Dynamic Power Adjustment and Resource Allocation Framework for LTE Networks

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***Abstract*—In current LTE deployments, the unsupervised and unilateral installation of home or localized base stations, so called eNodeBs, may easily lead to excessive energy consumption and over-provisioning of network infrastructure. In this paper, we propose an energy efficient framework, which dynamically adjusts the power requirements of the system and performs Resource Block (RBs) allocation based on needs. It specifically optimizes power consumption of LTE networks consisting of under-utilized eNodeBs. The Energy Efficiency (EE) issue is formulated as an optimization problem, which trades off EE for SE without adversely impacting the downlink throughput. In order to solve this problem, we develop a heuristic approach called as Two Phase Enhanced Branch and Bound Algorithm (TPEBB) [1]. End-to-end latency, modeled by Markov queues, is used as the main metric for QoS in this study [2]. Finally, we compare the proposed framework with various competing methods to show almost 70% improvement in EE and end-to-end latency.**

***Index Terms*—Power Adjustment, Resource Allocation, Co-tier Interference, Energy Efficiency, Branch and Bound Algorithm**

I. Introduction

The rapid growth of mobile data traffic [3] has motivated service providers to increase their network capacity so that user QoS requirements can be fully met. Extensive research undertaken by both the academic and the industry sectors have resulted in several proposals for enhancing the standards-supported features of Long Term Evolution (LTE). Network densification is one such solution that will ensure that emerging network needs are satisfied. The ability for users to install local, short-range base stations called eNodeBs, enables such densely packed deployments. In this transformative scenario, cellular data can now be offloaded at the network edge to the closest eNodeB, and does not have to congest the long distance link set up with the macro-cell tower. This step of incorporating a very large number of eNodeBs at short distances offers significant increase the overall network capacity. However, we argue that simplistic and unilateral placement of eNodeBs can actually hurt the overall network, and instead, advocate careful tuning of the transmission settings given the deployment geometry. The benefits of this approach is twofold- First, it encourages users to safely install their own eNodeBs, thereby aiding in the desired network densification efforts. Second, it allows reduced maintenance cost and one time capital expenses for sustained, high quality access to spectrum.

The specific focus of this paper concerns developing a technique to solve the problem of how to manage a group of under-utilized eNodeBs from an energy viewpoint. We believe this is an important problem as haphazard placement of eNodeBs contributes to degradation both in network performance as well as in maintenance costs. Our work is motivated by the need for dynamically adjusting the power levels of eNodeBs to decrease high power consumption and reduce wastage of energy resources without impacting the QoS of end-users [4]. Indeed, this reduction in power for certain eNodeBs cannot be arbitrary, but must be carefully chosen based on the prevailing interference characteristics of the network.

Several previous works have attempted to address the problem of decreasing energy consumption in an LTE network infrastructure. In [5], a broad taxonomy for major trade-offs related to EE is defined and analyzed. The comparison metrics include Deployment-Efficiency (DE) vs EE, Spectrum-Efficiency(SE) vs EE, Power-Consumption vs Bandwidth-Consumption, Power-Consumption vs Delay-Performance. Moreover, the authors present simple analysis to provide insights for the characteristics of these trade-offs. Different from the above, a trade-off between EE and SE is examined in [6]. In [7], the authors propose a multi-objective optimization that tackles both EE and SE. To this end, they provide a comprehensive framework to emphasize how and where the optimal tradeoff lies between the opposing considerations of EE and SE.

To decrease energy consumption, different sleep-mode techniques have been proposed. For instance, for small cell networks, authors classify these techniques by their sleep-trigger mechanisms and examine the reduction in the overall energy consumption. The resulting fine-grained comparison among these different trigger mechanisms is included in [8]. In [9], a subset of small cells are placed in a sleep-mode and the traffic load is offloaded in a balanced manner to the others by considering both EE and QoS of end users. In [10], the authors propose a traffic-aware energy optimization framework for LTE systems that utilizes an on/off mechanism for energy savings. By using such simple on/off (sleep) mechanisms, the approach limits the EE dramatically. In this paper,

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we exploit how additional gains can be achieved in energy saving by utilizing dynamic power adjustment mechanisms. Additionally, the authors in [11] proposed green resource allocation that minimizes energy consumption during channel usage in OFDMA cellular networks.As opposed to this, this paper minimizes energy consumption in an LTE network by rearranging RBs which includes a number of consecutive sub-carriers for a number of consecutive OFDM time/frequency symbols [12]. Therefore, it reduces the number *wake up* time slots for the user equipments (UEs). Therefore, the power consumption of UE is reduced because of having less wake-up duration. However, it does not consider co-tier interference and the global view of the network.

