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GreenLoading: Using the citizens band radio for energy-efficient offloading of shared interests

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ABSTRACT

Cellular networks are susceptible to being severely capacity-constrained during peak traffic hours or at special events such as sports and concerts. Many other applications are emerging for LTE and 5G networks that inject machine-to-machine (M2M) communications for Internet of Things (IoT) devices that sense the environment and react to diurnal patterns observed. Both for users and devices, the high congestion levels frequently lead to numerous retransmissions and severe battery depletion. However, there are frequently social cues that could be gleaned from interactions from websites and social networks of shared interest to a particular region at a particular time. Cellular network operators have sought to address these high levels of fluctuations and traffic burstiness via the use of offloading to unlicensed bands, which may be instructed by these social cues. In this paper, we leverage shared interest information in a given area to conserve power via the use of offloading to the emerging Citizens Broadband Radio Service (CBRS). Our GreenLoading framework enables hierarchical data delivery to significantly reduce power consumption and user fairness variation and includes a Broker Priority Assignment (BPA) algorithm to select data brokers for users. With the use of in-field measurements and web-based Google data across four diverse U.S. cities, we show an order of magnitude power savings via GreenLoading over a 24-hour period, on average, and power savings up to 97% at peak traffic times. Finally, we consider the role that a relaxation of wait times can play in the power efficiency of a GreenLoading network.

1. Introduction

While the focus of cellular congestion is frequently placed on the frustration that users experience when they lack the ability to call, text, or receive web-based information, there is a byproduct of excessive re-transmissions in a congested state: severe battery expenditure. The problem could be even more extreme for battery-limited devices associated with the emergence and potential explosive growth expected for Internet of Things (IoT), Vehicle-to-Vehicle (V2V) and Machine-to-Machine (M2M) based communication in LTE and 5G networks [1,2]. Such congestion is hard to alleviate since the data-intensive services and scale of mobile devices has grown the global data traffic 18-fold over the last 5 years and expected to reach 49 exabytes per month by 2021 [3].

One promising solution is to deploy traffic offloading, where cellular traffic is moved to less-congested, often unlicensed spectrum [4]. The primary objective of traffic offloading is to support more capacity-hungry services while simultaneously preserving satisfactory Quality-of-Service (QoS). Small cells, WiFi networks, and opportunistic communications have recently emerged as the main cellular offloading technologies [5]. While smaller cells have helped, simply offloading traffic from macro cells to small cells may not increase the transmission rate, improve the user experience, or reduce power expenditure. Some work has investigated this relationship between energy savings and traffic offloading to small cells [4]. Other work has focused on the switching times and performance improvements for cellular offloading to WiFi [6]. The use of WiFi or even white space bands has also been advocated for energy-efficient cellular offloading [7].

However, there remains a yet untapped spectrum resource for cellular offloading: the Citizens Broadband Radio Service (CBRS) for shared wireless access using the carrier frequencies of 3550–3700 MHz (3.5 GHz Band). Unlike WiFi and white spaces, CBRS is expected to be fully operational in the context of 5G. CBRS access will be managed by a dynamic spectrum access system, conceptually similar to the databases used to manage TV white space devices but at faster time scales. The three tiers of access are: Incumbent Access (existing users of 3650–3700 MHz), Priority Access (network operators may purchase up to seven 10 MHz Priority Access Licenses (PALs) in a census track from 3550–3650 MHz), and General Authorized Access (unallocated bandwidth from the first two tiers). Hence, up to 150 MHz may be available in a given area for opportunistic use [8].

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Nomenclature

t	Time slot
N	Set of users
U	Regular users
B	Selected data brokers
F_C	Set of cellular channels
F_s	Set of CBRS channels
f_m	Max–min fairness ratio
f_j	Jain fairness index
$G(t)$	User access channel schedule
D	User demand
W	User tolerance time window
η	Channel capacity
γ	Channel bandwidth
σ	Degree, number of connected neighbors
h	Background noise
P_s	Standby power consumption
P_t	Transmission power consumption
λ_s	Arrival rate of a queue

Acronym List

CBRS	Citizens Broadband Radio Service
FIFO	First-In First-Out
IoT	Internet Of Things
M2M	Machine to Machine
PALs	Priority Access Licenses
QoS	Quality of Service
SNR	Signal-to-Noise Ratio

The time and place of network congestion can often stem from mutually-shared environmental factors, causing a surge in data (*e.g.*, roadway conditions, audio/video from live events, or emergency situations). These shared interests and the data redundancy thereof have largely been overlooked when optimizing offloading strategies in terms of capacity and power consumption [9]. In this paper, we leverage shared interest information in a given area to conserve power via the use of offloading to the emerging CBRS spectrum. To do so, we use a data broker where mutual information can be broadcast to the interested parties with the following hierarchical structure: consider one extreme where all devices connect directly to the macro cell and no data broker is needed. In this situation, the channel will be divided for all users and the interference generated could cause poor data rates over the network. Now, consider the other extreme where all devices work through a data broker to receive their information. If the amount of overlap in the shared interests is extremely high, there are tremendous savings of the spectrum. However, if the amount of overlap in the shared interests is extremely low, there could be severe delays and *greater* power consumption in working through a data broker to deliver unique content to individual users.

Hence, the crux of our work is establishing when it would be beneficial to use a data broker based on the number of users in an area, their mutual overlap of shared interests, the QoS response time required for a given application, and the availability of spectrum for offloading. These five factors are considered in our Broker Priority Assignment (BPA) algorithm. With the use of crowdsourced Google Maps measurements, we build a data transformation model that allows analysis across four diverse U.S. cities. We show that GreenLoading with shared interest data in a given area and the use of CBRS channels can reduce the power consumed by an order of magnitude over a 24-h period, on average. At peak traffic times, we find that our framework can reduce power expended by 97%.

