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Low-Carb: A practical scheme for improving energy efficiency in cellular networks

Muhammad Saqib Ilyas[a,*], Ihsan Ayyub Qazi[b], Bilal Rassool[c], Zartash Afzal Uzmi[b]

[a] Namal College, Mianwali, Pakistan
[b] SBA School of Science and Engineering, LUMS, Lahore, Pakistan
[c] Warid Telecommunications, Lahore, Pakistan

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ABSTRACT

Electricity cost constitutes a significant fraction of the total operations costs in a cellular network. We present Low-Carb, a practical scheme which reduces the power consumption in such networks. Low-Carb achieves this by coupling *Base Transceiver Station (BTS) power savings* with *Call hand-off*—two features widely available to cellular operators. Motivated by the observation that most callers are in the vicinity of multiple BTSs, Low-Carb allows calls to hand-off from one BTS to another so that BTS power savings can be applied to a maximal number of BTSs throughout the cellular network. The resulting reduction in energy consumption is shown to be governed by an optimization problem. We also provide optimal and heuristic solutions to this problem. We use BTS locations and traffic volume data from a large live GSM network to evaluate the power savings possible using our proposed approach. Our results indicate that performing coordinated call hand-off and BTS power-savings, a GSM 1800 network operator with about 7000 sites nation-wide can reduce annual electricity consumption by up to 35.36 MWh. This is at least 9.8% better than the energy savings achievable by using BTS power savings alone.

1. Introduction

Cellular networks consume several tens of TWhs (terawatt-hours) of electrical energy worldwide every year [1], exacerbating the rising ecological concerns. Beyond these concerns, the corresponding cost of electricity makes up a significant proportion of the overall operational cost of a cellular service provider. In European markets, for example, the electricity cost is estimated to be around 18% of the operational costs [2]. This fraction is even higher in developing regions due to the shortage of grid electricity and the use of small-scale generation powered by diesel fuel. Thus, cellular operators are keen on reducing the power consumption of their networks.

Cellular networks in the energy-starved developing countries are pre-dominantly based on Global System for Mobile communication (GSM). For instance, more than 98% of the cellular subscribers in Nigeria are using GSM [3]. Similarly, almost 91% of Pakistan's 131 Million cellular subscribers are using GSM [4]. The 3G/4G subscribers in Pakistan are mostly concentrated in the large cities. The large rural population is still covered by legacy GSM networks. Transition of these rural cellular networks to 3G/4G is expected to be slow due to the high cost of handsets and low demand for higher bandwidth services. Furthermore, upgrade from GSM to 3G/4G/5G requires equipment upgrade and licensing costs. Since profits are low in today's cut-throat competition, upgrade to 3G/4G/5G in developing countries is expected to be slow. Thus, GSM networks are here to stay for a considerable period of time. Therefore, in this paper, we focus on energy efficiency of legacy GSM cellular networks.

This paper presents Low-Carb[1], a practical scheme which uses *Base Transceiver Station (BTS) Power Savings* and *Call Hand-off* to reduce the consumption of electricity in a GSM cellular network. Using deployment and traffic data from a cellular provider in a large metropolitan area in a developing region, we show that Low-Carb can save about 10% in the amount (and cost) of electrical energy. This translates into millions of dollars in annual savings, just for this one service provider.

Low-Carb achieves this saving in energy consumption by reducing the power consumption at BTSs, which account for 60% to 80% of a cellular network's total power consumption [1,5,6], by making them more energy proportional. Fig. 1 shows the normalized load

* Corresponding author.
E-mail addresses: saqib.ilyas@namal.edu.pk, msaqib@gmail.com (M.S. Ilyas), ihsan.qazi@lums.edu.pk (I.A. Qazi), bilal.rassool@waridtel.com (B. Rassool), zartash@lums.edu.pk (Z.A. Uzmi).

[1] Short for Lower Carbon footprint.

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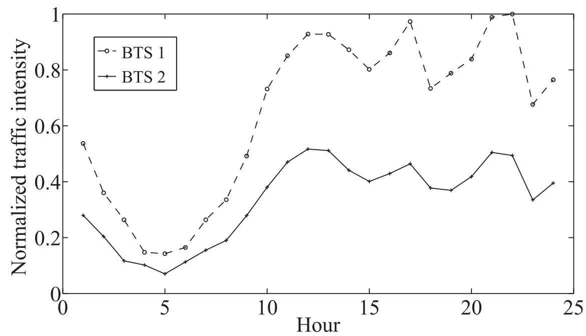

Fig. 1. Traffic load variations at two neighboring BTSs during a single day from our data set. For most of the day, the instantaneous load is a fraction of the peak traffic load.

of consumer traffic at two neighboring BTSs in our data set. Observe that while the traffic load peaks for a short period of time, it mostly stays at a fraction of its peak[2].

However, the radio circuitry at BTSs is provisioned in accordance with the peak load. This radio circuitry lacks energy proportionality, i.e., its power consumption does not scale in proportion to the traffic load. As a result, a BTS also lacks energy proportionality and consumes power at about the same level as it would at the peak load [6]. This leads to wasted energy, which Low-Carb aims to reduce—by varying the power consumption at a BTS in accordance with its traffic load.

If the instantaneous power consumed at a BTS can be made proportional to the instantaneous workload, savings in power consumption will ensue. For the provider data available to us, a fully energy proportional BTS subsystem of a cellular network would save between 44% – 52% of electrical energy depending on the BTS model. Thus, there exists potential to save electricity cost in a cellular network by reducing the energy consumption at low workloads. Low-Carb exploits this potential in two ways: (i) by shutting down part of the radio circuitry, and (ii) by rerouting calls from one BTS to a nearby BTS.

1.1. Description of Low-Carb

Coarse-grained energy proportionality in BTSs may be achieved in one of the following two ways:

- BTSs may be turned off when traffic is low and turned on later when traffic load increases [1,7–11]. However, operators are often reluctant to switch on/off entire BTSs due to coverage and equipment lifetime concerns (see Section 2.2).
- *Frequency dimming* [12] proposes to turn off a fraction of the radio circuitry when traffic is low, such that the traffic may be handled by the circuitry that stays on. Most vendors' BTSs support such a feature, which we term as *BTS power savings* in this paper. Our conversations with cellular operators reveal that they regularly use this feature. Low-Carb also makes use of this feature.

Traffic traces collected from a large network operator indicate that if some calls are handed off between neighboring BTSs, the number of BTSs that can be put in BTS power savings mode can be increased. Thus, Low-Carb proposes to hand-off calls between neighboring BTSs, without making a negative impact on the network quality of service, such that the *BTS power savings* can be applied to a maximal number of base stations throughout the cellular network. In comparison to uncoordinated *BTS power savings*, as used in current cellular network deployments, Low-Carb offers additional power savings as it may allow a larger number of radio circuits to be deactivated.

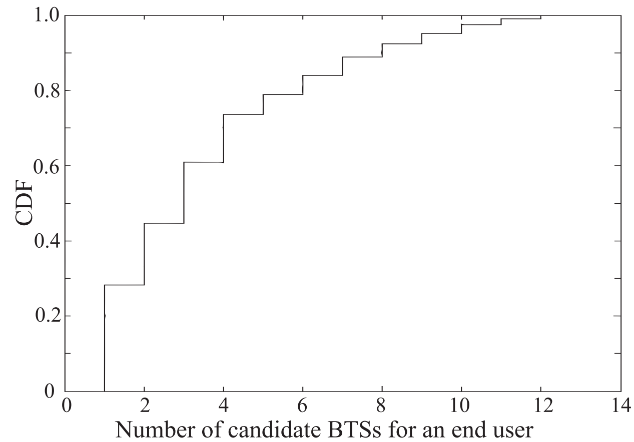

Fig. 2. CDF (cumulative distribution function) of the number of potential serving BTSs for a call in our dataset (large metropolitan area).