As a design choice, we bias the operation of our approach towards preferentially reducing the energy consumption rather than further increasing the SE. The reason behind this is that the dense network of eNodeBs is assumed to already incorporate high levels of spectrum availability, almost to the point of over-provisioning access resources. As we explain in the subsequent sections of the paper, we ensure that all RBs are fully utilized by every eNodeB in the network, rather than splitting RBs among adjacent cells controlled by these eNodeBs. With this approach, we significantly simplify the calculation of CIR (Carrier-to-Interference Ratio) values for every UE, and distribute RBs and adjust power levels of eNodeBs accordingly. We use the well known *D'Hondt* algorithm as the starting point to develop our resource allocation algorithm. Determining the best RB distribution and selecting the eNodeB power level that achieves the maximum EE is still a Non-deterministic Polynomial (NP) time problem. In order to overcome this challenge, we propose a heuristic called a Two Phase Enhanced Branch and Bound Algorithm (TPEBB) [1], which provides sub-optimal solutions in acceptable time intervals. Additionally, we note that there is a finite penalty in SE for the sake of energy saving, as we quantify such trade-offs while evaluating the work. Our framework results in a self-contained resource allocation module, which simplifies the modeling of interference and enables further energy saving.

The paper is organized as follows; the network architecture and system model are explained in sections II and III . The performance of the proposed model is evaluated in Section IV and, we conclude the paper by summarizing the contributions in Section V.

II. Network Architecture

We assume that network consists of N number of eNodeB and M number of immobile UEs. In the initial configuration, each UE is assigned to the closest eNodeB. We only consider co-tier interference and aim to optimize EE during the downlink transmissions. In Figure 1, we introduce two distinct processes that reside within the Mobility Management Entity (MME): the "Wireless Access Controller" and "Dynamic Power Manager". These processes are connected to the eNodeBs through the cellular backbone and control the network operations over the S1-MME link. The first process, Wireless Access Controller, decides the allocation of RBs among UEs for each eNodeB. The second one, Dynamic Power Manager, adjusts the power level of every eNodeB via the proposed TPEBB algorithm.More detailed information is given in the system model section III.

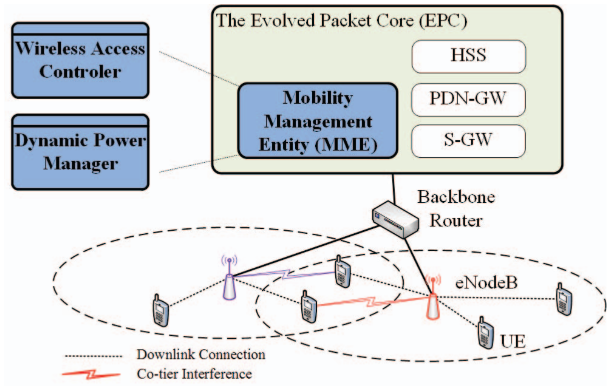

Fig. 1: The proposed network model

III. Power Control Method for eNodeBs

A. Wireless Access Controller

The main purpose of this controller is to distribute RBs among UEs at every eNodeB . The decisions concerning the ratio of RB distribution are made on the basis of the CIR and Bandwidth Requests (λ) of the UEs. The controller uses additional location information for both UEs and eNodeBs, and then combines this knowledge with an indoor path loss model to calculate the respective CIR levels. The indoor path loss model that we chose is standardized in ([12], [13]) and given in Eq 1.

$$L_{ij}(t) = 37 + 30\ log_{10} d_{ij}(t) + 18.3\ n^{\frac{(n+2)}{(n+1)} - 0.46} \tag{1}$$

where $d_{ij}(t)$ is the distance between UE_i and $eNodeB_j$ in meters, n indicates the number of floors within the indoor environment path.