The main contributions of our work are as follows:

- We leverage Google Maps data to create a relationship between the travel time and number vehicles over a 24-h period in four major U.S. cities so that the commuting pattern of users on the road can be characterized.
- We consider the data demand characteristics of these users in these four cities and use it to motivate and analyze a GreenLoading data sharing framework, which uses our BPA algorithm to quantify the power savings of our scheme.
- We perform measurement-driven numerical evaluations of various QoS scenarios and user distributions to show that CBRS offloading can reduce the power consumption by up to 97%. We further show that the power savings can be reduced by 95% from a cellular-only configuration with a CBRS channel and the GreenLoading framework. In dense urban areas, we show the *average* power consumption over a 24-h period can be reduced by over 10 times versus a cellular-only network.
- We perform measurement-based evaluation of user fairness to show that CBRS offloading can improve the max–min ratio by 81% and Jain fairness index by 64%.
- We show the role that the relaxation in user wait times plays on the energy savings that one may experience using the GreenLoading framework with a wide range of realistic scenarios in our analysis.

The remainder of the paper proceeds as follows. In Section 2, we motivate the use of shared interest demand profiles to construct the GreenLoading framework, introduce our BPA algorithm, and analytically model the key aspects of their performance. We then consider four major U.S. cities and quantify various QoS scenarios and the energy savings that our GreenLoading framework offers in Section 3. We discuss related work in Section 4. Finally, we draw conclusions in Section 5.

2. GreenLoading framework

Cellular offloading refers to the mixed use of cellular data traffic with various available unlicensed bands such as Bluetooth, WiFi, white space, and CBRS networks. Cellular network operators are motivated to leverage these unlicensed bands for greater capacity and higher QoS. If offloading additionally provided power savings, there would be a reduction in ongoing operating costs of the network and potentially a solution in select rural infrastructures that have begun to depend on solar power [10]. From the user perspective, if the offloading prevents high levels of congestion and frequent re-transmissions, a higher level of QoS may be possible with significantly reduced power savings, extending the life of user and IoT devices. In this section, we discuss the shared user interest information that may exist in a given area, formulate the problem of energy-efficient cellular offloading, introduce the GreenLoading network architecture, and explain the Broker Priority Assignment (BPA) algorithm.

2.1. Shared interest data demands

Today, people live in intertwined social circles consisting of in-person and online communities where digital content is commonly exchanged. Frequently, the information being exchanged has a mutual interest based on regional events at a particular moment in time. For example, when traffic occurs on the roadways via unforeseen circumstances or through normal peak commute times (especially in dense urban areas), cellular users in a particular region will access similar traffic data for construction or accident updates or alternate route information as shown with Google Maps in Fig. 1. Even in rural areas, natural disasters such as the recent hurricanes and wild fires, have caused both physical and cellular congestion, where users sought weather and navigation information such as with the Hurricane

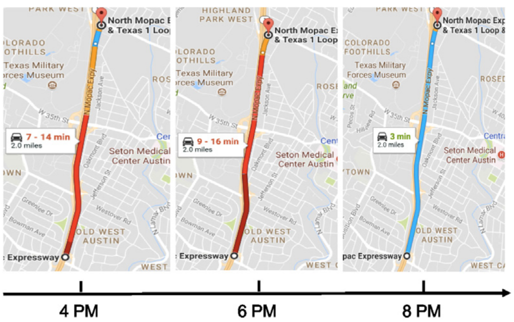


Fig. 1. Travel time variation on google maps.

Fig. 2. Hurricane Harvey evacuation (2017).

Harvey evacuation, as shown in Fig. 2. Special events occur across sports, concerts, or theater that can attract a surge in demand that ultimately prevents access to cellular networks. Here, data delivery could be optimized if the mutual interest of that community event is considered. These examples of shared interests is in contrast to the individual interest that users uniquely possess.

More formally, for a group of users, we model the total demands ($D_i(t)$) at a given point in time (t) of each user (i) as a mixture of shared interests ($D_i(t)[S]$) and individual interests ($D_i(t)[I]$) data:

$$D_i(t) = D_i(t)[S] + D_i(t)[I] \tag{1}$$

While prior work leveraged the population diversity variation among multiple area types [7], they have not included the shared interest demand of users in a given area. The multiple transmission rounds of shared interest data for users from an eNodeB can also result in lack of fairness and potential starvation of users. Thus, how to leverage the shared interest information in data offloading and organize data sharing across multiple available frequency bands for a particular group of users becomes the unique challenge for our GreenLoading network design.

2.2. Energy-efficient cellular offloading problem

As it has previously been utilized in social networking for other applications, the user data demand consists of a mixture of shared and individual interests. Hence, when the users are requesting data, the cellular eNodeB could recognize the common data being demanded and apportion the users into small groups with an assigned data broker for each group to broadcast the shared interest data. From the perspective of Internet of Things (IoT), the eNodeB enables data and computing power closer to the location where it is needed by the users as an edge computing device. Edge computing refers to the enabling technologies allowing computation to be performed at the edge of the network. In particular, edge devices could circumvent end-to-end downstream data on behalf of cloud services and upstream data on behalf of IoT services. Here we define *edge* as any computing and network resources along the path between data sources and central data centers. In terms of edge computing device, the data can be processed at the edge for quicker response time, more efficient processing, and reduced network congestion. The data produced or required by users will scale exponentially, making conventional central servers potentially unable to handle the load. To alleviate this demand, processing could be performed at the edge of the network [11]. We assume the system can adapt the channel resource allocation according to the variation in traffic demand to reduce power consumption. Generally, the N users that are connected to a particular eNodeB in a cellular network can have M shared interest groups. In our scenario, we assume that all N users are equipped with radios that are able to simultaneously transmit and receive over the cellular and CBRS frequency bands with a log-normal path loss channel model. Accordingly, a Shannon-based capacity of channel η can be given by:

$$\eta = \gamma log_2(1 + \frac{P}{h}) \tag{2}$$

Here, γ bit/s is the channel capacity, P is the transmit power, and h is the background noise.

We assume that sufficient memory space exists to buffer traffic to the users from each eNodeB. For this work, we consider only the potential offloaded traffic to the CBRS band and the power consumption thereof based on the network in which the traffic is served. Hence, the traffic aggregated at the eNodeB could be distributed via cellular or CBRS frequency bands in each mutual interest group. The traffic is served in a first-in, first-out (FIFO) scheduling strategy.