The underlying assumption in Low-Carb is that calls can be handed off to neighboring BTSs without being dropped and without exceeding their traffic capacity. This is possible because (a) traffic load in cellular networks exhibits significant variation over time and space and (b) most callers often receive sufficiently strong signal from *several* nearby BTSs [6,13]. This coverage diversity is evident in Fig. 2, which shows the CDF of the number of BTSs available to an end-user in our dataset of live traffic. Observe that the results show that about half of the callers have 3 or more candidate BTSs available at all times Thus, some calls may be handed off from one BTS to a nearby BTS in order to increase energy savings over those possible through BTS power savings alone.

1.2. Contributions

This paper makes the following contributions:

1. We formulate Low-Carb as a mathematical optimization problem to maximize energy savings in a cellular network, by using call-handoff and BTS power savings in a coordinated manner.
2. We propose a heuristic algorithm for solving the Low-Carb power optimization problem in polynomial time.
3. We use real datasets from a large GSM network operator to evaluate Low-Carb.
4. We evaluate the sensitivity of Low-Carb electricity savings to various system parameters.
5. Turning off TRXs to save energy consumption results in an associated increase in call blocking probability. We find quadratic fits to fairly accurately determine the increase in call blocking probability as a function of the achievable savings in electricity consumption.

The rest of the paper is structured as follows. In Section 3, we discuss related works. The formulation of Low-Carb optimization problem is presented in Section 4. Experimental setup and the results are presented in Sections 5 and 6, respectively. In Section 7, we offer concluding remarks.

2. Background and motivation

2.1. BTS radio resources in GSM

In a GSM network, the cell covered by a BTS is typically split into three *sectors*. A BTS is equipped with several transceivers

[2] Operational cellular networks have been widely observed to exhibit traffic load variations both over time and space [6].

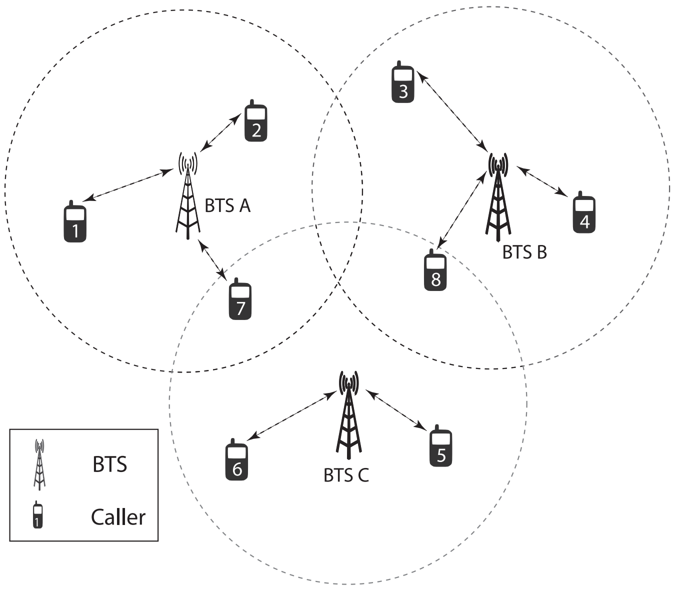

Fig. 3. The scenario for the motivating example. Three BTSs (A, B and C) are shown along with eight active calls. Each call is handled by the BTS from which it receives the strongest signal (the default in GSM networks). The serving BTS for each call is shown using arrows. If the power savings mode can be enabled at a BTS only if it has up to two active calls, then only BTS C can be put in the power savings mode. However, if calls 7 and 8 were handed off to BTS C, both BTS A and B can be put into the power savings mode, thereby resulting in greater energy savings.

(TRXs) for each sector. A typical configuration is "6+6+6", depicting a BTS serving three sectors each with six TRXs.

Each TRX is allocated a pair of frequency channels, one for transmission (downlink) and the other for reception (uplink) of radio signals. For each frequency channel, GSM handles upto eight simultaneous calls by using time-division multiplexing. The number of TRXs installed on a BTS, therefore, determines its (peak) traffic capacity.

When planning a network deployment, the BTS in a cell is commissioned with enough TRXs to handle the peak traffic load. Since the traffic peaks only for a short duration, the GSM networks generally operate in an over-provisioned state.

Over-provisioned BTSs would be fine if they also consumed little power at no traffic load. However, the no-load power consumption can be as high as 95% of the power at full traffic load [6]. Thus, with fixed BTS capacity that is over-provisioned for low traffic loads, today's cellular networks are energy inefficient.

2.2. Power savings

During low traffic periods, network operators often use a feature available in most vendor's equipment that deactivates TRX circuits at locations that serve very few customers. Huawei calls this feature *TRX shutdown* while Ericsson calls it *BTS power savings*. We use the latter term generically in this paper. Turning off one TRX cuts down BTS power consumption anywhere from 20W to 100W, depending upon the frequency band (900 or 1800) and deployed equipment [14,15]. Thus, scaling a "6+6+6" to a "2+2+2" configuration, by deactivating 12 TRXs will result in a saving of 240W to 1200W on a single site.

2.3. Motivating example

To illustrate the working principle of Low-Carb, we consider an example deployment consisting of three BTSs serving eight calls in neighboring cells as shown in Fig. 3. By default, each call is served by the BTS from which the mobile station receives the strongest signal. Assume that each BTS may handle up to six simultaneous calls and that the power-saving threshold is two calls, i.e., a BTS serving up to two calls may be put into power-saving mode.

Table 1
A comparison of schemes for BTS power savings.

Scheme	Calls being handled by BTSs			
	A	B	C	BTSs in power saving mode
Default	1, 2, 7	3, 4, 8	5, 6	None
Power saving	1, 2, 7	3, 4, 8	5, 6	C
Low-Carb	1, 2	3, 4	5 – 8	A, B

The first row in Table 1 indicates that under default call association, no BTS in the example deployment of Fig. 3 is placed in power saving mode. With this default call association, the operator may still save some electrical energy by activating the power saving mode on BTS C (second row in Table 1). Additional energy savings are possible by deploying Low-Carb, which hands off calls 7 and 8 to BTS C and enables power saving mode on two BTSs (A and B), as shown in the third row in Table 1.

This example shows that the current practice of enabling power savings mode based on traffic conditions that are local to a BTS can result in sub-optimal energy savings. Low-Carb achieves greater energy savings by jointly using call hand-off and BTS power savings.

3. Related work

The power consumption of a BTS depends on a number of factors. A BTS's power consumption increases with the number of TRXs. The frequency band, modulation scheme, transmit power and operating conditions also influence a BTS's power consumption [16,17]. Accordingly, various researchers have attacked the BTS energy efficiency improvement problem from various angles.

For a given traffic load, the power consumption of a BTS may be reduced by using more energy efficient designs for the components such as TRXs. One such technique is to use switch mode power amplifiers instead of linear analogue power amplifiers [18–21] or other architectural improvements [22,23]. In [23], the authors showed that the energy efficiency of macro-cell based deployments deteriorates with increasing demand for higher data rate services and proposed that a hybrid deployment of residential pico cells and macro-cells be used instead. They showed that this can result in a 60% reduction in energy consumption. Mukherjee et al. proposed using a mix of macro, pico and femto cells to green ceullular network [24].