With the definition of path loss model, the $CIR_{ij}(t)$ of the UE (u_j) in the presence of an interfering $eNodeB_k$ (v_k) is calculated as follows.

$$CIR_{ij}(t) = C_{ij}(t) - I_{kj}(t) \tag{2}$$

where C and I are both in *dBi* and defined as:

$$\begin{aligned} C_{ij}(t) &= P_i(t) - max(L_{ij}(t) - G_i - G_j, MCL) \\ I_{kj}(t) &= P_k(t) - max(L_{ik}(t) - G_i - G_k, MCL) \end{aligned} \tag{3}$$

where P is the transmission power in *dBi*, G is antenna gain and MCL is the minimum coupling loss.

The implemented allocation algorithm contains two consecutive phases. In the first phase, the algorithm assigns each UE the minimum whole number of RBs ($\lceil \lambda \cdot \gamma \rceil$) which satisfies its request (λ) with respect to its current link performance as given in the lines 3 to 5 in Alg 1. The performance of the each downlink between an eNB and UE is represented by γ [13] and defined in Eq 4.

$$\gamma_{ij}(t) = \begin{cases} 0, & CIR_{ij}(t) < CIR_{min} \\ \alpha \cdot S(CIR_{ij}(t)), & CIR_{min} < CIR_{ij}(t) < CIR_{max} \\ T_{max}, & CIR_{max} < CIR_{ij}(t) \end{cases} \tag{4}$$

where α is the attenuation factor representing implementation losses, $S(CIR)$ indicates the Shannon bound and is calculated as $log_2(1 + CIR)$ (bps/Hz), CIR_{min} is the minimum CIR , T_{max} indicates maximum service capacity (bps/Hz), CIR_{max} represents CIR at which max throughput is reached $S^{-1}(T_{max})$ (dB).

Then, in the second phase, if there are remaining unallocated RBs, eNB is forced to utilize these RBs by distributing them among UEs by the modified *D'Hondt* algorithm. The *D'Hondt* algorithm is currently used in election to allocate seats to the parties proportional to their votes. In this modified version, we modelled UEs as parties and bandwidth request as the votes they have received and distributes RBs among them. However, in the *D'Hondt* algorithm, the number of taken resources is used as the denominator after assigning a RB and this action favors the UE with the highest bandwidth request. In order to provide slightly more balanced distribution, we have modified *D'Hondt* algorithm and re-defined the denominator as 2^r where r is the number of already assigned RBs.

Algorithm 1 Allocation Algorithm

Require: UE requests (λ_j) and Link Level Performances (γ_{ij})
Ensure: RB array for the $eNodeB_i$ ($\mathbf{B}_i$) and Modified downlink Throughput
1: **function** AssignResourceBlocks(List $users$)
2: Initialize *assignedRB* with 0;
3: **for all** $u_j \in users$ **do** ▷ First Phase
4: $B_{ij} \leftarrow \lceil \lambda_j \cdot \gamma_{ij} \rceil$ ▷ Initial assignment of RB to u_j
5: $assignedRB += \lceil \lambda_j \cdot \gamma_{ij} \rceil$
6: **end for**
7: **if** $assignedRB > availableRB$ **then**
8: **return** -1; ▷ not Feasible
9: **end if** ▷ Second Phase
10: **while** $availableRB - assignedRB > 0$ **do** ▷ Modified D'Hondt Alg.
11: Sort $users$ according to their request (λ)
12: Increase B_{ij} by 1
13: $\lambda_j \leftarrow \lambda_j / 2$
14: Increase $assignedRB$ by 1
15: **end while**
16: update downlink Throughput;
17: **return** B_i and Throughput;
18: **end function**

We assume that each eNodeB is forced to utilize all its RBs to reduce energy consumption. This allows us to simplify the resource allocation and co-tier interference calculation in the lines 4 and 10 in Alg 1. Since, every eNodeBs utilizes every RBs in the network, we can state that every UEs is the victim of interference by its neighbor cell and we could determine the aggressor cell by using only the distance information between the victim UE and adjacent eNBs without using complex algorithms like graph-coloring or matching.

Furthermore, eNBs are able to reduce their transmission power further by allocating more RBs than what are requested by the UEs, while still meeting throughput expectations. This action is realized by the second phase of the allocation algorithm which is defined in the lines from 10 to 14 in Alg 1. As a conclusion, the given allocation algorithm decides how to distribute RBs within every eNB individually. Since, the result of the distribution in one of the eNB does not effect the other one, this algorithm runs concurrently for each eNB in a centralized entity (MME).