We assume the coherence time is sufficiently large to allow a constant channel capacity during any given time slot. Since the devices are assumed to all have simultaneous transmission capability on the cellular and CBRS frequency bands, the switching time is assumed to be negligible in the system. We will introduce the calculation of achieved channel capacity in Section 3. We further assume that the traffic demand of a given user obeys a Poisson distribution, with the vector noted as $D(t) = [D_1(t), D_2(t), \ldots, D_N(t)]$ and the sum demand rate of $D(t) = sum_{i=1}^{N} D(i)$. The sum demand rate $D(t)$ is the total demand generated from all N users. To focus on the energy expenditure of the choice of which band and which traffic to offload, we ignore the sleeping energy and that a given operating radio will expend an equal standby power per unit time, regardless of which frequency band is in use.

Previous human factors research [12–14] shows that users have a certain level of patience for a response. While the tolerance time of users has been shown to vary across the traffic type (*e.g.*, text, voice, video), we assume an average value for the tolerated response time W of all the users in the system to simplify the analysis. Since we assume that the channel capacity is the maximum achievable per spectral resource and that the resource is equally divided in time among users, we could serve users faster with less response time by adding channel capacity. However, the power consumption would increase according to the amount of spectral resources allocated per unit time. Thus, if users tolerate a relaxation in response time, less channel resources (bandwidth and resulting energy) are necessary. Once users are in the same group, each user will have peer-based comparison of their service. The peer pressure is able to be modeled by fairness metrics. Here, we employ two metrics to quantify the fairness in response time, the max–min fairness ratio and Jain fairness index. The max–min fairness ratio is:

$$f_m = \frac{max\{w_i\}}{min\{w_i\}} \tag{3}$$

The max–min fairness ratio is achieved by an allocation if and only if the allocation is feasible and an attempt to increase the allocation of any flow necessarily results in the decrease in the allocation of some other flow with an equal or smaller allocation. A max–min fair allocation is achieved when bandwidth is allocated equally and in infinitesimal increments to all flows until one is satisfied and then among the remainder of the flows until all flows are satisfied or the bandwidth is exhausted.

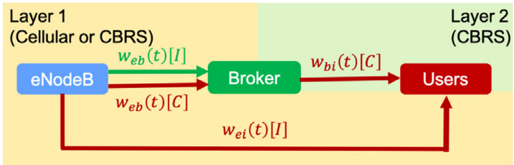


Fig. 3. User response time.

Jain fairness index measures the variation of the allocation of the resource [15]. Generally, the Jain fairness index measures the throughput of the resource allocation. We convert the response time to average throughput as:

$$f_j = \frac{(\sum_1^n \frac{1}{w_i})^2}{n \sum_1^n \frac{1}{w_i^2}} \tag{4}$$

The Jain fairness index rates the fairness of a set of resources where $\frac{1}{w}$ is the average throughput, converted from the response time. The result ranges from the best case of 1, when all users receive the same allocation, to the worse case of $\frac{1}{n}$, when only a single user gets all the resources.

For broker nodes, the response time ($w_b(t)$) includes the common data from the eNodeB to broker ($w_{eb}(t)[C]$) and individual data demand of the broker ($w_{eb}(t)[I]$). Then, the broker response time is shown as Fig. 3:

$$w_b(t) = w_{eb}(t)[C] + w_{eb}(t)[I] \tag{5}$$

For each general user, response time ($w_i(t)$) contains two parts: a shared common data from broker transmission time ($w_{bi}(t)[C]$) and unique data from the transmission time of the eNodeB ($w_{ei}(t)[I]$).

$$w_i(t) = max\{(w_b(t) + w_{bi}(t)[C]), w_{ei}(t)[I]\} \tag{6}$$

Here, via $w_b(t)[C]$, we see that the response time from the eNodeB to the data broker has a direct impact on all users. The greater the number of available cellular or CBRS bands that are used by the data broker, the less channel capacity is available for individual interests, as represented by the wait time ($w_i(t)[I]$). Hence, there is a trade-off between the channel distribution for individual user interests and shared interests via data brokers.

2.3. GreenLoading network architecture

To leverage the impact of shared interests to efficiently offload cellular traffic to CBRS, we propose the GreenLoading network framework and the BPA algorithm to form shared-interest user groups to be serviced by the data brokers. To do so, we first formulate the wireless network system as a discrete-time queuing system shown in Fig. 4. The cellular and CBRS channels are represented as servers in the queuing model. Multiple user groups may share the same CBRS channel, but we assume there is no overlap of their service areas through power control and spatial spectrum reuse. Thus, the queuing system has M queues of user groups and two layers to process the requests. Layer 1 exists from the eNodeB to either users or brokers via cellular or CBRS channels (F_C + F_s servers in total). Layer 2 exists from the brokers to the users via CBRS channels $G * (M, F_s)$.

In GreenLoading, the matrix $g_{i,j}(t), i \in (F_C + F_s), j \in M$ denotes the wireless resource allocation for Layer 1 (data brokers and users connected to the eNodeB directly) as shown below:

$$G_{i,j}(t) = \begin{cases} 1 & if\ D_j,\ is\ associated\ with \\ & radio\ i \in (F_C + F_s) \\ 0 & Otherwise \end{cases} \tag{7}$$

Layer 2 (from the data brokers to users) has a similar resource association representation as Eq. (7) with just F_s (removing F_C).

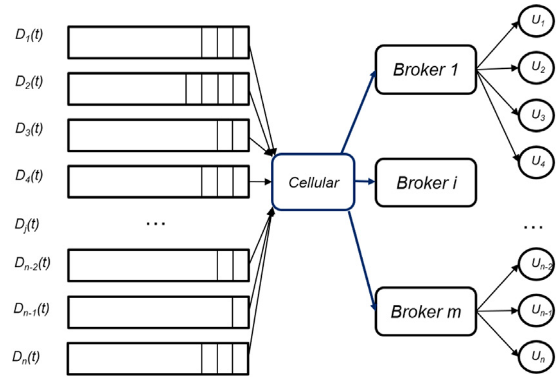


Fig. 4. Greenloading system model.

