Low-Carb: Reducing Energy Consumption in Operational Cellular Networks

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Abstract—Electricity costs are a significant fraction of a cellular network’s operations costs. We present Low-Carb, a practical scheme to decrease electrical energy consumption in operational cellular networks by coupling Base Transceiver Station (BTS) power savings with call hand-off—two features commonly used by cellular operators. Motivated by the practical observation that most callers are in the vicinity of multiple BTSs, Low-Carb presents and solves an optimization problem, allowing 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.

We use BTS locations and traffic volume data from a large live GSM network to evaluate the power savings possible using our proposed approach in Low-Carb. Our results indicate that for a GSM 1800 network operator with 7000 sites in an urban setting, a total of up to 35.36 MWh may be saved annually. This is at least 9.8% better than the energy savings obtained by just using BTS power savings alone. Other cellular operators can use the Low-Carb formulation with their own network data to estimate the electricity savings they may achieve on their networks.

I. INTRODUCTION

Cellular networks consume several tens of TWhs of electrical energy every year worldwide [1]. This not only results in significant operational expenditure, which is increasing with rising electricity and fuel prices, but is also a source of concern for ecological reasons. These concerns have motivated a lot of research aimed at reducing energy consumption in cellular networks.

In this paper, our discussion focuses on the legacy 2G GSM cellular networks, which have a significant market share. Our focus on GSM is also due to its dominance in the typically energy-starved developing countries with a large subscriber base. These GSM networks are expected to persist for the foreseeable future due to the upgrade expenses and return on investment (ROI) concerns of the operators. It is, therefore, important to optimize such GSM networks. The energy-saving techniques proposed in this paper may be applicable to 3G and 4G networks, but we make no claims as to the effectiveness of the same.

The major sink of power in a cellular network are Base Transceiver Stations (BTSs), accounting for 60% to 80% of the total power consumption [1–3]. Every BTS is equipped with several transceivers (TRXs), each of which is allocated a single frequency band for transmission and reception of radio signals. Each TRX further uses time multiplexing to handle up to 8 full-rate voice calls over its assigned frequency band in GSM systems. A typical configuration is “6+6+6” depicting a BTS serving three sectors each with six TRXs. Thus, a BTS offers a fixed capacity, as determined by the total number of TRXs installed. Sites are deployed such that this fixed BTS capacity can handle the peak traffic load. However, traffic peaks only for a short duration dropping off to a much lower trough each day, which means that the GSM networks are over-provisioned during low-traffic regimes.

Over-provisioned BTSs would be fine if they were also load-proportional, i.e., consumed little power at no traffic load. However, according to [3] the no-load power consumption can be as high as 95% of that at full load. With fixed BTS capacity that is over-provisioned for low traffic loads, today’s cellular networks are highly energy inefficient.

There are generally two approaches to increase cellular network energy efficiency. First, a clean-slate redesign which includes innovations in communication systems, circuits and components. This approach is not attractive for existing GSM operators, which are the most prevalent in the developing world and are expected to stay as such for several years to come, primarily due to the required expensive upgrades. A second approach is to make optimizations to the existing system and equipment to get an improvement in overall energy efficiency. Our present work is aligned with this latter philosophy.

One can improve the energy efficiency of a cellular network by adapting its “online” capacity to changes in traffic load. Recent work has proposed turning off base stations to reduce energy consumption during times of low traffic load [1–4]. In such solutions, to offer the same amount of coverage, the transmit range of some of the remaining BTSs has to be increased. Our conversations with multiple network operators indicate that they are reluctant to employ such techniques citing three reasons:

- Power cycling of entire base stations is expected to reduce equipment life time.
- Turning off some BTSs may require an increased up-link power which may not be handled by many low-cost/power-limited mobile stations (MSs). This raises a risk of customer churn and is not acceptable to the operators in cut-throat competition prevalent in today’s market.
- These techniques of turning off BTSs may underestimate the increase in power needed for indoor MSs.

Our conversations with wireless providers reveal that during low traffic periods, they often use a feature available in most
vendor’s equipment that power-gates TRX circuits at locations that serve very few customers. Huawei calls this feature TRX shutdown while Ericsson calls it BTS power saving. We use the latter term generically in this paper.