B. Dynamic Power Manager

The Dynamic Power Manager process aims to minimize the energy consumption by reducing the transmission power (P_{tx}) of eNodeBs with respect to predefined QoS constraints, after the allocation of the RBs is completed. Towards this aim, each downlink connection in a given eNodeB is modeled as a queue to estimate the end-to-end delay. Thus, the packet waiting time (W) is used as the main performance metric to evaluate the QoS. As stated earlier, the Wireless Access Controller process uses Alg. 1 to distribute all available RBs among UEs, but the actual capacity of the assigned RBs may differ based on the SE. To accommodate for this disparity, the CIR values for each connection is required and this is used to determine actual channel capacity.The actual channel capacity (μ) is calculated in Eq 5 by using a link level performance multiplier defined in Eq 4.

$$\mu_{ij}(t) = \begin{cases} 0, & CIR_{ij}(t) < CIR_{min} \lor \rho_{ij}(t) > 1 \\ B_{ij}(t) \cdot \gamma_{ij}(t), & \begin{array}{c} CIR_{min} < CIR_{ij}(t) \land \\ CIR_{ij}(t) < CIR_{max} \land \ 0 < \rho_{ij}(t) < 1 \end{array} \\ B_{ij}(t) \cdot \gamma_{ij}(t), & CIR_{max} < CIR_{ij}(t) \land 0 < \rho_{ij}(t) < 1 \end{cases} \tag{5}$$

where B_{ij} is the calculated amount of the assigned bandwidth of the $eNodeB_i$ to UE_j by Alg. 1. The traffic type is modeled by using a $Gamma\ Arrival$ - $G/G/1$ Markov model. According to the characteristics of this model, the average waiting time, i.e. queuing time ($W_{ij}(t)$), is defined as follows [14] and used as the end-to-end delay in the framework:

$$W_{ij}(t) = \frac{\rho_j(t)}{2\mu_j(1 - \rho_j(t))} + \lambda_j^2(t)\sigma_A^2 + \mu_j^2\sigma_B^2 \tag{6}$$

where λ_j is arrival rate, μ_j is service rate, and ρ_j is utilization of the link. Moreover, σ_A and σ_B represent the standard deviation of the arrival and service rates, respectively.

1) Formulation of the Optimization Problem: EE parameter, formally defined below, is used as the objective function of the optimization problem.

$$EE_i = \frac{\sum_{0<j\leq M_i} \lambda_j}{P_{tx,i} + P_{cir,i}} \tag{7}$$

where $P_{tx,i}$, $P_{cir,i}$ and λ_j represent transmission and circuit power consumption of the i^{th} eNodeB and the throughput of the j^{th} UE, respectively. The following optimization problem is defined to represent the objective and the constraints of the framework.

$$\begin{aligned} &\max \sum_{0<i\leq N} EE_i \qquad ;\forall i \in \{1, ..., N\} \\ &\text{w.r.t.} \begin{cases} P_i \in \{0, ..., 7\} \\ C_{ij} \leq C_{min}, \qquad ;\forall j \in \{1, ..., M\} \\ W_{ij} \leq \delta \\ \sum_{0<j\leq M_i} \lambda_i \leq \Upsilon_i \end{cases} \end{aligned} \tag{8}$$

where $P_{tx,i}$ is the transmission power (in Watts) of the $eNodeB_i$. We have pre-defined eight power levels (P) [0, ..., 7] for eNodeBs. The 0^{th} power level represents the case when an eNodeB is turned off and the 7^{th} power level indicates that it is working at the maximum power level. W_{ij} models the end-to-end delay between UE_i and $eNodeB_i$. λ_j is the throughput (bps) of the UE_j, and finally, Υ_i is the overall capacity of the $eNodeB_i$ for open access users which are admitted to eNodeBs in order to use serving channels without any permission. Each change of the transmission power of an eNodeB effects both the link performance multipliers in the given cell, and also in the adjacent cells. Additionally, link performance multipliers impact the service times of the connections and necessitate an update for the waiting times of the downlink connections. Moreover, in a search space, the simple optimization methods can easily have higher probability to get stuck at the local optima. As a result of this, in a search space, finding an optimal solution for the global optima becomes complex when using a simple optimization method.We propose a novel algorithm (TPEBB), described in Alg 2, which provides a sub-optimal solution for optimizing the problem formulated in Eq 8. In the first phase of TPEBB, new network topologies result by altering the association of the UEs to the eNodeBs by reducing power level of each eNodeB. Then, the algorithm checks the feasibility of these created association topologies. During the second phase that immediately follows, TPEBB forces a handover for those UEs that estimate their CIR value to be below a pre-determined handover threshold (set at $3dB$ in this work). If the handover improves both the end-to-end delay (W) and offers a feasible topology, then TPEBB chooses to take that action and adds the newly created topology to the candidate solution list.