To maintain the QoS, the queuing system restricts the expected response time of the system w to no more than the tolerance threshold W:

$$E[w] \leq W \tag{8}$$

In this work, we focus on analyzing the power savings for the GreenLoading framework. To model the power consumption of the system, we take the summation of the power consumed by each operating radio when in two operating modes: *standby* and *transmission*. We assume the on–off switching power consumption and the power consumed when the device is asleep are comparable across both network types. The value of P_i denotes the total power consumption of the radio for standby and transmission modes. In other words, when the radio is in the sleeping state, $P_i = 0$. Otherwise, P_i is:

$$P_i(t) = \begin{cases} P_s \cdot t + P_t \cdot \mu & \sum_{j=1}^{N} G_{i,j}(t) \geq 1 \\ 0 & Otherwise \end{cases} \tag{9}$$

Here, P_s is the standby power consumption of a radio, which has a constant rate over time, P_t is power consumption to transmit, and μ is the transmitted data, whose upper bound is the allocated channel capacity of the radio. $P_i(t)$ is the power consumption of the radio during each time slot.

Thus, to reduce the power consumption for GreenLoading, P_i is minimized subject to the QoS constraints. Specifically, the objective is to minimize the power consumption:

$$P^*(t) = \min\{\sum_{i=1}^{(F_C+F_s)} P_i(t)\} \tag{10}$$

Here, P^* represents the minimum operating power consumption required of the system for the response-time QoS. Our work focuses on energy efficiency analysis, whereas previous work using game theory, spectrum bidding, and economics has focused on policy, cost profit, and user motivation [16]. Broker motivation and cost reimbursement are implemented by counting the data retailed by the brokers, but the exact details of the brokerage protocol are out of the scope of this work.

2.4. Broker priority assignment

Carriers typically provide a QoS agreement to customers. In our work, the response time W represents the duration of time from when the user sends a request to when the server responds. With GreenLoading, the response time W constraint has to be satisfied to maintain the QoS. The channel quality in multiple cells varies throughout a single time slot, which is mentioned as part of multi-user diversity in previous works. Multi-user diversity is a form of diversity inherent in a wireless network provided by independent time-varying channels across the different users [17]. The diversity results from either interference inside or outside of the network or environmental variations. Some cells may have idle CBRS channels, while the other cells may suffer from other spectral activity. To address the channel capacity variation, we apply a queuing model to estimate the QoS response time.

User density is one of the key points in wireless resource allocation. As more users stay in or move into a cell, greater gains could result from data sharing of common interests. Thus, the user distribution is a critical aspect of GreenLoading. To identify the user mobility patterns, we parse a data set from Google Maps regarding user density along highways and other roadways. The experimental setup and results are shown in Section 3. Our previous work formulated a multi-channel system as an $M/M/m$ queuing system for network analysis [7,18]. However, WhiteCell used a single-layer approach to reduce the power consumption through offloading cellular data to white space and WiFi channels without the notion of shared interests. Other previous works have also overlooked user shared interests for cellular offloading, especially for emerging CBRS spectral resources. To leverage the users shared interests and CBRS channels for power savings, we first model the queuing system with the aforementioned two layers and apply our previous work on $M/M/m$ queuing theory to approach a solution for the architecture of GreenLoading.

We label any channel allocation (cellular or CBRS) occurring on the eNodeB to either the users directly or to a data broker as Layer 1 and the channel allocation for the data broker to the user (CBRS) as Layer 2. Since CBRS channels could be used across both layers and there exists dynamic assignment of channel bandwidth via the emerging CBRS standardization, there could be variation of channel capacity in the queuing model, contradicting the equal service capacity assumption of the queuing system. Hence, a traditional $M/M/m$ queuing system often used in previous multi-channel works is not directly applicable for the GreenLoading system model. Channel switching can occur through central channel control or a handover process [19].

For the case in which variation occurs either across CBRS channels or between cellular and CBRS channels, we observe a heterogeneous server queuing system when the maximum over minimum ratio is greater or equal to 2 from Eq. (14). We apply the transformation model in [20] to estimate the response time $\bar{w}$. In the transformation model, the actual arrival rate for one specific server λ_s is defined as:

$$\lambda_s = D_{cell}/(F_C + F_s) \tag{11}$$

Here, D_{cell} is the traffic aggregated from the users in the cell, F_s represents the set of CBRS channels assigned in the cell, and F_C denotes the cellular channels in the cell. In this work, the arrival rate λ_s is defined in terms of the statistical average for a specific channel.

The other parameters are defined in Eq. (12) through (14).

$$\mu_{min} = \min(\mu_1, \mu_2, \dots \mu_{(F_s+1)}) = \bar{\mu} \tag{12}$$

$$\mu_{max} = \max(\mu_1, \mu_2, \dots \mu_{(F_s+1)}) \tag{13}$$

$$k = \lfloor \frac{\mu_{max}}{\mu_{min}} \rfloor \tag{14}$$

When $k \geq 2$ the average response time of the heterogeneous system [20] could be represented as:

$$\bar{w} = \frac{1}{\frac{1}{3}\bar{\mu}(2k+1) - \lambda_s} \tag{15}$$

Another interesting case occurs when only a single channel serves the cell, either the cellular channel or part of a single CBRS channel. This case can be simplified to a $M/M/1$ queuing system that only has one server in the model. When the traffic is able to be served by part of a single CBRS channel, as in the latter scenario, the system converges to a $M/M/1$ queue. The response time $\bar{w}$ can then be estimated from [21]:

$$\bar{w} = \frac{1}{\mu^+ - D} \tag{16}$$

Here, μ^+ represents the capacity of a single channel allocated in the cell.

A third case may occur (which has similarities to the first case discussed) when multiple channels are in use in the cell. However, the key distinction is that the capacity of the channels is approximately the same (*i.e.*, when $k = 1$). This scenario becomes a queuing system, which has multiple equal capacity servers in the model. We label this equal-capacity server case as a homogeneous $M/M/m$ system and is in contrast to the first case, which is a heterogeneous $M/M/m$ system.

The average response time can be found through a search strategy [21]:

$$\bar{w} = \frac{1}{\mu^*}(1 + \frac{c(m,\rho)}{m(1-\rho)}) \approx \frac{1}{\mu^*}\frac{1}{1-\rho^m} \tag{17}$$

where μ^* is the average capacity of channels in the $M/M/m$ queuing system. A half-search strategy is applied to find the minimum value of μ^* to reduce the power consumed by transmission. Here, $\rho = \frac{\lambda}{m\mu^*}$ is the traffic density, and $c(m,\rho)$ is the Erlang-C formula [21]. Through the transformation model, we can further search the channel capacity required for the response time constraints. We estimate the power consumption jointly using the radio model of Eq. (9) and channel capacity model of Eq. (2).