BTS power consumption’s traffic-independent component depends largely on the number of active TRXs [3]. Therefore, deactivating TRXs reduces the BTS power consumption. For instance, 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 [5, 6]. 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. The decision to use BTS power saving feature is generally local to the BTS without any coordinated effort at the network level.

This paper presents Low-Carb which combines the BTS power saving with hand-off, another commonly used feature in cellular networks that facilitates user movement from one location to another. Low-Carb proposes to hand-off calls from one BTS to another, 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. As compared to the use of uncoordinated BTS power savings, Low-Carb offers additional power savings as it may allow a larger number of TRXs to be deactivated. In present day deployments, this is possible since most callers receive sufficiently strong signal simultaneously from several nearby BTSs some of which may have relatively lower traffic [3]. Fig. 2 shows coverage diversity evident in the urban data from a large cellular provider that we used in our evaluations; one can see that about half of the callers have 3 or more candidates for serving BTS. Furthermore, Fig. 3 shows normalized traffic at two neighboring sites in our dataset for a 24 hour period, which confirms the presence of geographic diversity in traffic.

We formulate a binary integer program (BIP) to minimize the power consumption in a GSM network by shuffling active calls between nearby BTSs while keeping in check the MS uplink budget. Since BIP is NP-Hard, we also propose a heuristic for Low-Carb and evaluate it’s performance compared to the optimal solution.

Our work is very similar in spirit to the concept of frequency dimming in [7] albeit at a different level of abstraction. A similar approach is also proposed in [8] with some rough estimates of expected savings. We, on the other hand, use site locations and 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. A key benefit of our approach is that it does not require any additional hardware and works within the GSM specifications.

The rest of the paper is structured as follows. The formulation of Low-Carb optimization problem is given in section II. Experimental setup and the results are presented in sections III and IV, respectively. In section V, we draw the conclusions highlighting the power saving strategy for providers.

II. FORMULATION

A. Single Base Transceiver Station (BTS)

Power consumed by a BTS, as a function of traffic load, can be well approximated as a linear curve with a non-zero y-intercept [3] given as $P_1 + l(P_2 - P_1)/t_{max}$. Here $P_1$ and $P_2$ are the power consumption at no load and full load, respectively, $l$ is the number of calls presently being handled, and $t_{max}$ is the maximum number of calls that can be handled.

Let $\delta$ be the traffic threshold below which the BTS power savings may be applied. Since all TRXs are identical, the per call increase in power consumption, and hence the slope of the power consumption profile in Fig. 4, remains the same whether or not some TRXs are deactivated. As also indicated in Fig. 4, the no-load power consumption drops to $P_1 - \gamma$ in the low-power mode, where $\gamma$ is a constant that depends on the equipment type and the number of TRXs deactivated. If $x$
is an indicator variable which is 0 when BTS power savings is applied, and 1 otherwise, then the BTS power consumption may be given by $P_i + l(P_2 - P_1)/t_{\text{max}} - (1 - x)\gamma$ (indicated in Fig. 4 by the piecewise linear solid line).

**B. Multi-BTS Cellular Setting**

Consider an area with $n$ active callers being served by $m$ BTSs. We introduce indicator variable $w_{i,j}$, which is 1 if call $i$ is being handled at BTS $j$ and 0 otherwise. We assume availability of an $n \times m$ matrix whose entry $c_{i,j}$ is 1 if caller $i$ can be served through BTS $j$ without exceeding the uplink or downlink budgets. This information can be extracted by the data periodically transmitted by each MS comprising the received signal strength from nearby BTSs during a call. We also introduce indicator variable $x_j$, which is 1 if BTS $j$ is operating in high-power mode (i.e., without BTS power savings) and 0 otherwise. The total power consumption may, therefore, be given as $\sum_{j=1}^{m} P_1 + \sum_{i=1}^{n} w_{i,j}(P_2 - P_1)/t_{\text{max}} - (1 - x_j)\gamma$. Using this as the objective function, we can formulate the Low-Carb optimization problem, subject to appropriate constraints. However, some of the terms in the above summation are constant and will be omitted from the objective function. The term $P_1$ in the above summation is a constant, so it can be excluded from the objective function. Furthermore, in order to not affect the grade of service, we will not drop any active calls. Therefore, the summation over $w_{i,j}$ is also constant and can also be excluded from the objective function. After removing the constant additive and multiplier terms from the summation, the Low-Carb optimization may be stated as:

