Connected cars in cellular network: A measurement study

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ABSTRACT

Connected cars are a rapidly growing segment of Internet of Things (IoT). While they already use cellular networks to support emergency response, in-car WiFi hotspots and infotainment, there is also a push towards updating their firmware over-the-air (FOTA). With millions of connected cars expected to be deployed over the next several years, and more importantly persist in the network for a long time, it is important to understand their behavior, usage patterns, and impact — both in terms of their experience, as well as other users. Using one million connected cars on a production cellular network, we conduct network-scale measurements of over one billion radio connections to understand various aspects including their spatial and temporal connectivity patterns, the network conditions they face, use and handovers across various radio frequencies and mobility patterns. Our measurement study reveals that connected cars have distinct sets of characteristics, including those similar to regular smartphones (e.g. overall diurnal pattern), those similar to IoT devices (e.g. mostly short network sessions), but also some that belong to neither type (e.g. high mobility). These insights are invaluable in understanding and modeling connected cars in a cellular network and in designing strategies to manage their data demand.

CCS CONCEPTS

• **Networks → Network measurement**;

KEYWORDS

cellular, connected car, IoT

ACM Reference Format:

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1 INTRODUCTION

The rapid adoption of connected devices is fueling a growth in Internet of Things (IoT). Since the communication characteristics of typical IoT devices are different from traditional cellular devices, there is a widespread expectation that they will have an impact on cellular networks. In particular, the common wisdom is that the signaling load of IoT devices differs significantly and will motivate a different approach to managing IoT device connectivity.

In this paper, we focus on connected cars, a rapidly growing segment of IoT that defies this wisdom. Connected cars today use cellular networks to support emergency response, in-car WiFi hotspot, infotainment, and other forms of vehicular communication. They also use the network to convey telemetry information and manufacturers are seriously considering cellular networks to push firmware over-the-air (FOTA) updates [10]. Forecasts predict that 90% of cars will be connected by the year 2020 [17].

The different types of use cases supported by connected cars result in unique communication patterns. Connected cars differ significantly from traditional IoT in terms of data volumes they generate given the infotainment capabilities they support and because of the large volume FOTA downloads (updates ranging from Megabytes to even Gigabytes are not unheard off [7]). At the same time, the fact that they show up in the network periodically, and are almost always mobile (and traveling at high-speed) makes them different from mobile phones. Next, given that the average life of modern cars is over 11 years [6] and rising, connected cars that come out today need to be supported for a lot longer than typical cellular phones (life expectancy of 4.7 years [3]). This fact can potentially be an issue as shown by the case of San Francisco Muni bus system. Heavily dependent on GPRS, the upgrade to 3G/4G equipment in the buses was delayed which caused several issues due to the shutdown of 2G networks [14]. Finally, many of the updates to cars tend to be time critical given the types of features that are controlled by software as well as the safety and regulatory implications of these updates [13]. Managing large volume downloads, at high speeds, and supporting devices that are typically considered legacy is going to require innovative network planning and management strategies. It may necessitate the use of smart policies and network control mechanisms for the management of network demand, especially at peak hours.

To design the right kinds of policies and mechanisms, it is necessary to understand connected car behavior and the potential impact that they may have on the cellular network. In this paper, we conduct a large-scale measurement study of connected cars in a major cellular network to provide insights and basis for studying and modeling connected car impact in such environments. Using anonymized call detail records for a random set of one million connected cars from one manufacturer over the 90-day period, we seek to understand various aspects of connected cars, including the spatial and temporal distribution of cars' connections to the network, the mobility patterns of connected cars, the typical network conditions that connected cars face, and the distribution of their connections and handovers over various radio frequencies.

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Based on our analysis, we make several important observations. Connected cars have a very *different connectivity pattern than smartphones*. In particular, cars' *sessions are shorter* and in many cases *concentrated in network busy hours*. This is not entirely surprising given that most of them can connect only when their engines are running, and commute happens during network busy hours. However, this has implications when it comes to delivering software updates in a timely manner. We also observe that *connections to each radio cell are generally short*, which is a combination of mobility (handovers) and small data transfers. Furthermore, cars can concentrate in large numbers within cells increasing the potential for congestion. Most importantly, we observe that cars *can be clustered according to predictability in their behavior*. This indicates a potential for intelligent capacity and network management in terms of connectivity and content delivery for connected cars.