According to the queue-based QoS model and power consumption model, we further analyze the GreenLoading system and propose our greedy heuristic detailed in the BPA algorithm. In non-offloaded cellular systems, each user's data demand is served by the eNodeB. In this case, the power consumption includes both the standby power ($P_s * D_i/r_c$, where r_c is the transmission rate of the radio) and transmission power ($P_t * D_i$). The standby power consumption increases with the transmission time, while the transmission power consumption increases only according to the data transmitted. The power consumption of a single user is represented as:

$$P_i(t) = P_s \cdot \frac{D_i}{r_c} + P_t \cdot D_i, i \in N \tag{18}$$

With GreenLoading, the power consumption of each user's demand is satisfied across two layers: via the eNodeB directly or through a data broker. The power consumption of each broker's traffic to and from the eNodeB would be the same as Eq. (18), since all the data is from the eNodeB (and is synonymous with a user that is directly connected to the eNodeB without the use of a data broker). However, each user of a data broker has a power consumption from connections to both the eNodeB and data broker. Hence, the power consumption is noted as:

$$P_i(t) = P_s \cdot \frac{D_{iI}}{r_c} + P_t \cdot D_{iI} + P_{sO} \cdot \frac{D_{iC}}{r_O} + P_{tO} \cdot D_{iC}, i \in N \tag{19}$$

P_{sO} is the standby power consumption of offloading radios in CBRS, and P_{tO} is the transmission power of offloading radios in CBRS. D_{iI} is the individual traffic demand of user i, and D_{iC} is the shared interest traffic demand of user i. P_s is the standby power consumption of access point radios in cellular or CBRS, and P_t is the transmission power of access point radios in cellular or CBRS. With the GreenLoading framework, the power consumption savings can be represented for cellular offloading by (from Eqs. (18) and (19)):

$$\begin{aligned} P_G = P_s \cdot \frac{\sum^U D_{iC}}{r_c} + P_t \cdot \sum^U D_{iI} - P_{sO} \cdot \frac{\sum^{U+B} D_{iC}}{r_O} \\ - P_{tO} \cdot \sum^U D_{iC}, i \in N \end{aligned} \tag{20}$$

Here, B is the set of data brokers, and U is the regular users in the group. The total users of the cell can be represented by $V = B + U$. According to Eq. (20), the more Greenloading users, the more power savings is achievable from the data broker layer. However, having more Greenloading users requires more data brokers for offloading, which will also increase the power consumption in the data broker layers.

To apply GreenLoading to the users with a hierarchical structure, there are two questions that must be addressed: (*i.*) Which users should be assigned data brokers? and (ii.) To which data broker should Greenloading users associate? To solve these questions, we identify the most important vertices within a graph to the user graph, employing centrality analysis. Centrality analysis has been widely used in various areas, including pattern recognition, social networks, and software defined networks [22–24]. As shown before, the channel capacity of GreenLoading will be allocated to both brokers and regular users. For the layer from the data broker to users, the spatial reuse of CBRS channels enables the transmission power to be the highest allowable by the FCC to reduce the transmission time for power saving.

In other words, the cover distance of the brokers is restricted by the transmission power. As shown in Eq. (20), to achieve more power savings, our target is to cover the users with less data brokers. *Centrality* is an indicator of a node's degree of connectivity for network analysis. In the GreenLoading structure, we consider one-hop offloading to restrict the delay for users. Thus, we choose the metric of *degree* to identify which user is the best fit for a data broker. The degree is the number of connected neighbors of the user with a certain transmission power.

$$\sigma(i) = \sum_{j} Connected\ Neighbors, i, j \in N, j \neq i \tag{21}$$

In the GreenLoading structure, reducing the response time of brokers will benefit all users according to the transformation model. The key point of power savings in each broker group is to alleviate the use of the decentralized CBRS radios with the centralized cellular and CBRS channels. To implement the division of the user groups and user-broker association, we propose a Broker Priority Assignment (BPA) algorithm to minimize power consumption in the system, as shown in Algorithm 1.

The input parameters to the BPA algorithm are the measurement-based residual channel capacity, the crowdsourced user distributions, the number of CBRS channels, and the capacity of cellular channels for a given region. The more broker-covered users, the more power savings could be realized for users in Greenloading. The user radios could save power by communicating to closer brokers instead of the eNodeB. The users must be sorted according to node degree, and a breadth-first search is performed for users associating with a given eNodeB. The time complexity would be $O(nlogn)$ and $O(n+E)$, where n is the number of total users, and E is the total connections of the users. To turn off (or disable) more cellular radios, the algorithm starts to replace the cell radios that were directly providing access to users with data brokers. The algorithm compares the three configurations of channel capacity assignment in each cell and chooses the setup with the lowest power consumption. The process is repeated until all traffic demand is served or the channel resources have been completely allocated. Finally, BPA outputs the power consumption and channel allocation of the system.

With the GreenLoading framework, a user's response time will be divided into two parts as shown in Eq. (6). Thus, the fairness metrics defined in Eq. (3) and (4) will change with these two parts. Users who associate with the same broker, share the same value of $w_b(t)$ which will restrict the variation inside the group. Also, further reducing the inter-group variation is the reduction in cellular traffic as the user is offloaded. As a result, the two factors will lead to better fairness results for Greenloading topologies.

Algorithm 1: Broker Priority Assignment (BPA)

Require:
N: Users
$\sigma^f_{i,j}$: Connectivity of Users
D: Traffic Demand
F_s: CBRS Channels

Select or increase transmit power
if Users can be covered by brokers **then**
  Calculate degree of each user
  Rank users with connectivity degree $\sum_{i,j}\sigma_{i,j}$, break ties according to smaller index
  Select brokers from users according to the ranking and remove covered users
  Repeat process until all users are covered by brokers or brokers reach the upper bound
  Rank brokers according to the user group size
end if
Repeat process for all users
Assign cellular and CBRS channel capacity to brokers
Calculate power consumption with Eq. (15), (16), and (17)
if channel allocation is feasible & unserved traffic demand exists **then**
  List available options
  if Single channel is chosen ($M/M/1$) **then**
    Apply half-interval search to find minimum capacity for users
  else if Homogeneous $M/M/m$ is chosen **then**
    Allocate resources for cell
    Find minimum capacity for users
  else if Heterogeneous $M/M/m^*$ is chosen **then**
    Add CBRS capacity to cell
    Calculate power consumption with Eq. (15), (16), and (17)
  end if
else
  Get wait time of cell with all available resources
end if
Update system information
Calculate power consumption

Ensure:
Power consumption, resource allocation, and maximum wait time

3. Evaluation of GreenLoading framework

In this section, we introduce the experimental setup and evaluation. In particular, we analyze the Broker Priority Assignment (BPA) Algorithm in our GreenLoading framework and compare the power consumption of BPA across various levels of cellular offloading in a variety scenarios in four major U.S. cities.