Heterogeneous networks (HetNets) are a promising new architecture whereby a network is composed of cells of various sizes as well as diverse access networks. Zou et al. considered a scenario whereby user terminals equipped with multiple network interfaces cooperate with each other for service to improve network energy efficiency [25]. The authors also considered a scenario where instead of end-users, heterogeneous networks cooperate with each other to the same end. Similarly, Li et al. studied energy consumption minimization in a multihop cognitive cellular network architecture to support high data rates in cellular networks [26]. Morosi et al. considered the use of traffic prediction along with transmit power adaptation on macro base stations and sleep modes on micro base stations to improve energy efficiency [27]. Lee et al. proposed that mobile handsets form an overlay network for peer to peer data sharing over wireless LANs so as to mitigate the load in the cellular network [28]. This is expected to reduce power consumption in the BTSs at the expense of increased power consumption in the handsets and wireless access points. Reduction of power consumption, however, was not a primary objective of this work. DRONEE is another scheme which exploits multiple interfaces on smart phones to reduce energy consumption in cellular networks by relaying cellular traffic between smart phones over WiFi [29]. Other recent work on improvement of energy efficiency through HetNets include [30–39].

In [6], the authors proposed that when the traffic in an area being served is low, the serving BTS may be completely turned off to save power. Later, when the traffic volume rises, such BTS may be turned on again. To avoid lack of coverage when a BTS is turned off, its neighboring BTSs must, however, increase their transmit power. Similar proposals are also reported in [1,7–11,40–43]. Moreover, conversations with operators indicate that they are reluctant to turn off entire BTSs due to reduced expected lifetime of the installed electronic equipment.

Several centralized as well as distributed algorithms for placing maximal number of BTSs in sleep mode or turning them off during low traffic load have been proposed recently. For instance, it was proposed in [44,45] to group nearby BTSs in an LTE network into energy partitions and then hand-off traffic out of lightly loaded BTSs to put them into sleep or turn them off. Also in the context of LTE networks, Viering et al. proposed an algorithm that adjusts transmission power levels for BTSs in response to traffic load variations with small changes to the coverage area. Kokkinogenis et al. also proposed centralized as well as pseudo distributed schemes for turning base stations off or in sleep mode while expanding the coverage radii of neighboring base stations in [46].

Frequency dimming [12] proposes to turn off some TRXs on a BTS when the traffic is low. Low-Carb goes beyond frequency dimming — it reroutes the calls and can potentially enable power savings mode on a larger number of BTSs. Coarse estimates of the energy saving potential of TRX deactivation were presented in [2]. In contrast, we use site locations and real traffic traces from a large cellular network with more than 13 million subscribers to run a simulation study assessing the benefits of dynamic equipment scaling coupled with call hand-offs.

Cell zooming is a technique whereby base stations dynamically adjust their coverage radii to conserve power [47,48]. Balasubramanian et al. proposed three novel approaches to cell zooming [49]. Their evaluation showed a 40% decrease in power consumption. Conte et al. proposed cell sleep and wake up strategies and transients under various conditions in [50]. They considered a 0.64 km^2 region of Munich, Germany covered by different cell sizes to evaluate these strategies. According to their results, the duration of sleep and wake up transients is very short and have negligible impact on the amount of achievable energy savings.

Wu et al. studied the joint application of transmit power control and sleep modes for a single base station in [51]. This work is done in the context of delay-tolerant workloads. They presented optimal strategies for coverage planning by using sleep modes in base stations [52]. Zappone et al. considered non cooperative allocation of sub-carrier and transmit power scheduling in case of multi-cell FDMA cellular system with multiple base station antennas in [53]. Zappone et al. also studied resource allocation in relay assisted DS/CDMA systems in [54]. Recent work studying energy efficient scheduling and power allocation for OFDMA networks include [55,56].

Some prior work that has used call hand-off to optimize power consumption includes [57–59]. In [57], the authors determined the optimal association between mobile stations and base station in an LTE network to minimize BTS power consumption while considering only data traffic. In Pakistan, and many developing countries, voice traffic is still quite dominant in cellular networks. Data traffic and text messages are considered low-priority traffic. Hence, in our context, considering data traffic to minimize power consumption is not useful. In [58], the authors used relay stations to hand off calls to other BTSs in order to minimize power consumption. The use of relay stations within cellular networks in developing countries is rare, hence we do not consider their use in this work.

Whitaker et al. addressed the network design problem, i.e., they determined the optimal locations of new base stations to increase coverage in a cellular network [60]. While our work aims to reduce the operational cost, Whitaker et al. focused on controlling the capital cost of cellular networks. The key research challenges in energy efficient network design are summarized in [61]. Chiaraviglio et al. considered the network planning as well as management problem for a 3.24 km^2 portion of Central London using various schemes [62]. Their results indicate that base station sleep modes can achieve up to 30% energy savings even in existing deployments. Koutitas et al. used genetic algorithms for the network design problem, with energy efficiency as the objective, on a 3.24 km^2 area of Central London while also proposing a power control algorithm in [63].

Another interesting idea is cooperation between operators with overlapping coverage areas to provide access while saving energy by switching off a subset of the access networks. This idea was proposed by Marsan et al. in [64] and further investigated in [65].

Combes et al. proposed a distributed algorithm that schedules sleep mode for base stations in a cellular network [66]. This is quite similar to [12] and our work. Our work differs from [66] in that we have proposed a centralized optimizing scheme. Centralized optimization schemes are never worse off than a corresponding distributed one. The primary challenge to centralized schemes is scalability. We believe that scalability may be addressed by using our scheme to have each BSC control the state of every BTS in its control.

There exists a large body of work on solutions to constrained resource optimization problem, like the one we formulate for Low-Carb. For example, such problems have been addressed in the context of data centers [67–71], scheduling in compute clusters [72], System on Chip (SOC) [73], electric power systems and smart grids [74–77], WiFi access points [78,79], optical backbone networks [80] and high performance computing [81–86].

A number of researchers have studied the use of renewable sources of energy to green the cellular networks. Chia et al. proposed transporting energy between nearby BTSs that have diversity in availability of renewable energy [87]. Zhou et al. proposed optimal sleep mode strategies for a set of base stations some of which are powered by the grid and the rest are powered by renewable energy sources [88]. They proposed that the grid connected base stations can enter sleep mode to conserve grid energy whereas those powered by renewable sources can enter sleep mode due to mismatch between traffic demand and energy supply or to store renewable energy.

Much of the recent work in the area considers LTE and LTE-A networks. One energy saving feature supported in LTE-A networks is discontinuous receive (DRX) whereby user equipment stops receiving for a while to save battery power. The trade off in this case is that the latency would be increased. Koc et al. evaluated the trade-off between the saving in energy and the associated increase in latency for various applications [89]. The energy-delay trade off in case of base station sleep mode is also studied in [90] and three sleep strategies are proposed. Gupta et al. studied the impact of the data traffic profile of newer applications such as Facebook and Twitter on the energy consumption of LTE mobile devices [91]. Hossain et al. proposed dynamically switching redundant sectors in evolved node Bs(eNBs) in LTE networks [92]. Data traffic, which is significant in third generation and later cellular networks, is hard to predict. Li et al. proposed a learning based framework for base station switching for conservation of energy [93]. Huq et al. have proposed packet scheduling algorithms for LTE-A that achieve overall energy savings [94].