2 RELATED WORK

Adoption of IoT is imminent and projected connected "things" far outnumber smartphones and computers, with connected cars becoming a significant segment [17]. With widespread geographic distribution of various devices, cellular networks are expected to bear the majority of IoT traffic demand. In fact, the 3GPP report projects on the order of 200,000 IoT devices per cell site, as opposed to the current several hundred or thousand [1].

An early large study finds that IoT devices exhibit different characteristics from the mainstream cellular devices, such as smartphones, in particular that the ratio of their uplink to downlink traffic is much larger, their mobility is much lower, and the diurnal traffic pattern is different [15]. However, early indications with the increasing, but currently limited numbers of connected cars, is that their characteristics are significantly different. Hence they deserve a dedicated study to understand their impact on the network.

IoT devices are expected to primarily introduce high signaling load into cellular networks, but a subset will add a large data volume. When connected cars are considered, from a smaller sample of 2,100 connected cars, we know that signaling intensity they generate can be 4-7 times higher than regular LTE devices [2], while the average flow sizes in both uplink and downlink are similar. In the future, connected cars are expected to introduce two types of high data demand: user traffic, such as web browsing and multimedia via in-car WiFi hotspots, and FOTA updates [5, 10]. Some work already exists in the area of managing FOTA, mostly related to efficient compression of updates [9, 16]. Specifications and protocols for remote device management are defined by the Open Mobile Alliance Device Management (OMA DM) [12]. While OMA DM can be used to manage devices for FOTA, it is limited to protocols for data exchange, data formats, security and fault management. Understanding of how cars behave, what is the impact on the network and when to deliver their particular downloads is still heavily dependent on the network context.

General car mobility insights and traffic patterns have been inferred from cellular phone connections in the past, indicating commute patterns and network trajectories [4]. We, however, argue that while there is correlation between connectivity and mobility, it does not automatically imply that one could apply general mobility patterns to cars. First, not all cars are connected. Hence it is unclear how accurately general mobility patterns match connectivity patterns of cars. Second, just because a car connects to the network, it does not mean it is mobile. Finally, by the time all cars become connected, the technology may evolve and the correlation between connectivity and mobility may cease to exist. We aim to expand knowledge by directly studying connected cars as opposed to inferring their behavior from user devices like phones.

3 DATA SET AND METHODOLOGY

At the high level, we use network measurements from a large cellular network in the United States to understand the network behavior of connected cars. User devices, such as smartphones, tablets or modem cards connect to a radio cell (or simply a "radio" or a "cell") over a certain radio frequency or a carrier. Each cell covers a geographic area with a directional antenna and it is common to find 3 such cells covering a full circle, approximately 120 degrees each, but there can be more or fewer cells with different coverage areas. Multiple cells covering the same direction and area can be called a sector. For coverage and capacity, there are typically multiple cells per base station, anywhere from 3 to 12, sometimes even more. There can be hundreds of thousands of cells in the networks and the cars connect to a subset of these cells.

Our data, based on Call Detail Records (CDRs), provides information about radio-level connections made by cars to the cellular network, such as times and durations of connections, as well as radio cells that they connect to, but not data volumes transmitted. These records are anonymized and aggregated and do not contain sensitive personal or identifiable information about owners of devices or connected cars. The data set consists of over 1.1 billion connections from a random sample of 1 million cars equipped with cellular 3G/4G modems. These provide connectivity to support emergency services, telemetry, FOTA updates and in-car WiFi hotspot. We constrain the data set to a single car maker, also known as Original Equipment Manufacturer (OEM). A single OEM with a large car population allows us to reason about potential FOTA management, since this is managed by each OEM independently. That said, many of the dimensions that we analyze in this paper are independent of the OEM and really dependent on car usage patterns. Hence the lessons from this paper are applicable to connected cars in general with the caveat that these usage patterns may change as connected car technology evolves.

Our study spans a 90-day period in 2017. We believe that this period is long enough to be representative as a predictor, and to account for variability in daily and hourly load as well as any trend. There can be a vast range of connection durations at radio level due to the normal timeout of 10 to 12 seconds after no data is left to transmit in either direction [8]. We concatenate all connections that are up to 30 seconds apart into aggregate sessions where appropriate. Normally, the cars from this OEM can connect to the network only when the engine is running, so connections correlate to car usage and driving. We then derive patterns of connections across time and space (in terms of network location, i.e. radio cell) and analyze them against general car and network usage patterns. Therefore, our focus is on current connectivity patterns that tell us when and for how long cars use the network rather than the volume of data that they generate.