3.1. Experimental setup and BPA run time

To evaluate the GreenLoading framework, we use crowdsourced data from Google Maps across multiple variations of parameters. For our analysis, all the users are covered by cellular service and have the ability to access the CBRS frequency band. Previous work focused on security, sensor networks, and social media networks having enabled data sharing and exchange across distributed devices, applications, and locations [25,26]. Other work has enabled data brokers to regular users in a ratio of 1:3 or 1:4 [27,28]. Vehicular networks utilize cellular networks and are expected to utilize CBRS networks as well. Since vehicular nodes are frequently spatially clustered, one might expect increased shared interests as opposed to other user groups [29]. Guided by these prior works, we set the traffic demand per user as 0.5 Mbps and assume 40% of the user demand will be shared among the total user demand. Unless otherwise stated, we assume the tolerated response time by users is 200 ms. We use a cellular channel bandwidth of 20 MHz and CBRS channel bandwidth of 40 MHz [30]. The transmit power is set according to that specified by the FCC for both types of channels. We set the noise level as -80 dBm for use in Eq. (2). The user number is set to 2000 in the experimental setup unless otherwise stated. In the simulation, the user traffic demands are modeled as the total data payload. The throughput per second per session is stable for each user and base station. The results are based on the summation data of all users and base stations.

With the setup, we investigate the configuration of: (*i.*) cellular, (*ii.*) cellular GreenLoading (shared interest only, no CBRS usage), (*ii.*) CBRS and cellular (use of both bands but no shared interest consideration), and (*iv.*) CBRS and cellular GreenLoading. With multiple scenarios to consider the power consumption performance, we analyze the user density impact using in-field Google Maps traffic profiles. To convert Google Maps data to the total population of vehicular users, we apply the Department of Motor Vehicle (DMV) safety restrictions and estimate the resulting number of users on the road according to the estimated travel time. In our analysis, we assume each vehicle has only one mobile user.

To understand the ability of the BPA algorithm to stabilize quickly with shifting user demands and interests, we simulate the framework on a Dell R730 server with Intel Xeon 2.6 GHz Dual 12 Core CPU with 320 GB of RAM. With the complexity discussed in 2.4, we measure the simulation time in MATLAB with the Tic-Toc Technique. The run time of dynamic random user demand varies between a minimum of 24.32 s and a maximum of 27.92 s over 20 iterations with an average of 26.15 s.

3.2. Greenloading fairness characteristics

To ensure that the power savings observed in the following subsection are not at the expense of user starvation, we first establish the fairness characteristics of GreenLoading. There are two predominant metrics for doing so (as discussed in Section 2.2): max–min fairness and Jain fairness index (see Figs. 5–7).

In Fig. 5(a), max–min fairness analysis across a range of user density, focusing on 1500 to 2500 users, representing a macrocell deployment. The users with cellular-only connectivity have the most diversity in throughput. Users are fully competing for limited spectrum resources in the cellular-only configuration. As shown in Fig. 5(a), the cellular-only configuration has the poorest max–min ratio for the four experimental scenarios. The Cellular with GreenLoading configuration has improved the ratio by 53% on average (lowering the metric). In GreenLoading, the shared data is distributed to the brokers first and then received by the users. Both the competition reduction and the second-layer broadcasting decrease the gap between the performance among all users. The users who are located in these regions have worse cellular performance, but the users who have better cellular access have to wait on the first-layer transmission of shared data, thereby balancing their total response time. The max–min fairness ratio is improved by GreenLoading's two layers of access, as all users have part of the wait time cost of the broker, as represented in Fig. 6. Thus, the max–min fairness is significantly improved when applying GreenLoading for the cellular-only scenario. The scenario containing both cellular and CBRS bands reduces the competition among users, allowing even better max–min fairness among users due to additional resources and drastically improving the performance of the users that were previously starved of resources. The max–min fairness ratio improves by an average of 72%. When GreenLoading is added to the scenario with both cellular and CBRS bands, the improvement of the max–min fairness ratio continues (now improved by 81% on average).

The results of the Jain fairness index is shown in Fig. 5(b). The Jain fairness index is a representation of the distribution of a group of users' throughput. The cellular scenario gets the lowest Jain fairness index with the worst fairness out of all scenarios. GreenLoading improves the Jain fairness index with cellular-only bands since the broker layer reduces the competition and improves the second-layer throughput. The additional resources of the CBRS bands with the cellular bands improve the Jain fairness index compared to the cellular-only scenario. GreenLoading with cellular and CBRS bands reaches the best Jain fairness index result with an average improvement of 63% (corresponding to an increase in the metric). Thus, with the GreenLoading framework, the fairness among the users would improve as another feature of the two-layer implementation.

Table 1
Number of users 24 h in urban areas.