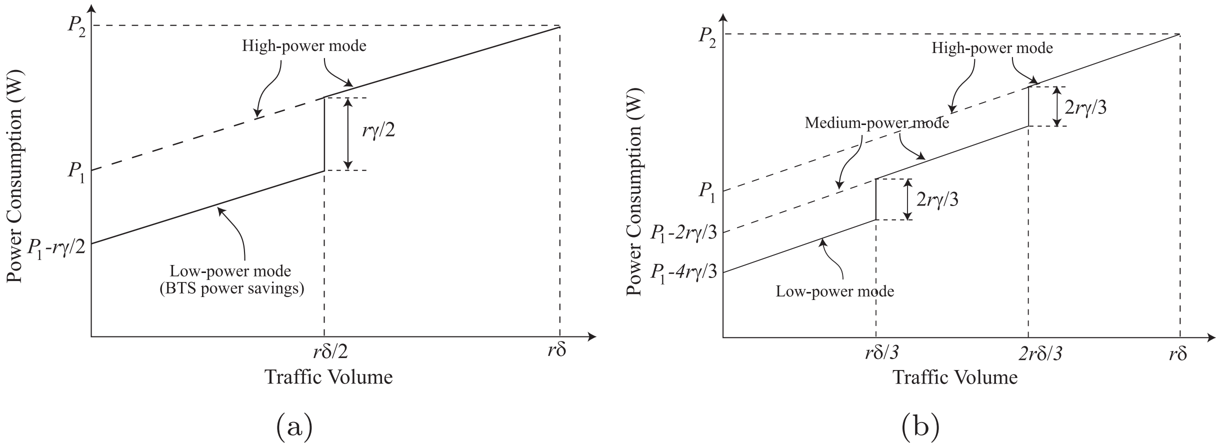

Fig. 4. Power consumption model for a BTS with r TRXs. (a) Low-power (BTS power savings) mode is optional and kicks in at low loads. (b) BTS power savings is applied in a more granular way (3-state power consumption model).

Bounds on the energy savings achievable using base station sleep modes have been determined in [95]. The authors used regular as well as random base station deployment locations in their study. Their study considered only best effort traffic.

While backbone networks are not the largest energy consuming segment of telecommunication networks, their share of power consumption is expected to grow due to increasing traffic demands. Recent examples of work focusing on energy efficient backbone networks include [96–100].

4. Problem formulation

4.1. Single base transceiver station (BTS)

If δ is the traffic capacity of a single TRX, then the traffic handling capacity of BTS with r TRXs is $r\delta$. If l is the number of calls currently in progress, and the power consumed by the BTS under no load and full load is P_1 and P_2, respectively, then the instantaneous BTS power consumption[3], P, approximated as an affine function of its traffic load [6], is given by

$$P = P_1 + l(P_2 - P_1)/r\delta. \tag{1}$$

If a TRX's no-load power consumption is γ (its value depends on the equipment type [14,15]), then $P_1 = a\gamma$, where a is the number of active TRXs. Thus, by scaling the number of active TRXs in response to traffic volume changes, BTS power consumption may be reduced. For example, if the traffic volume at a BTS falls below a power-saving threshold $r\delta/2$, then half of the TRXs may be turned off. As a result, the BTS will transition to the low-power mode whereby the power consumption profile drops by an amount $r\gamma/2$ as shown in Fig. 4(a). The slope of the power consumption profile remains the same whether or not the BTS is operating in low-power mode.

If the BTS is switched into low-power mode as soon as traffic falls below $r\delta/2$, then short time scale variations in traffic might cause a TRX to turn on/off rapidly. Since this may be detrimental to a TRX's lifetime, low-power mode is activated only when traffic reaches threshold $r\delta/2 - \epsilon$. Here, ϵ is a parameter which may be set equal to 0 to achieve an aggressive power saving strategy of turning off a TRX as soon as opportunity presents itself. On the other extreme, ϵ may be set equal to $r\delta/2$ in which case a TRX is never turned off. These two extremes relate to a trade off between equipment lifetime and energy savings.

Instead of the all-or-half approach of Fig. 4(a), power-saving may also be applied in a more granular way, such as that shown in Fig. 4(b), whereby one-third of the TRX may be switched on/off independently in response to current traffic volume. In general, the number of granular steps in the power-saving strategy is limited by the number of TRXs installed on a BTS.

4.2. Multi-BTS cellular setting

Since BTS power consumption is an additive function of the number of active TRXs, to minimize the power consumption over the network, we must minimize the total number of active TRXs. Consider a cellular network consisting of m BTSs and n callers. Let $c_{i,j}$ be a binary variable which is equal to one if caller i *can be* served through BTS j and zero otherwise. This information can be extracted at the Base Station Controller (BSC) in a GSM network as every calling MS periodically sends the received signal strength from all nearby BTSs to the BSC. Also, let $w_{i,j}$ be a binary variable which is equal to one if caller i *is* served through BTS j and zero otherwise. Suppose that on a particular BTS, we may independently turn on/off a block of β TRXs at a time. If x_j is the number of active TRX blocks at BTS j, then the Low-Carb optimization problem may be given as:

$$\text{minimize} \quad \sum_{j=1}^{m} x_j \tag{2}$$

subject to the following constraints:

$$\sum_{j=1}^{m} w_{i,j} = 1 \qquad \forall i \tag{3}$$

$$w_{i,j} \le c_{i,j} \qquad \forall i, j \tag{4}$$

$$\delta\beta x_j - \alpha - \sum_{i=1}^{n} w_{i,j} \ge \epsilon \tag{5}$$

$$1 \le x_j \le r/\beta \qquad (x_j \in \mathbb{N}) \qquad \forall j \tag{6}$$

The first constraint (Eq. (3)) ensures that every call is served by exactly one BTS. The second constraint (Eq. (4)) ensures that a call is served by a BTS that *can* serve it, thereby securing the uplink and downlink TX power budget. The third constraint (Eq. (5)) ensures that the number of active TRXs is large enough such that there is

[3] In the following discussion, when we refer to BTS power consumption, the implication is the component of BTS power consumption due to TRXs only. Since TRXs account for a large fraction of BTS power consumption [14], minimizing TRX power consumption will reduce BTS power consumption.

a residual call capacity for at least ϵ more calls[4]. The fourth constraint (Eq. (6)) specifies the range of values that x_j may take.

The granularity of applying power-saving is determined in the above optimization formulation through the value of β. For instance, if β equals 1, then each TRX may be independently turned on/off. Similarly, if β equals $r/2$, the problem reduces to the two-step model of Fig. 4(a). Setting β equal to $r/3$ results in the three-step model of Fig. 4(b).

4.3. Heuristic solution to Low-Carb

In Appendix A, we have shown that Low-Carb is NP-Hard. For a 26 site dataset that we collected from a live cellular network, we were able to find the Low-Carb optimal solution within a few seconds. However, for an entire cellular network, Low-Carb becomes computationally infeasible. We propose two ways to handle this intractability. First, the entire network can be divided into several smaller regions and Low-Carb can be applied to each region independently. Second, a heuristic solution to Low-Carb, such as the one given in Algorithm 1, may be applied to the entire network.

The pseudocode for our proposed heuristic is given in Algorithm 1. In the first iteration of the outer loop (lines 1 through 29), our heuristic divides the set of BTSs into two sets. Set B_1 consists of those BTSs that have traffic volume greater than $(r-\beta)\delta$. The set B_2 consists of all other BTSs. The heuristic algorithm picks a BTS from the set B_1 uniformly at random. It then attempts to move this BTS to set B_2 (lines 23–26) by handing off some calls to other BTSs in B_2 without exceeding the power-saving threshold[5] (lines 12–19). In the end, blocks of β TRXs may be turned off on all members of B_2 (line 28). Further iterations of the outer loop attempt to turn off more blocks of β TRXs in a similar manner.

Our heuristic is a $O(rm^2n/\beta)$ randomized algorithm, which is not guaranteed to find the optimal solution. However, a high quality solution is likely to be obtained if the best solution is picked from amongst several invocations of the algorithm.