$$\text{minimize} \sum_{j=1}^{m} x_j \quad (1)$$

subject to the following constraints:

$$\sum_{j=1}^{m} w_{i,j} = 1 \quad \forall i \quad (2)$$

$$w_{i,j} \leq c_{i,j} \quad \forall i, j \quad (3)$$

$$\sum_{j=1}^{m} w_{i,j} - \delta \leq M x_j \quad \forall j \quad (4)$$

$$\sum_{i=1}^{n} w_{i,j} \leq t_{\text{max}} \quad \forall i \quad (5)$$

The first constraint ensures that no active call is dropped just to save on power. The second constraint secures the uplink budget by ensuring that no call is routed to a BTS that is too far away. The third constraint picks the correct value for the decision variable $x_j$. The fourth constraint is the capacity constraint on all BTSs, while the last constraint is the binary value constraint on the decision variables.

The above optimization problem is a Binary Integer Program (BIP), which is NP-Hard. It is intractable to solve for an operator’s entire network. For a large network, it could be applied separately and independently to small disjoint network segments. Alternatively, a heuristic solution to Low-Carb could be deployed over the entire network. We present a heuristic for Low-Carb in Algorithm I.

Our heuristic first partitions the set of BTSs $B$ into disjoint sets $B_1$ and $B_2$ where the latter includes all the BTSs in low-power mode and the former consists of all other BTSs. The heuristic iterates over a random permutation of the BTSs in $B_1$. Once a BTS $b_j$ from $B_1$ is selected (line 3), our heuristic determines the minimum number of calls that must be handed off from $b_j$ before it can be moved to $B_2$. Our heuristic iterates over the calls that are presently being handled on $b_j$ and for each such call it attempts to find a candidate serving BTS in $B_2$. The choice of the new serving BTS ($b_q$) is made while ascertaining that the hand off will not cause $b_{2_q}$ to move out of $B_2$. If such a BTS is found, the call is handed off to it. Calls are handed off from $b_j$ in this manner, until it moves into $B_2$, or we exhaust the set of active calls with other candidate BTSs ($b_j$ remains in $B_1$).

**III. DATA AND EXPERIMENTAL SETUP**

Our dataset is obtained from a cluster of 26 BTSs operated by a large network operator with more than 7000 sites. These sites are spread over a 31.25 km² urban terrain (see Fig. 1). We obtained each site’s coverage prediction using a tool popular amongst the operators called Forsk Atoll. With this information, along with a caller’s location, we can determine the candidate set of BTSs for the corresponding call (the $c_{i,j}$ parameters). Note that in this work, we do not incorporate user mobility into our model, since we are only interested in instantaneous optimization at small time scales and in determining bounds on the energy savings that Low-Carb can offer.

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 datasets, we conducted a set of experiments mimicking a 24-hour operation of a subset of a cellular network. Each experiment is a discrete event simulation of the arrival and placement of calls. Since our dataset does not include the arrival times and duration of calls, we synthetically generated this information using the assumption of Poisson
Require: δ: the power-saving traffic threshold,
B (the set of BTSs) = \{b_1, b_2, ..., b_n\},
A (the set of active calls) = \{a_1, a_2, ..., a_n\},
W (current call association) = \{w_{i,j} = 1 \text{ if } a_i \text{ is being served through } b_j, 0 \text{ otherwise}\},
C (Possible call association matrix) = \{c_{i,j} = 1 \text{ if } a_i \text{ can be served through } b_j, 0 \text{ otherwise}\}

