski, "Potential of energy-oriented network optimisation: Switching off over-capacity in off-peak hours," in *21st Annual IEEE International Symposium on Personal, Indoor and Mobile Radio Communications*, Sept 2010, pp. 1660–1664.

[31] M. A. Marsan, L. Chiaraviglio, D. Ciullo, and M. Meo, "Optimal energy savings in cellular access networks," in *2009 IEEE International Conference on Communications Workshops*, June 2009, pp. 1–5.

[32] I. Ashraf, F. Boccardi, and L. Ho, "Sleep mode techniques for small cell deployments," *IEEE Communications Magazine*, vol. 49, no. 8, pp. 72–79, August 2011.

[33] Z. Niu, "Tango: traffic-aware network planning and green operation," *IEEE Wireless Communications*, vol. 18, no. 5, pp. 25–29, October 2011.

[34] F. Z. Kaddour, E. Vivier, L. Mroueh, M. Pischella, and P. Martins, "Green opportunistic and efficient resource block allocation algorithm for lte uplink networks," *IEEE Transactions on Vehicular Technology*, vol. 64, no. 10, pp. 4537–4550, Oct 2015.

[35] E. Katranaras, M. A. Imran, M. Dianati, and R. Tafazolli, "Green inter-cluster interference management in uplink of multi-cell processing systems," *IEEE Transactions on Wireless Communications*, vol. 13, no. 12, pp. 6580–6592, Dec 2014.

[36] E. Katranaras, M. A. Imran, and R. Hoshyar, "Energy aware transmission in cellular uplink with clustered base station cooperation," in *2011 IEEE 73rd Vehicular Technology Conference (VTC Spring)*, May 2011, pp. 1–5.

[37] A. Imran, A. Zoha, and A. Abu-Dayya, "Challenges in 5G: how to empower SON with big data for enabling 5G," *IEEE Network*, vol. 28, no. 6, pp. 27–33, November 2014.

[38] S. Zhang, D. Yin, Y. Zhang, and W. Zhou, "Computing on base station behavior using erlang measurement and call detail record," *IEEE Transactions on Emerging Topics in Computing*, vol. 3, no. 3, pp. 444–453, Sept 2015.

[39] P. D. Francesco, F. Malandrino, and L. A. DaSilva, "Assembling and using a cellular dataset for mobile network analysis and planning," *IEEE Transactions on Big Data*, vol. PP, no. 99, pp. 1–1, 2017.

[40] https://www.telecomitalia.com/tit/en/bigdatachallenge.html.

[41] S. Navaratnarajah, A. Saeed, M. Dianati, and M. A. Imran, "Energy efficiency in heterogeneous wireless access networks," *IEEE Wireless Communications*, vol. 20, no. 5, pp. 37–43, October 2013.

[42] D. Lopez-Perez, X. Chu, A. V. Vasilakos, and H. Claussen, "Power minimization based resource allocation for interference mitigation in ofdma femtocell networks," *IEEE Journal on Selected Areas in Communications*, vol. 32, no. 2, pp. 333–344, February 2014.

[43] B. Badic, T. O'Farrrell, P. Loskot, and J. He, "Energy efficient radio access architectures for green radio: Large versus small cell size deployment," in *2009 IEEE 70th Vehicular Technology Conference Fall*, Sept 2009, pp. 1–5.

[44] F. Cao and Z. Fan, "The tradeoff between energy efficiency and system performance of femtocell deployment," in *2010 7th International Symposium on Wireless Communication Systems*, Sept 2010, pp. 315–319.

[45] F. Richter, A. J. Fehske, and G. P. Fettweis, "Energy efficiency aspects of base station deployment strategies for cellular networks," in *2009 IEEE 70th Vehicular Technology Conference Fall*, Sept 2009, pp. 1–5.

[46] G. Wu, L. Dong, Z. Qin, and Z. Xu, "Dynamic programming-based pico base station sleep mode control in heterogeneous networks," *International Journal of Communication Systems*, vol. 30, no. 2, pp. e2967–n/a, 2017, e2967 dac.2967. [Online]. Available: http://dx.doi.org/10.1002/dac.2967

[47] 3GPP, "3rd Generation Partnership Project; Technical Specification Group Radio Access Network; Study on Minimization of drive-tests in Next Generation Networks; (Release 9)," 3GPP, Tech. Rep. TR 36.805 V9.0.0, 2009.

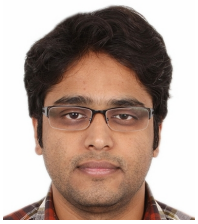
[48] BEREC, "Termination rates at european level january 2016," Tech. Rep., May 2016.

[49] Tripadvisor. [Online]. Available: https://www.tripadvisor.com/

[50] H. Farooq and A. Imran, "Spatiotemporal Mobility Prediction in Proactive Self-Organizing Cellular Networks," *IEEE Communications Letters*, vol. 21, no. 2, pp. 370–373, feb 2017.

[51] B. Partov, D. J. Leith, and R. Razavi, "Energy-aware configuration of small cell networks," in *2014 IEEE 25th Annual International Symposium on Personal, Indoor, and Mobile Radio Communication (PIMRC)*, Sept 2014, pp. 1403–1408.

[52] A. Saeed, E. Katranaras, M. Dianati, and M. A. Imran, "Dynamic femtocell resource allocation for managing inter-tier interference in downlink of heterogeneous networks," *IET Communications*, vol. 10, no. 6, pp. 641–650, 2016.



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