Algorithm 1: Energy-saving heuristic.

input : B (the set of BTSs) = $\{b_1, b_2, \ldots, b_m\}$,
n (the number of calls),
W (call association) = $\{w_{i,j} | 1 \le i \le n, 1 \le j \le m\}$,
C (Adjacency matrix) = $\{c_{i,j}$ = 1 if c_i can be served through b_j, 0 otherwise$\}$

output: A new and potentially more energy efficient mapping of calls to BTSs

1 **for** $k := 1$ *to* r/β **do**
2 $B_2 = \{b_j | \sum_{i=1}^{n} w_i^j < k\delta\}$;
3 B_1 = random_shuffle($B - B_2$);
4 **forall the** $b_j \in B_1$ **do**
5 $a = \sum_{i=1}^{n} w_i^j - \delta$;
6 $d = 1$;
7 $s = 0$;
8 **while** $d < n$ *AND* $s \le a$ **do**
9 **if** $w_d^j = 1$ **then**
10 $e = 1$;
11 $m = 0$;
12 **while** $e \le m$ *AND* $m = 0$ **do**
13 **if** $e \in B_2$ *AND* $c_{d,e} = 1$ **then**
14 $w_d^e = 1$;
15 $w_d^j = 0$;
16 $s = s + 1$;
17 **end**
18 $e = e + 1$;
19 **end**
20 $d = d + 1$;
21 **end**
22 **end**
23 **if** $\sum_{i=1}^{n} w_i^j < (r - k\beta)\delta$ **then**
24 $B_1 = B_1 - \{b_j\}$;
25 $B_2 = B_2 + \{b_j\}$;
26 **end**
27 **end**
28 Deactivate β TRXs on all BTSs $\in B_2$;
29 **end**

5. Experimental setup

Our dataset is obtained from a cluster of 26 BTSs operated by a large network operator with more than 7000 sites. These 26 sites are spread over a 31.25 km^2 urban terrain. We obtained each site's coverage prediction using a tool called Forsk Atoll which is quite popular in the cellular network operators community. Using this BTS coverage prediction and a caller's location, we can determine the candidate set of BTSs for the corresponding call (the c_i^j parameters).

Also available to us are the hourly cumulative traffic, in Erlang, for each of the sites, spanning two consecutive weekdays. The traffic remained remarkably similar across both days for each site. We have, therefore, only used one day's traffic data in our experiments.

Using the above data sets, we conducted a set of simulation experiments mimicking a 24-hour operation of a cellular network comprising 26 cells. Each experiment is a discrete event simulation of the arrival and placement of calls. Under the assumption of Poisson call arrivals and given the hourly traffic intensity (in Erlang) for each BTS, we use Little's law to determine the corresponding Poisson call arrival rate. Our simulator schedules call arrivals for *each* BTS according to this Poisson call arrival process. For each call, it's departure event is also scheduled based on an exponential distribution of call durations with a mean of 180 seconds [101].

The location where each call originates in a cell is uniformly distributed over the corresponding BTS's coverage area. Based on the randomly picked location at which a particular call originates, the entries $c_{i,j}$ are determined such that $c_{i,j} = 1$ if call i is within service range of BTS j.

To mimic present day practices in operational networks, our simulator associates each call to the BTS from which the received signal is strongest. Using this call-BTS association, a time series of traffic load for each BTS is calculated, which determines the power consumption profile for each BTS. Integrating the power consumption time series for each BTS gives its energy consumption over a 24 h period. Summing the energy consumption for all BTSs gives the network's total energy consumption. This number represents a baseline for assessing the performance of the energy efficiency improvement techniques that we investigate in this paper.

Iterating over the traffic load time series for each BTS, our simulator places those BTSs that have sufficiently low traffic into power-saving mode. Using the power consumption functions shown in Figs. 4(a) and 4(b), our simulator calculates the energy consump-

[4] A number of logical channels are reserved for control purposes in each sector. Here, α is the number of control channels per BTS

[5] Note that if the traffic exceeds the power-saving threshold for one or more BTSs in the set B_2 after the calls are handed off, it would cause BTSs to move to set B_1, which is undesirable.

Table 2
BTS model parameter values.

Parameter	Value		
	Model 1	Model 2	Model 3
P_1	1425	2401.8	2341.5
P_2	1500	3887.5	2973.9
γ	20	50	100

Table 3
Energy savings by using BTS power savings only.

Energy saving	Model 1	Model 2	Model 3
Percentage	4.73%	5.43%	12.89%
Daily absolute saving over 26 BTSs (in kWh)	43.28	109.68	217.12
Country-wide daily saving over 31,000 sites (in MWh)	51.6	130.77	258.87

tion for the network over a 24 h period when BTS power-saving is applied.

During the simulation, at a configurable frequency, we also invoke the Low-Carb optimization problem on the current call traffic. We thus determine the energy consumption for the network over a 24 h period when call hand off and BTS power saving are applied in a coordinated fashion.

If Low-Carb is invoked very frequently, the network will remain in an optimal state most of the time. Therefore, an aggressive re-optimization scheme will enable greater energy savings. In order to study how the energy savings scale with re-optimization frequency, we experimented with a range of intervals between successive optimizations, ranging from a minute to an hour.

5.1. Site characteristics

All sites in our dataset had three sectors, each equipped with 6 TRXs. The maximum number of simultaneous calls for each site is 132.[6]

The BTS power consumption model parameters may vary from one equipment to another. In this paper, we use three different sets of model parameters as listed in Table 2. We now describe the sources and methods from which we obtained these models.

5.1.1. Model 1

For the first model, we have used 1.5 kW as the maximum power consumption [102], a 20 W per TRX saving when scaling the BTS down [15] and a 5 % variation in power consumption between no-load and full-load [6].

5.1.2. Model 2

Lorincz et al. reported the single sector DC power consumption for a GSM 900 BTS [14]. The sector under consideration had 7 TRXs, as opposed to 6 TRXs in our case. To approximate the DC power consumption for a site with 3 sectors, each with 6 TRXs, we scaled the power consumption by a factor of $3 \times 6/7$. The DC power consumption does not include the AC power consumed in the power supply units and in air-conditioning. We must, therefore, also compensate for those, to obtain the overall site power consumption. Power supply unit load is negligible compared to air-conditioning (typical A/C power consumption of 1 kW [102]). We applied this scaling and addition to the minimum reported DC power consumption for the GSM 900 site to obtain an approximate value of P_1 for a site comparable to ours. Similarly, we used the maximum reported DC power consumption and applied the scaling and AC load correction to approximate the value of P_2. Furthermore, the authors measured a drop of 50 W in power consumption when a TRX is disable, which gives us the value of γ as listed in Table 2.

5.1.3. Model 3

We used the measurements for the GSM 1800 BTS reported in [14] to determine the values for P_1 and P_2 in the same manner as described in Section 5.1.2. The value of γ was reported to be 100 W [14]. The parameter values for this model are given in Table 2.

6. Results

6.1. BTS with two possible power states

First, we consider the benefit of BTS power-saving alone, compared to running the network in the default configuration. The percentage reduction in energy consumption is listed in Table 3. The results indicate that a saving of between 4% and 12% can be achieved in a network just by activating BTS power savings. We note here that some of these results are in agreement with Ericsson's claim of saving 10-20% energy by using BTS power-saving on Germany's Vodafone network [103].

In absolute terms, this represents a cumulative saving of between 43 kWh and 217 kWh per day on 26 BTSs. Now, consider that there are five cellular oeprators in Pakistan: Mobilink with more than 8500 sites [104], Ufone with more than 8000 sites [105], Zong with more than 5500 sites [105], Telenor with more than 7000 sites [106] and Warid with more than 4500 sites [105]. Overall, there were more than 31,000 sites in Pakistan at the end of 2011. We extrapolated the daily energy savings number over 26 BTSs to calculate the daily energy savings possible for a country like Pakistan with over 31,000 BTSs (see the last row of Table 3). The results indicate that mere activation of BTS power saving option itself can save quite a bit of electrical energy, a critical resource, especially in a developing country. As we shall see next, greater energy savings are possible if we couple periodical call shuffling with BTS power savings in the network.