Algorithm 2 TPEBB

```
Require: G(V, U, E)
 1: function MAIN((G))
 2:     create List topologies and add topology G to the List
 3:     Optimize (topologies)
 4: end function
 5: function OPTIMIZE(List topologies)
 6:     Initialize newItem as false;
 7:     for all eNodeB v_i in the topology G do
 8:         Clone G to G'
 9:         Reduce P_Tx of (v_i, G')
10:         if isFeasible(G') then
11:             Update newItem as true;
12:             add (G') to topologies
13:         else                                            ▷ Second Phase
14:             for all UE u_j which is assigned to eNodeB v_i do
15:                 if u_j ∈ H then                  ▷ UE is Handover Candidate
16:                     offload(u_j)
17:                     if isFeasible(G') then
18:                         Update newItem as true
19:                         add (G') to topologies
20:                     end if
21:                 end if
22:             end for
23:         end if
24:     end for
25:     if ( then newItem )
26:         Optimize(topologies - G)    ▷ Exclude the explored topology from the List
27:     end if
28: end function
```

2) Temporal Complexity Analysis of Algorithm 2: At any given point in the algorithm execution, the network topology may evolve in terms of transmission powers of eNodeBs and connections between eNodeB and UEs. This, a number of different topologies in the solution space is possible and given as:

$$|S| = K^N \cdot \begin{pmatrix} M + N - 1 \\ N - 1 \end{pmatrix} \tag{9}$$

where S is the solution space, K is the number of power levels for eNodeBs, M and N are number of UEs and eNodeBs, respectively. The size of the solution space necessities a heuristic algorithm to achieve a sub-optimal solution within a reasonable time period. In the worst case, using a simplistic branch and bound approach results in a time complexity directly equivalent to an exhaustive search in the solution space. To mitigate unnecessary search complexity, the proposed TPEBB algorithm incorporates pruning and priority mechanisms to improve the output of the process. Pruning provides significant reduction in the solution space by controlling QoS levels in every iteration. Priority mechanisms manipulate the order of discovery within the solution space w.r.t. achieved EE. Moreover, with any real-time constraint, the algorithm can be preempted at any time while still providing an acceptable sub-optimal solution for the problem. We note that it is hard to determine a generic function mapping the convergence time to the optimal solution because of its high dependence to the spatial attributes of the network.

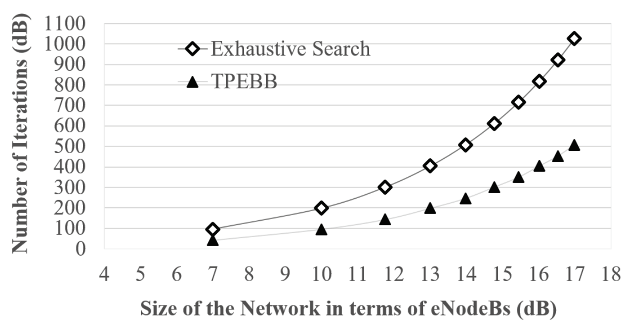

Fig. 2: Temporal Complexity Analysis of the algorithms

We conduct an empirical study to provide insight about the convergence time of the algorithm. We define ten different scenarios that vary in terms of the size of the network, from 5 eNodeBs to 50 eNodeBs in step size of 5 eNodeBs as seen in Table I. Additionally, we define 5 UEs that have average downlink traffic of 540KBs for each eNodeB. Since, TPEBB utilizes pruning during the search, as seen in the lines 9, 16 of Alg. 2, it does not explore infeasible regions of the solution space. We compare *TPEBB* to an *exhaustive search* and provide the results in Figure 2. However, since both of the algorithms have exponential complexities, we define x-axis and y-axis in *dB* ($10log_{10}(x)$) to provide observable results.