Ensure: A new and potentially more energy efficient mapping of calls to BTSs
\begin{align*}
1: & \quad B_1 = \{b_j| \sum_i w_{i,j} > \delta\}; \quad B_2 = B - B_1 \\
2: & \quad B_1 = \text{random} \_\text{shuffle}(B_1) \\
3: & \quad \text{for all } b_j \in B_1 \text{ do} \\
4: & \quad a = \sum_i w_{i,j} - \delta; \quad d = 1; \quad \text{shuffled} = 0 \\
5: & \quad \text{while } d < n \text{ and shuffled} \leq a \text{ do} \\
6: & \quad \text{if } w_{d,j} = 1 \text{ then} \\
7: & \quad e = 1; \quad \text{mapped} = 0 \\
8: & \quad \text{while } e \leq m \text{ and mapped} = 0 \text{ do} \\
9: & \quad \text{if } e \neq j \text{ and } e \in B_2 \text{ and } c_{d,e} = 1 \text{ then} \\
10: & \quad w_{d,e} = 1; \quad w_{d,j} = 0 \\
11: & \quad \text{shuffled}++; \quad \text{mapped}++ \\
12: & \quad \text{end if} \\
13: & \quad e++ \\
14: & \quad \text{end while} \\
15: & \quad d++ \\
16: & \quad \text{end if} \\
17: & \quad \text{end while} \\
18: & \quad \text{if } \sum_i w_{i,j} < \delta \text{ then} \\
19: & \quad B_1 = B_1 - \{b_j\}; \quad B_2 = B_2 + \{b_j\} \\
20: & \quad \text{end if} \\
21: & \quad \text{end for} \\
\end{align*}

Algorithm 1: Heuristic for the Low-Carb problem

call arrivals and exponentially distributed call duration with a mean of 180 seconds [9].

For every hour, the simulator determines the Poisson call arrival rate for each BTS, using Little’s Law and the BTSs traffic intensity for that hour. Using the resulting Poisson process, calls are generated such that it is equally likely for a call to be anywhere in the serving BTSs coverage area.

Our simulator tracks the call volume at every BTS on a minute’s granularity. This enables us to calculate the power consumption level (in Watts) of the BTS during each minute. Accumulating these numbers over the 24 hour period leads to the daily amount of energy consumed (in kWh) if no optimization is used in the network. Our simulator also monitors each BTSs call volume every minute and places the ones with sufficiently low traffic into power-saving mode. This enables us to calculate the possible energy savings using BTS power-saving feature. In addition, our simulator also periodically determines the instantaneous optimal call placement configuration that minimizes the power consumption level by handing-off some calls, thereby placing a maximal number of BTSs in power-saving mode. This allows us to determine the energy savings possible by combining call hand-offs with BTS power-saving.

The call placement re-optimization may be done at various frequencies. A very aggressive re-optimization regime would keep the network in an optimal state more often than a conservative one, thereby enabling greater energy savings. In order to study the scaling of energy saving with re-optimization frequency, we experimented with a range of intervals between successive optimizations, ranging from a minute to an hour. For a deployment, the re-optimization frequency that can be used would depend on the costs associated with each re-optimization. Let us now consider such costs.

First and foremost, a computational cost is incurred with each optimization. In our case, an optimization run to determine the optimal state over 26 BTSs required an average running time of about 50 seconds on a Core i3 laptop with 4 GB of RAM. An optimization requiring 50 seconds would not be practical to use every minute but may be fine if used less often. For a practical deployment the computational time can be reduced by using a combination of a more powerful machine, distributed optimization and approximation algorithms.

In addition to the computational overhead, for every unit of energy saved some extra energy may be consumed in the network to perform call hand-offs or transitions into and out of BTS power-saving mode. Call hand-offs and TRX (de)activation involve signaling between a Base Station Controller (BSC), BTSs and MSs. The additional energy incurred thus, should be small, because it has been observed that variation in power consumption of network equipment with changes in traffic volume (data or control) is quite small [10]. As far as increased power consumption on MSs due to a greater number of call hand-offs is concerned, we opine that it may be negligible because the MSs energy consumption is far outweighed by that of BTSs.

\begin{itemize}
\item\textit{A. Site Characteristics}
\item All sites in our dataset had three sectors, each equipped with 6 TRXs, for a maximum of 132 simultaneous voice calls\(^1\). The GSM standard includes a provision for half-rate calls, which enables handling greater traffic at the expense of reduced voice quality by allowing a single voice channel to be shared amongst two calls, each using a half-rate codec. In this paper, we only shuffle full-rate calls around, which may be, in reality, two half-rate calls. We do not foresee any significant error arising from using this convention.
\item We consider a scaling down from a “6 + 6 + 6” site to a “2 + 2 + 2” site, which means that \(\delta\) should be strictly less than \(t_{max}/3\) to avoid quick oscillations into and out of BTS power-saving mode due to short-term traffic variations. We have arbitrarily set \(\delta\) equal to \(\lfloor t_{max}/3 \rfloor - 5\), because 5 seemed to be a good enough number compared to a sector’s overall capacity and the typical utilization of a site in our datasets.
\end{itemize}

\(^1\)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.
The BTS power consumption model parameters may vary from one BTS model to another. In this paper, we use three different sets of model parameters as listed in Table I. We now describe the sources and methods from which we obtained these models.