If periodic optimization of call placement is coupled with BTS power-saving, the energy saving improves, as shown in Fig. 5(a). For all three BTS models, we see an almost linear increase in power saving as the duration of the re-optimization interval is decreased. Recall that the three models are significantly different in terms of power consumption (see Table 2). Therefore, we can not directly say that since Model 3 BTS offers the highest percentage reduction in energy consumption, it also saves the most energy (in kWh).

To *compare* the three BTS models in terms of energy saving potential, we also present the absolute reduction in energy consumption for the three BTS models in Fig. 5(b). We see the same linear trend along with the same relative order of the three models in terms of amount of saved energy, as in Fig. 5(a).

Re-optimizing at an interval less than the mean call duration should offer greater savings than a less frequent re-optimization, because the former regime is able to optimally assign BTSs to most of the calls at least once. This is confirmed in our results. For instance, the gain in energy savings for Model 1 BTS when going from a 60 min inter-optimization interval to 30 min gains an energy saving of only 0.0506 kWh per minute, while decreasing the inter-optimization interval from 2 min to 1 min gains 12.5421 kWh.

[6] Each TRX's frequency is shared in time-domain by 8 calls for a total of $3 \times 6 \times 8 = 144$ channels. Four channels in each sector were reserved for control and broadcast purposes, resulting in 132 channels available for voice calls. The half-rate codec feature of GSM standard can be used to handle greater traffic volume, but we do not consider it in the present work in favor of model simplicity.

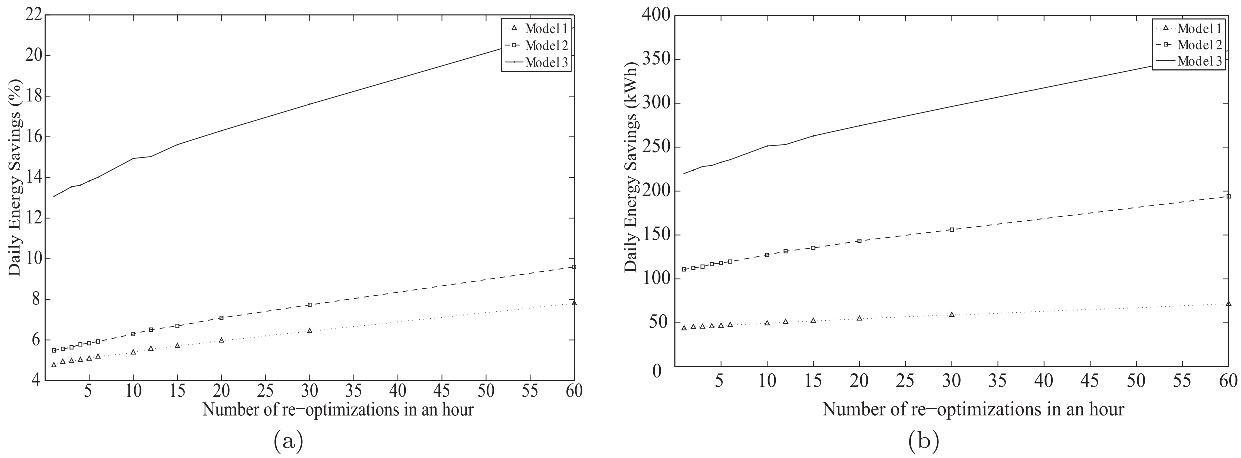

Fig. 5. (a) Percent reduction in energy consumption vs re-optimization interval, (b) Reduction in energy consumption vs re-optimization interval.

Table 4
Percentage electricity savings for different granularity of resource pruning.

Granularity	BTS Model 1	BTS Model 2	BTS Model 3
2-State	5.38%	6.29%	14.94%
3-State	6.81%	7.73%	18.62%
r-State	8.70%	9.65%	23.37%

Let us now interpret what these results mean physically in terms of ecological impact. If we extrapolate our results, the total energy saving for Pakistan are projected to be 60.72 MWh, 156.84 MWh and 301.61 MWh daily, respectively, according to the three BTS models. These savings in energy are significant, especially for small and developing countries. Since network deployments and traffic patterns are similar in different countries, we also expect that similar savings should be achievable in many other countries as well.

In the above extrapolation, we have assumed that the same amount of energy saving would be applicable in rural as well as urban settings. While this may not necessarily be true because the deployments are sparse in rural settings, resulting in reduced potential to save energy by means of call hand-off to neighboring sites, the potential to save energy merely by BTS power-saving should be higher in a rural setting because traffic loads are typically lower.

6.2. Multi-state BTS

In our experimental results discussed so far, we have observed that going from a 6+6+6 configuration to a 2+2+2 configuration can save a significant amount of energy. Intuition suggests that going to a finer granularity of resource pruning should enable greater energy savings. We now present two cases that are different from the configuration considered so far. In the first case, we consider the ability to (de)activate TRXs in pairs, i.e., a site may be in one of three configurations at a given time: 6+6+6, 4+4+4 or 2+2+2. In the second case, we consider the ability to (de)activate each TRX on a site independently.

In this scenario, we conducted simulation experiments where a re-optimization was performed every six minutes using model 1 BTS. The results of these experiments are given in Table 4. For all three BTS models, we see that going from a 2-state model to a 3-state model gives a relatively small increase in energy savings compared to the jump from 3-state to 6-state model.

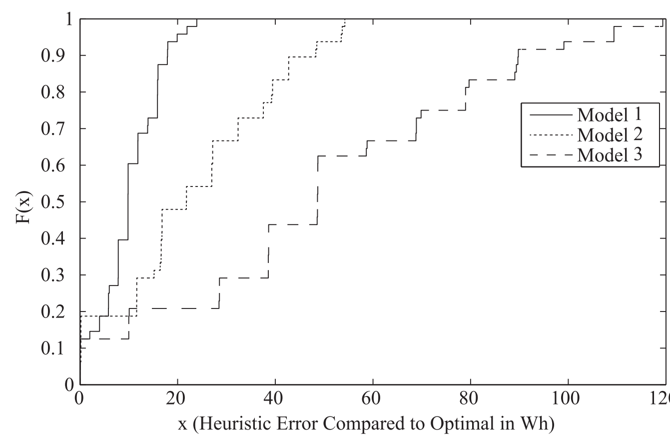

Fig. 6. Empirical CDF of the difference between the cost offered by our heuristic compared to the optimal.

6.3. Performance of heuristic algorithm

We also ran experiments for each BTS model in which the electricity cost for the optimal as well as the heuristic algorithm (Algorithm 1) was computed. We assessed the performance of our heuristic by computing the difference (error) in the electricity cost of the two solutions. For statistical significance, we computed the error in our heuristic relative to the optimal solution over 48 different experiment runs for each BTS model. The resulting CDF of the heuristic error (in Wh) is plotted in Fig. 6. We can see in Fig. 6 that our heuristic algorithm 1 is quite close to the optimal solution most of the time, especially for the Model 1 and Model 2 BTS. For Model 3 BTS, although the error is comparatively larger, but since the amount of savings with the optimal solution is quite high (Fig. 5(a)), the heuristic will still result in significant energy savings.