IV. Performance Evaluation

The various components of the setup environment are as follows:

TABLE I: Simulation Parameters

Different Scenarios & Parameters	Complexity Analysis of Alg. 2	Boundaries of Under-Utilized Network	Analysis on EE
Number of eNBs	$5k \mid k \in (1, 2, ..., 10)$	1 eNB	6 eNBs
Number of RBs (each 375 KHz [13])	50 RBs [13]	50 RBs [13]	50 RBs [13]
Number of UEs	5 UEs for each eNB	10 to 50 UEs w.r.t $\frac{Cell-CenterUE}{Cell-EdgeUE} \in (1, 2, ..., 50)$	25 UEs
Maximum Downlink Throughput	540 KBs	Gathered as 400 to 1600 KBs	$60k \mid k \in (1, 2, .., 11)$

- A *Virtual Machine (VM)* with the VirtualBox Graphical User Interface with Version 5.0.10r104061, is the platform where the entire simulation code is run.
- A desktop computer with Ubuntu 14.04 OS equipped 16 GB RAM and Intel Core i7-3770 CPU @ 3.40GHz x 8, is chosen to run the simulations.
- The simulator is written in JAVA language which version is 1.8.0_31.

The performance of the proposed TPEBB approach is evaluated in two different scenarios, with parameter settings given in Table I. Specifically, we focus on architectures that have under-utilized network conditions resulting in UE demands that are already satisfied completely with remaining RBs available (see settings in the third column of the table). We compare TPEBB with the Adaptive Fractional Frequency Reuse (FFR) method [15] against increasing UE density to identify the maximum downlink throughput demand that can be satisfied. After this boundary condition is crossed, we show that TPEBB degrades gracefully, with further improvement in EE obtained at the expense of the maximum downlink throughput. Secondly, we evaluate the performance of our approach by analyzing the relationship between the power consumption and average waiting times w.r.t. average arrival rates in the downlink traffic of UEs.

A. Performance Boundaries of Under-utilized Network

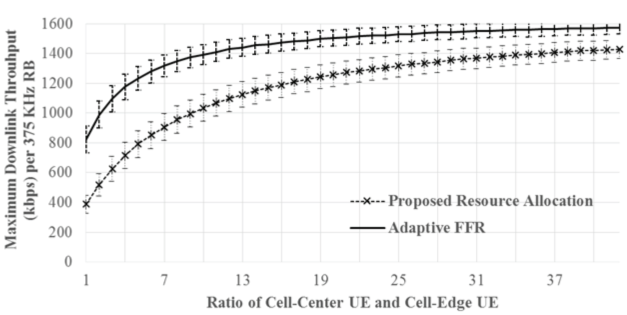

Fig. 3: Max. throughput of network

In this section, we compare the TPEBB resource allocation method in Alg.1. with the optimal adaptive FFR. For FFR, we assume that the fraction of the assigned RBs allotted to the cell-edge users and cell-center users are optimally set to achieve the theoretical upper bound for maximum downlink throughput. If the majority of the users are located at the cell-center, this conventional method utilizes greater portion of the available RBs for cell-center UEs dynamically with reduced transmission power in order to create less interference. However, if users are concentrated at the cell-center, the fraction of assigned RBs is high as there is limited interference with neighbor cells. Our modified resource allocation algorithm TPEBB, as given in Alg.1, behaves as an optimal adaptive FFR algorithm without any dynamic decision because it does not consider intercell interference instead of affected by it . In the performance evaluation scenario, we have one eNB with 50 RBs each spanning 375 KHz [13]. The number of UEs vary between 10 to 50 according to different ratios of $Cell - Center\ UE/Cell - Edge\ UE$. In Figure 3, the modified resource allocation method is compared with adaptive FFR w.r.t. this ratio of cell-center UE and cell-edge users. The $y - axis$ represents the gathered maximum downlink throughput according to changing ratios along the $x - axis$ with the confidence intervals set at 95%. When the increasing values on the $x - axis$ (i.e., number of cell-center UEs), the respective upper bounds of the traffic loads that can be accommodated by both of these methods approach to a common point. However, when the number of cell-edge UEs are greater or similar to cell-center UEs, the proposed framework is unable to satisfy heavy traffic demands because it does not consider intercell interference while allocating resource to UEs.