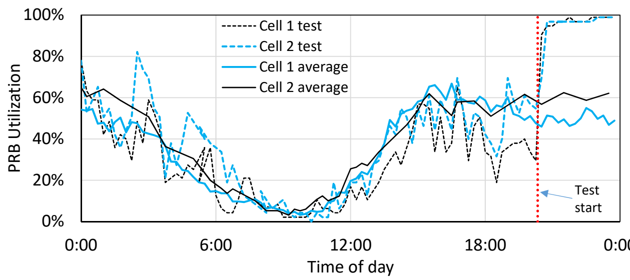


Figure 1: Large downloads start at 20:45 UTC in two cells and last for 4 hours, consuming nearly all available resources.

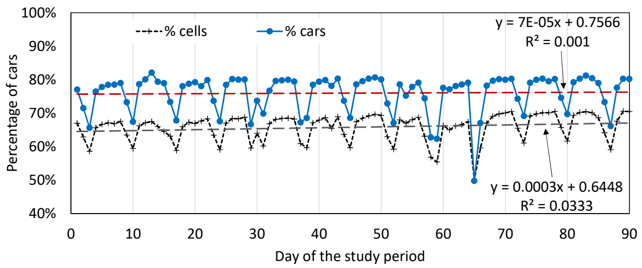


Figure 2: Number of cars that appear on the network is relatively consistent over the days throughout the study.

We pre-process the logs to remove erroneous records, such as the ones where connections appear to have lasted exactly 1 hour. These are presumably caused by an automatic periodic reporting feature of the network, where disconnections at the radio level were not recorded correctly. Then, during the data analysis, we also truncate long connections to a single cell to 600 seconds, to mitigate some modems tendency to improperly disconnect.

4 CONNECTED CAR ANALYSIS

In LTE, radio resources are finite and measured using Physical Resource Block (PRB) utilization, U_{PRB}. To motivate our study and demonstrate the impact on the network and other users, we show that even a single device can saturate the radio cell resources with a long, greedy download. Figure 1 shows an experiment where one device starts downloading data continuously (indicated by 'Test start'). Note that many such downloads can occur concurrently, as could happen during FOTA updates or multiple video streams when cars are concentrated in one cell.

We start with high-level data set analysis showing the percentage of unique cars that appear on the network and the percentage of cells that cars connected to on each day in Figure 2. Due to some data loss during 3 days in the second half of the study period, the number of cars appears smaller, but this does not affect the overall results. We clearly see a weekly pattern in both plots, with fewer cars and cells connecting on the weekend, but with most variability occurring on Friday and Saturday. We also show the trend lines, which indicate a slow increase over time. We can model the average numbers of cars and connected cells per Table 1. We see two-thirds of the cells, out of all the cells that had cars connect to them in our data set, have cars connecting to them on a given day.

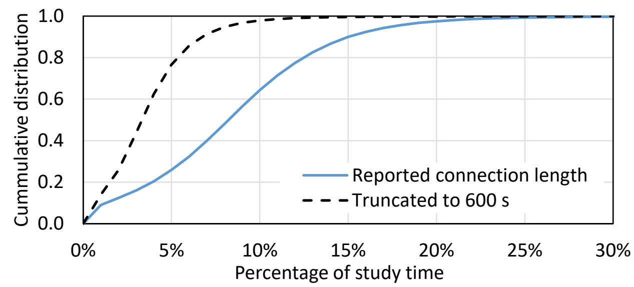


Figure 3: Cars' total time on the network is very short.

4.1 Macro-level temporal behavior

We analyze the temporal behavior of cars by considering how long and when the cars were connected to the network during the study period. We plot two distributions, one with full connection time as indicated by the CDRs, and another where connections are truncated to 600 seconds in Figure 3. We truncate the connections because we believe that some of the non-terminating connections are due to noisy data. Since picking the correct value for each device requires intimate knowledge of the working of the device, we conservatively choose 600 seconds as a threshold. The CDF shows the fraction of cars vs. the percentage of study period they were connected to the network.

Averages are about 8% for full and 4% for truncated connections, respectively. This is about 173 and 86 hours total, or 1.9 and 1 hours per day, respectively. Without truncation the 99.5th percentile of connected time is 27% (6.5 hours per day), and with truncation it is 15% (3.6 hours per day).

Clearly, cars spend much less time connected than smartphones, meaning that the window of opportunity to deliver large amounts of data is very small.

4.2 Weekly and daily temporal behavior

We next analyze car usage patterns compared to known weekly and daily network load and commute time periods. Network load follows known diurnal patterns while peak commute time patterns can be extracted either from CDRs or from known data [4]. Hence we encode important periods during the week in 24×7 matrices, where each hour of the day for 7 days is represented by a shaded box. Figure 4 shows example periods of interest in local time.