6.4. Sensitivity to the value of ϵ

If the value of ϵ in our optimization is set too aggressively, a BTS may oscillate at times between low power and high power states rapidly due to short time scale traffic variations. Such state oscillations may be undesirable and to avoid these, the value of ϵ must be set at a safe value. Furthermore, if ϵ is set too aggressively, a BTS placed in low-power mode would be operating very close to it's *new* and lower traffic capacity. If several calls arrive in a short time window, the BSC may not have sufficient time to bring

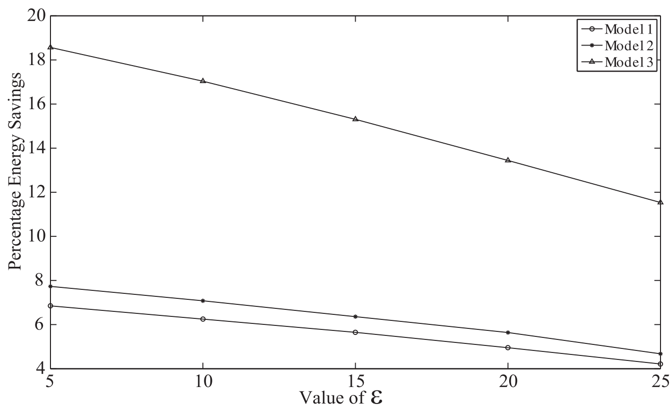

Fig. 7. The percentage energy savings for all three BTS models considered in this paper vs the value of ϵ, with a six minute inter-optimization interval.

the BTS back into high-power mode and, thus, some calls may be blocked. However, if ϵ is set too conservatively, the energy savings would be smaller.

We carried out experiments to assess the impact of the value of ϵ on the energy savings achievable through Low-Carb. For this purpose, we fixed the inter-optimization interval at 6 min and carried out Low-Carb optimizations for all three BTS models. Furthermore, we considered a two-state BTS model, i.e., a BTS may be placed in either a 6+6+6 or a 2+2+2 configuration. The range of possible values for epsilon were 5, 10, 15 and 25. Since the traffic capacity of a 2+2+2 BTS is 44[7], any larger value for ϵ did not make sense. Fig. 7 shows the results. As expected, the percentage savings deplete almost linearly with increasing values of ϵ.

6.5. Increase in call blocking probability

A measure of a cellular network's grade of service (GoS) is the call blocking probability (P_b), given by the Erlang B formula [107].

[7] The capacity of the 2+2+2 BTS is $3 \times 2 \times 8 = 48$, but 4 channels were reserved by the operator for control and broadcast channels.

The Erlang B formula is:

$$P_b = \frac{\frac{E^C}{C!}}{\sum_{k=0}^{C} \frac{E^k}{k!}}$$

Here, E is the traffic intensity in Erlang and C is the number of identical resources that are available to serve the traffic. According to this formula, if the offered traffic remains the same, but some serving resources, i.e., TRXs are turned off, the call blocking probability may increase. This makes intuitive sense because given a fixed call load, a new arriving call is more likely to find all TRXs busy if the number of active TRXs is reduced.

We calculated the increase in call blocking probability, averaged over all BTSs and over the day, due to periodic optimization of the network's resources, compared to the default assignment of calls with no TRX deactivation. It turned out that more frequent re-optimization resulted in a greater increase in call blocking probability.

The increase in call blocking probability with the amount of energy savings (kWh) is plotted in Fig. 8 for BTS model 1. Similar results were observed for BTS models 2 and 3 for increase in call blocking probability vs the amount of energy savings. These results have, therefore, been omitted from the paper. Similarly, the increase in call blocking probability as a function of percentage energy savings for BTS model 1 is plotted in Fig. 9. For BTS models 2 and 3, similar results were observed which have been excluded from this paper. For all the plots, the actual data points are plotted using the plus symbols, the linear fit and quadratic fit based on least squared errors are plotted using the solid black line and the dashed black line respectively. The linear and quadratic polynomials polynomials that best fit the increase in call blocking probability as a function of amount and percentage of daily energy savings are given in Tables 5 and 6, respectively.

In all cases, a linear polynomial based on least squared error minimization fits the data quite well. However, the connotation in the low-savings region are unreasonable. As an example, for model 1 BTS, as shown in Fig. 8, the linear polynomial fit implies a reduction in call blocking probability when saving around 40 kWh compared to the default network operation. This does not make sense because turning off some TRXs to save power should result in an increase in call blocking probability. A quadratic fit to the data, however, is reasonable in all cases.

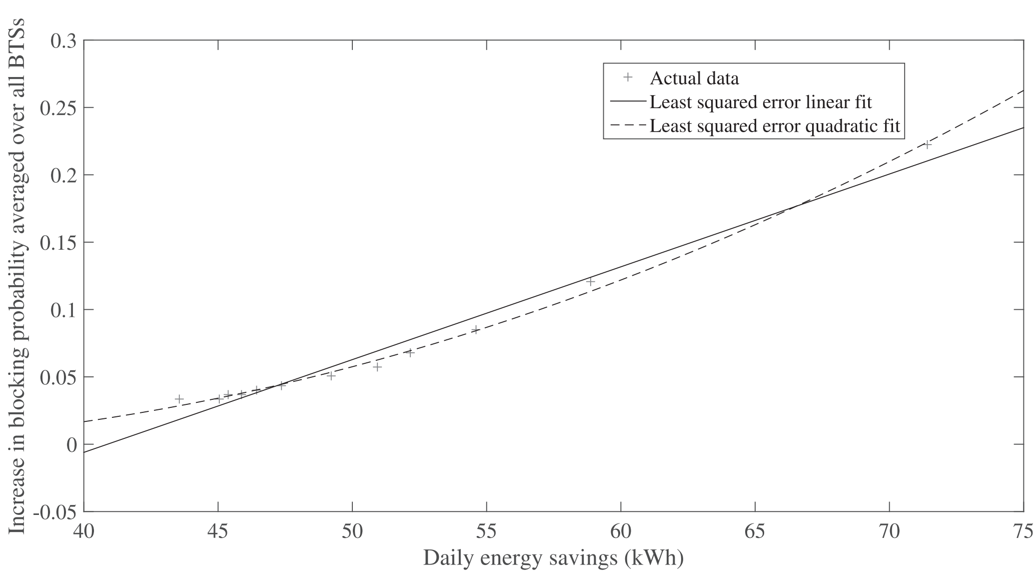

Fig. 8. Increase in call blocking probability, averaged over all BTSs versus the percentage reduction in energy consumption for BTS model 1. Similar results were observed for other BTS models.

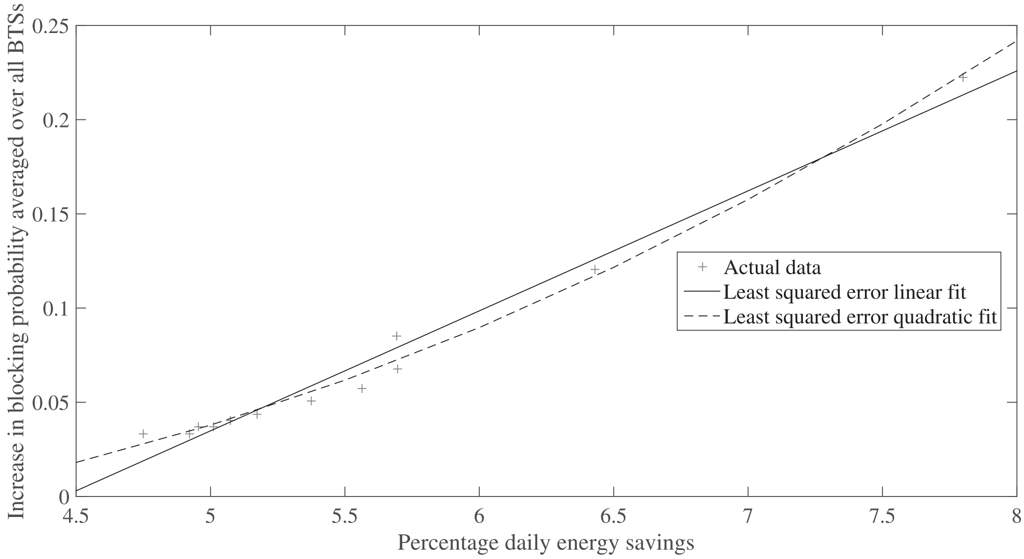

Fig. 9. Increase in call blocking probability, averaged over all BTSs versus the percentage reduction in energy consumption for BTS model 1.