Time	0	2	4	6	8	10	12	14	16	18	20	22
Austin	180	180	180	360	1620	960	1200	960	1440	1920	360	360
Detroit	120	120	120	180	720	480	720	540	720	960	180	120
NY	720	720	720	1080	1800	900	900	900	1080	1800	720	720
San Francisco	360	360	480	480	960	960	960	960	960	1080	480	360

3.3. Crowdsourced demand across four U.S. cities

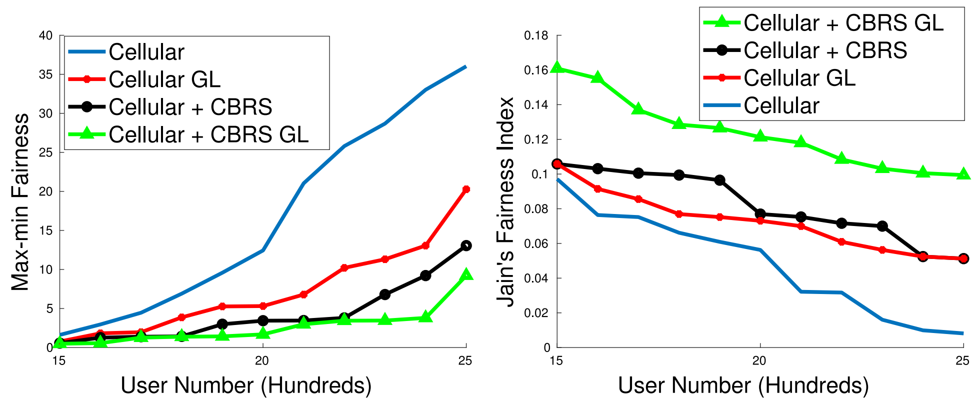
We now investigate the user density variation on the four offloading scenarios in terms of the total power consumption. In this particular experiment, the user number varies from 1500 to 2500 as before. The results from the user density variation are shown on Fig. 6(a). We see that the power consumption will exponentially increase as the user number increases to maintain the same QoS. Also, with an increasing number of users, the data demand and standby power consumption both increase linearly. However, if the users' data demand is served only by cellular channels, the transmit power required increases exponentially. This rapid increase in the power consumption is primarily due to the required increase in channel capacity to remain below the QoS threshold, resulting in exponentially-increasing power consumption to satisfy Eq. (2). Comparing the results across multiple offloading configurations, with the GreenLoading framework applied only to cellular channels with shared interests via data brokers, the power savings achieved is 46.1%. Without shared interests and adding CBRS channels to the cellular channel allows a power savings of 15%. By adding the CBRS channels and using the Greenloading framework (utilizing shared interests), the power savings is dramatic, reaching a mere 2.9% that of the cellular-only configuration without shared interest. This point occurs when the users scale to the greatest density. The power gains would be even more significant with greater user scale or when higher levels of demand are requested.

Since the 40% of shared interest information is an arbitrary choice, we now consider a broader range of shared interest overlap in a given user density. We expect the level of shared interest to greatly depend on the event type causing cellular congestion (*e.g.*, sports, concert, construction, accident) and the environmental setting (*e.g.*, home, office, campus). Hence, we vary the user shared interest percentage of the total data demand from 20% to 70% to investigate the impact on power consumption. The results are presented on Fig. 6(b).

With the general experimental setup, since the total data demand of users is held constant, the *cellular* and *cellular with CBRS* scenario power consumption stays the same since the amount of transmitted remains the same across all the variations of common interests. However, for the GreenLoading framework which can capitalize on the shared interests, even the cellular-only channels improve the power savings across all the common interest configurations. With the use of cellular *and* CBRS channels, as the shared common interests increases, greater power savings are achieved. However, observe that when the shared interest reaches a low point on the graph, there is an added overhead of using the GreenLoading framework due to the extra standby power consumption cost in the traffic being forwarded from the eNodeB through the data brokers to get to the users (as opposed to the eNodeB directly serving the users).

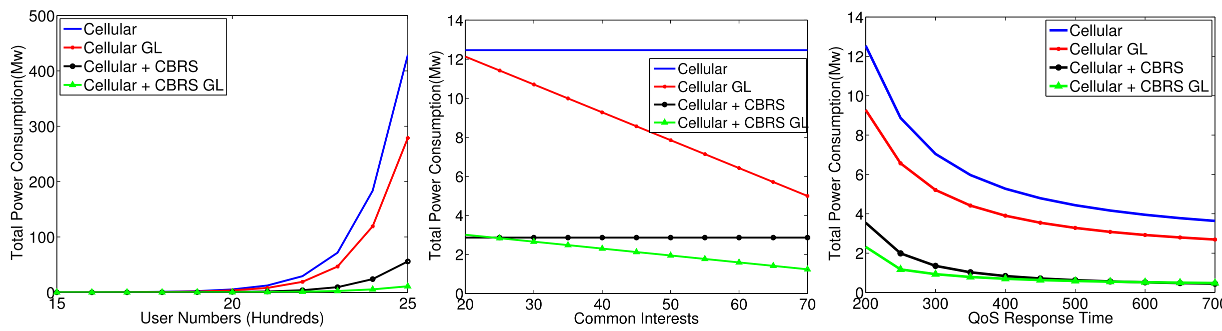
Further, we consider the impact of the QoS response time on power consumption of GreenLoading. To do so, we set the response time threshold from 200 ms to 700 ms with a 50-ms step size. The results are shown in Fig. 6(c). With a decreasing QoS requirement, the power consumption reduces exponentially. This can be explained by the lower QoS response time required, needing less capacity for the users. Thus, the power consumption reduces exponentially according to Eq. (2).

For the in-field analysis, we propose a data transformation model from Google Maps to the user density across four major U.S. cities. To estimate the number of users on the road, we record the driving time, t_c, at the first minute of each hour from a certain residential area using



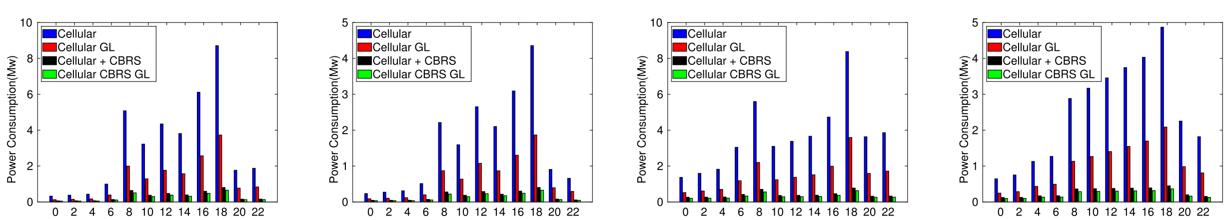
(a) Max-min Ratio. (b) Jain Fairness Index.

Fig. 5. User fairness analysis.



(a) User Variation. (b) Common Interests Variation. (c) Response Time Variation.

Fig. 6. Power consumption based on: (a) number of users, (b) common interest level, and (c) QoS response time.



(a) Austin. (b) Detroit. (c) New York. (d) San Francisco.