B. Study of EE

In this subsection, we study the EE performance of the proposed framework with the simulation details as given in right-most column of Table I. We run the proposed framework with two different sets of power level settings. The first one only contains 2 power levels (*TPEBBw2*) as seen in Alg.2, and works as on/off mechanism. The second one contains 8 different power levels (*TPEBBw8*) and benefits from dynamic power adjustment. Additionally, we compare the approach with the Traffic-Aware Energy Optimization (*TAEO*) [10] that also proposes an on/off switching mechanism for LTE networks, and include results without any energy-saving mechanism as a baseline case.

As mentioned earlier, *TPEBBw2* simply uses on-off switching for non-utilized $eNodeBs$ to minimize the overall energy consumption. However, different from [10], this mode also utilizes a branch and bound algorithm that can turn off eNodeBs. We define a topology with 6 eNodeBs and 25 UEs randomly distributed in the area. We evaluate the performance of the proposed framework for eleven different arrival rates.

In these scenarios, average downlink traffic rate of UEs differs from 240kBs to 840 kBs by units of 60 kBs, as seen in Table I.

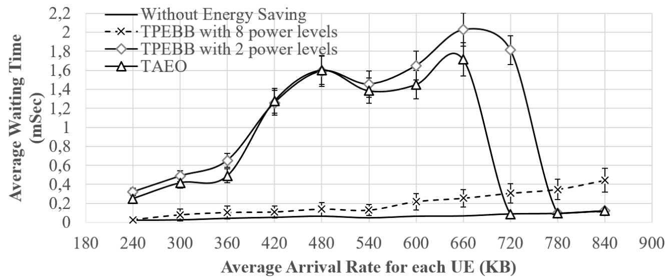

Fig. 4: Average waiting time ($W_{ij}(t)$) w.r.t. increasing arrival rate (λ)

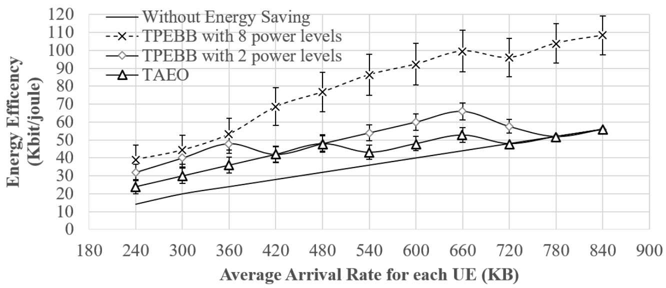

Fig. 5: EE w.r.t. increasing arrival rates (λ)

In Figures 4 and 5, the $x - axis$ represents average arrival rate for each UE (KB) (λ), and the $y - axis$ represents the average Waiting Time ($W_{ij}(t)$) (Eq. 6). This parameter is the main constraint of EE optimization formula in (Eq. 8) and obtained efficiency, which is the objective function of this optimization process and common to each of the different methods. The values for the initial topology are represented as the marker *'Without Energy Saving'*. Since, the simulation starts with a feasible initial topology configuration, it ensures desired throughout (except the scenarios that contain cell-edge users with too low CIR). Since all the eNodeBs are working at the max power level, it also returns the worst-case EE.

We see that *TPEBBw8* provides significant improvement in terms of EE ($\sum_{0<i\leq N} EE_i$ in Eq 8), and more than the other methods by utilizing dynamic power adjustment. While there is an increase also in the end-to-end delay (W in Eq. 6) these occur at acceptable intervals. As our approach uses exhaustive search within the given topologies (see loops included in lines 6 and 13 in Alg 2), it is able to search the solution space better and generate topology configurations with higher throughput that consume overall less power than simple sleep-awake methods. Furthermore, as the average arrival rate increases, power consumption in *TPEBBw2* and *TAEO* converge to the initial configuration. Thus, these methods provide better results in terms of throughput while they offer no improvement in EE. Consequently, we state that the proposed framework improves EE up to 70% percent for under-utilized networks, while considering end-to-end delays in downlink connections.

V. Conclusion

In this paper, we designed a framework to reduce energy consumption of under-utilized LTE networks. Our approach intelligently performs resource allocation by dynamically adjusting the RBs and transmission power of eNodeBs. We also propose a heuristic called $TPEBB$ that adapts the association of the UEs based on these transmit power variations. We show that the proposed framework improves EE up to %70 percent for under-utilized networks. In future work, we plan to optimize the energy consumption in heterogeneous networks, which consist of different sizes of cells considering both the access modes and user constraints.

Acknowledgment

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