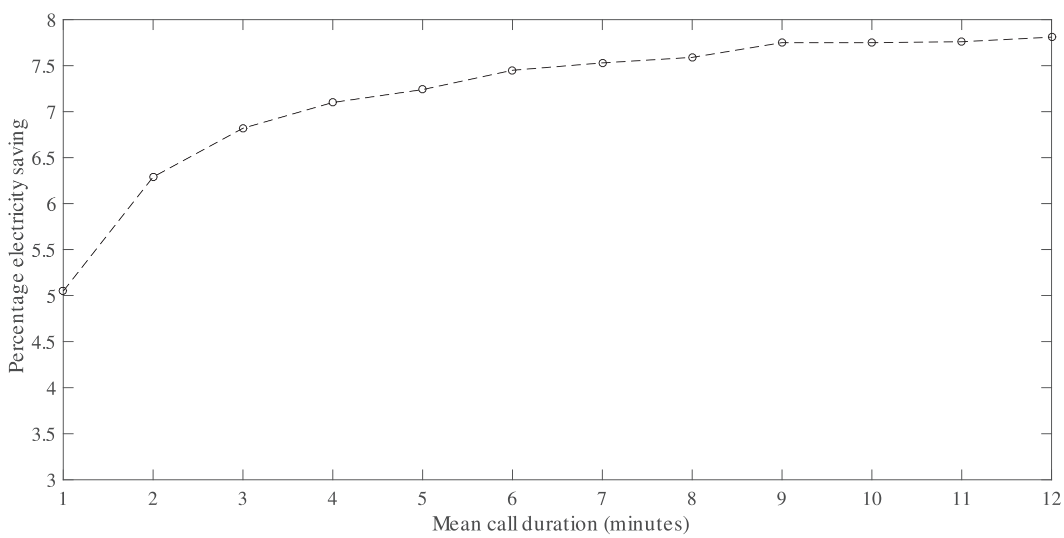

Fig. 10. The sensitivity of energy savings to mean call duration.

Table 5
Polynomial fits of increase in call blocking probability to amount of daily energy savings.

BTS Model	Increase in call blocking probability as a function of amount of daily energy savings (kWh)
Model 1	Linear fit: $0.006888x - 0.2816$
	Quadratic fit: $0.0001178x^2 - 0.006524x + 0.08914$
Model 2	Linear fit: $0.002262x - 0.2286$
	Quadratic fit: $0.00001297x^2 - 0.001623x + 0.05131$
Model 3	Linear fit: $0.001352x - 0.2766$
	Quadratic fit: $0.000004627x^2 - 0.001295x + 0.09101$

Table 6
Polynomial fits of increase in call blocking probability to percentage of daily energy savings.

BTS Model	Increase in call blocking probability as a function of percentage of daily energy savings
Model 1	Linear fit: $0.06368x - 0.2835$
	Quadratic fit: $0.008113x^2 - 0.03747x + 0.02244$
Model 2	Linear fit: $0.0457x - 0.2285$
	Quadratic fit: $0.005285x^2 - 0.03266x + 0.05084$
Model 3	Linear fit: $0.02276x - 0.2766$
	Quadratic fit: $0.001315x^2 - 0.02193x + 0.09201$

6.6. Sensitivity to mean call duration

The mean call duration may be different for different operators and may change from time to time. We conducted experiments in which we performed network optimization every 10 min for a total of 24 h while the mean call duration was varied from 1 min to 12 min. The call volume in these experiments was kept the same as the rest of the experiments. The results are plotted in Fig. 10. We observed that a higher mean call duration results in greater energy savings. However, the marginal increase in energy savings due to increase in mean call duration decreases.

7. Conclusions

Base Transceiver Stations (BTSs) account for most of the energy consumption of cellular networks. Motivated by the lack of load-proportionality of BTS energy consumption, we proposed to combine two widely available features i.e., *BTS power savings* and *call hand-offs*. This combination allows calls to be handed-off from BTSs with high traffic load to neighboring BTSs to maximize the benefits of BTS power-saving. We formulated this problem as a binary integer program and showed that it is NP-Hard. We then proposed a polynomial-time heuristic algorithm. Using real network topology and traffic traces in a simulation study, we found that merely using BTS power saving in an urban setting can result in considerable energy savings. Moreover, our results also indicate that periodic call-shuffling between BTSs can further reduce energy consumption in existing large GSM networks.

Appendix A. Proof of NP-hardness

This proof of Low-Carb's NP-hardness was done through personal communications [108]. For this proof, we define the Low-Carb problem as:

Problem Name: Low-Carb

Input:

- A set of callers C
- A set of BTSs B
- Scalar values P_1, P_2, δ, γ, $t_{\max}$

Output: An assignment of each caller to exactly one BTS that minimizes the cost as given in equation X.

We also define the modified dominating set problem (MDS) as follows:

Problem Name: Modified dominating set

Input: A bipartite graph $G = \{E, V\}$ with sets of vertices J, K such that every edge in E connects a vertex in J to a vertex in K.

Output: A minimum cardinality set of vertices belonging to J that cover every vertex in K.

We claim that we can use Low-Carb to solve MDS. If we set δ to 0 and P_1 to some non-zero value for Low-Carb, then there is a set-up cost on each BTS, i.e., a fixed cost of P_1 is incurred for the first call on each BTS. Hence, in this case, the optimal solution to Low-Carb will use the fewest number of BTSs to handle all calls. Therefore, if we invoke Low-Carb as follows:

- Set C equal to the vertices in K
- Set B equal to the vertices in J
- Assign P_1 some positive value greater than zero
- Assign P_2 some value greater than P_1
- Assign γ some positive value greater than zero
- Set δ equal to zero

then Low-Carb will solve MDS, i.e., use the fewest number of vertices in J to cover all vertices in K.

Now, consider the minimum dominating set problem (DS).

Problem Name: Minimum dominating set

Input: A graph $G = \{E, V\}$

Output: A minimum cardinality subset D of V such that every vertex not in D is adjacent to at least one vertex in D

We can solve DS using MDS as follows (see Algorithm 2):

Algorithm 2: Solving DS using MDS

input : A graph $G = \{E, V\}$
output: A minimum cardinality subset D of V such that every vertex not in D is adjacent to at least one vertex in D

```
V_1 = V;
V_2 = V;
V' = V_1 ∪ V_2;
E_1 = {(u, v) : u ∈ V_1, v ∈ V_2 if (u, v) ∈ E or u = v};
MDS(V', E_1);
```

We first create two copies of the set of vertices in G, named V_1 and V_2 and add them to set V'. We also create a set of edges E_1 as follows. If there is an edge between vertices u and v in graph G, then we add an edge from vertex u in V_1 to vertex v in V_2. Furthermore, we also add an edge between each vertex u in V_1 to vertex u in V_2. This results in a bipartite graph $G' = V', E_1$ where every edge in E_1 connects a vertex in subset V_1 of V' to a vertex in subset V_2 of V'.

Invoking MDS on G' finds the minimum number of vertices in V_1 that cover every vertex in V_2. Since V_1 and V_2 are essentially the same vertices, MDS finds the minimum cardinality set of vertices in V to which all other vertices are connected. Thus, MDS solves DS. It is well know that DS is NP-Hard [109]. Since Low-Carb can solve DS, by reduction it is NP-Hard as well.

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