Fig. 7. Power consumption of various offloading schemes across four major U.S. cities.

Google Maps and distance d_c from that residential area to a business district. Using this Google Maps data and our transformation model, we can observe how the diurnal patterns in major cities might impact the GreenLoading power savings. Google Maps records traffic data to estimate the drive time from one place to another. We did not find a way to parse the number of users on the road at any point in time. However, assuming drivers will maintain a safe driving distance from one another, we refer to the Department of Motor Vehicle (DMV) safety statistics and requirements to establish the user density on the road. From this, we are able to estimate the total number of users according to Google's estimated travel time t_c and travel distance d_c.

To perform the transformation, the DMV has a two-second rule for safe driving, meaning the driver needs at least a 2-s response time to react to the vehicle directly in front of that vehicle. The average speed of the vehicles on the road could be estimated from Google Maps data according to $v_{avg} = \frac{d_c}{t_c}$. Then, a safe following distance is $d_s = v_{avg} * 2$. Thus, the number of users in one direction is $u = \frac{d_c}{d_s}$. Using a simplified version of the previous equations, we can represent the total number of users a particular stretch of road as:

$$u = t_c \tag{22}$$

This approximately estimates the total number of users on the road to drive our user density variation according to real traffic patterns in U.S. cities. Furthermore, as self-driving cars and other IoT technologies enter the roadways, the vehicles will more strictly follow the safety guidelines to keep a safe distance between one another. This transformation model can be adjusted according to future traffic patterns as well. Specifically, we select the cities of Austin, Detroit, New York, and San Francisco to investigate the potential power savings from our GreenLoading framework. We list the user variation of each city according to alphabetical order and then investigate the power savings of each city with GreenLoading. Table 1 lists the number of users of a 2-h time slot of a given weekday.

First, we select an Austin commute that begins in an urban neighborhood with the zip code of 78613 and ends in business area with the zip code of 78759. In Texas, we observed that the population is widely-distributed across large areas. Hence, people often must travel during the morning and afternoon peak commute times. Then, we investigate a Detroit commute that begins in a suburb called Warren with a zip code of 48208 and ends in a business area with a zip code of 48201. In a Detroit metropolitan area, we observed that there are more users in the afternoon, which might be due to the cold weather in winter season. Next, we select a New York City commute that begins at an apartment complex with a zip code of 10019 and ends in the Central Park area with a zip code of 10028. New York has expensive rent and limited land for residents. Hence, the users on the road seemed to have similar characteristics during peak commute times like Texas. Though the two metro areas have very different neighborhoods and population densities, they have similar user variation on the road across a given weekday. Lastly, for the San Francisco commute, we choose to begin at an apartment complex with a zip code of 95054 to a company in San Jose with a zip code of 95134. We observed that the San Francisco traffic pattern seemed to have an increase in activity during all times of the workday as opposed to the early morning or late evening.

As shown in Table 1, there exists a peak time in the morning and in the afternoon when people start to work and go home after work for all 4 metro cities. Without a proper offloading protocol, the carrier has to deploy enough resources for the peak time during the entire course of the day to assure the QoS is satisfied, which can waste valuable network resources. The GreenLoading framework offers a solution for all types of areas and user densities.

With the experimental setup mentioned before, we investigate the power consumption variation across time over a regular (non-holiday) weekday. The results of the four U.S. cities are shown in Fig. 7(d). The main variation across time over a day is the number of users at peak commute times versus other times of the day. Through the analysis, GreenLoading is able to significantly reduce the power consumption for populated areas. In particular, leveraging shared interests, GreenLoading uses only 38.1% of the original power consumed with the use of only cellular channels. Without shared interests, using just cellular and CBRS bands gets down to 8.4% compared to using only cellular channels without shared interests. With the use of shared interests and CBRS channels, the power savings of GreenLoading reaches 6.92% of the original cellular-only configuration in the areas of greatest user density across the four U.S. cities.

4. Related work

Various forms of multiple radio and multiple channel opportunistic networking exist where devices can communicate with various radios, frequency bands, and/or channels [31]. While this simultaneous use of multiple radios for communication offers the opportunity for data sharing in small groups, previous works have focused on specific applications such as IoT or self-driving cars [32]. An opportunistic communication model for cellular traffic was proposed in [5]. More to the point, energy consumption, bandwidth, and user experience were considered in [33], and energy savings with respect to traffic offloading to small cells was studied [4]. Many works employing machine learning have been proposed for algorithms approaching in various areas, however, these approaching need more specific domain leveraging for wireless networks [34–36] . Other work has focused on the switching times and performance improvements for cellular offloading to WiFi [6]. Also, the taxonomy of various data offloading models were considered in terms of various technical and economic challenges [37]. In fact, white space and WiFi bands have been used to reduce the energy efficiency of a cellular network and increase the bandwidth [38]. These works lay a foundation for opportunistic offloading of mobile systems. However, these works do not exploit shared interests of users in a particular region or the mobility of such users for energy-efficient cellular offloading, especially to the emerging CBRS band.

Mobile social networking (MSN) refers to social networking where individual users request similar data through their mobile devices [9, 39]. There has been work that has notified users of potential data sharing content. Previous analysis of the social aspects exploited the structural information present in the network, such as existence and strength of communities, node centrality, network robustness to node removal, and topological evolution over time. These technologies could be applied to improve the wireless mobile communications. However, these works have not focused on energy-efficient cellular offloading as part of the work.

5. Conclusion

In this paper, we created the GreenLoading framework to efficiently offload cellular network traffic to the emerging CBRS band via the use of shared interest information and data brokers. To achieve this goal, we developed a Broker Priority Assignment (BPA) algorithm to select the shared-interest user groups for the data brokers to broadcast traffic. With the use of in-field measurements and web-based Google Maps data across four diverse U.S. cities in both dense and sparse areas, we showed that, on average, an order of magnitude power savings via GreenLoading to the CBRS band over a 24-h period and up to 97% at peak traffic times. In addition, the fairness improves up to 81% with the use of the max–min ratio and 64% with the use of the Jain fairness index. Lastly, we considered the role that a relaxation of wait times can play in the power efficiency of a GreenLoading network, showing an exponential reduction in power. In the future, multi-layer hierarchy, channel model, and more user experience will increase the application of the framework.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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