1) Model 1: For the first model, we have used 1.5kW as the maximum power consumption [11], a 20W per TRX saving when scaling the BTS down [6] and a 5% swing in power consumption between no-load and full-load [3].

2) Model 2: Lorincz et. al reported the single sector DC power consumption for a GSM 900 BTS with 7 TRXs [5]. We extrapolate the power consumption for a 6+6+6 site by multiplication of the DC power consumption reported in [5] by 3 × 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, which has a typical power consumption of 1 kW [11]. We used this scaling and AC load correction to obtain the values for $P_1$ and $P_2$ using the minimum and maximum reported power consumption in [5]. Furthermore, the authors measured a drop of 50W in power consumption when a TRX is disable, which gives us the value of $\gamma$ as listed in Table I.

3) Model 3: Using the same method as for model 2 in III-A2, we derived the values for $P_1$ and $P_2$ based on the measurements for a GSM 1800 BTS reported in [5]. As for the value of $\gamma$, the paper reported a 100W cut in power consumption when deactivating a single TRX. The parameter values for this model are given in Table I.

### Table I

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_1$</td>
<td>1425</td>
<td>2401.8</td>
<td>2541.5</td>
</tr>
<tr>
<td>$P_2$</td>
<td>1500</td>
<td>3881.3</td>
<td>2973.9</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>20</td>
<td>30</td>
<td>100</td>
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</table>

### Table II

<table>
<thead>
<tr>
<th>Energy saving</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage</td>
<td>4.73%</td>
<td>5.43%</td>
<td>12.89%</td>
</tr>
<tr>
<td>Daily absolute saving over 26 BTSs (kWh)</td>
<td>43.28</td>
<td>109.68</td>
<td>217.12</td>
</tr>
<tr>
<td>Country-wide daily saving over 31000 sites (MWh)</td>
<td>51.6</td>
<td>130.77</td>
<td>258.87</td>
</tr>
</tbody>
</table>

![Fig. 5. Percent and absolute reduction in energy consumption vs re-optimization interval](image-url)
BTS energy consumption, prior work proposed shutting down a counter-argument, however, is that in rural settings, call lower because few calls would have multiple candidate BTSs. Amount of energy saving would be applicable in rural as well as in other countries as well. Since network deployments and traffic patterns are significant. Since network deployments and traffic patterns are similar in different countries, the same extrapolation can be applied to 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. One may argue that in rural settings, due to sparse deployments the energy savings potential would be lower because few calls would have multiple candidate BTSs. A counter-argument, however, is that in rural settings, call traffic is already low, which implies that BTS power-saving is applicable to most BTSs most of the time.

We also ran experiments for each BTS model in which the electricity cost for the optimal as well as the heuristic solution (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 is quite close to the optimal solution most of the time, especially for the Model 1 and Model 2 BTS. For Model 3 BTS, while the error is comparatively larger, since the amount of savings with the optimal solution is quite high (Fig. 5), the heuristic will still result in significant energy savings.

V. CONCLUSION

BTSs account for most of a cellular network’s energy consumption. Motivated by the non-load-proportionality of BTS energy consumption, prior work proposed shutting down some BTSs when traffic is low. However, network operators are reluctant to do so for a variety of reasons.

To reduce energy consumption, operators often use a feature called BTS power savings that deactivates some TRXs at BTSs that have low traffic. This is typically done without any intelligence. 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.

We formulate an optimization problem that intelligently re-routes active calls to place a maximal number of BTSs in power-saving mode, thereby minimizing the electricity consumption. When re-routing active calls, our optimization keeps the MS uplink budget in check and does not drop any active calls either. Since our formulation is NP-Hard, we also propose a heuristic. Experiments using topologies and datasets from a live GSM operator indicate that Low-Carb can significantly reduce BTS power consumption and that our heuristic’s performance is quite comparable to the optimal solution.

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![Fig. 6. Empirical CDF of the difference between the cost offered by our heuristic compared to the optimal.](image)