We can encode car usage patterns in the same format. Figure 5 shows the 24×7 car usage frequency matrices rendered in respective local times for 3 sample cars. Darker colors represent a higher number of car's connections to the cellular network. A white box means that the car has not connected to the network during that

Table 1: Usage of cells by cars and occurrence of cars per day.

	% cells with cars		% cars on network	
Day	Mean	StDev	Mean	StDev
Monday	67.2%	1.1%	78.1%	0.8%
Tuesday	68.1%	1.6%	79.1%	1.5%
Wednesday	68.5%	1.4%	79.8%	1.2%
Thursday	68.2%	1.7%	79.3%	0.9%
Friday	67.2%	3.1%	78.0%	3.8%
Saturday	62.0%	4.3%	70.3%	7.0%
Sunday	59.3%	1.5%	67.4%	2.0%
Overall	65.8%	4.1%	76.0%	5.6%

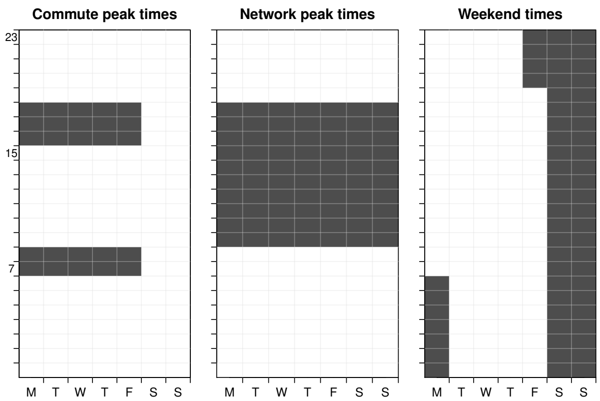


Figure 4: Significant time ranges in the week.

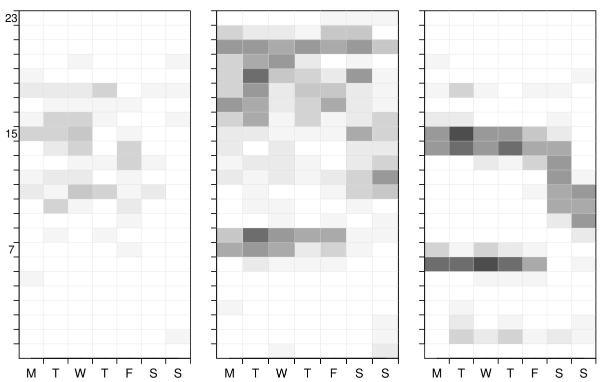


Figure 5: Usage patterns from 3 sample cars.

hour. Frequency of connections and their regularity during certain hours allow us to see strong patterns in the very dark colors. By aggregating data from multiple weeks onto a 24×7 matrix we can take this hourly and daily pattern into account and find the consistent patterns in the noise.

For these 3 cars, the weekly matrices tell us the following. Car on the left connects to the network mostly during Monday to Friday network busy hours (14-24 h), but rarely otherwise. Car in the middle exhibits more heavy usage and consistent Monday to Friday commute, stretching into the evenings and in addition has moderate weekend usage. Usage on Tuesdays is much more frequent and spread over multiple hours than on other days. Car on the right shows a very strong and consistent commute, though before start of peak commute in its time zone. Further it shows quite predictable weekend usage during peak network hours on Saturday and on Sunday mornings. These examples of consistency in cars' sessions indicate that we can look for patterns that can help predict the times and durations of their appearance on the network.

Predictable appearance of cars during busy or non-busy network hours allows for more intelligent management of large data demand.

4.3 Combining car and network data

From the individual car usage data and each cell load pattern, we can extract a variety of usage patterns of cars. An example of such pattern extraction follows. We would like to know what proportion of cars are commonly seen or rare on the network and do they

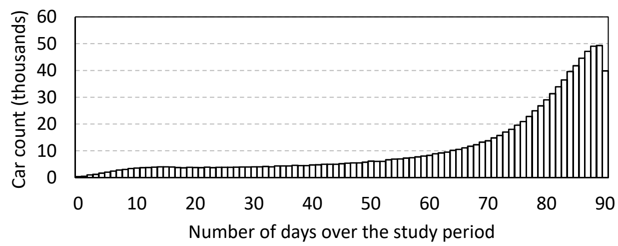


Figure 6: Number of days cars were on the network.

Table 2: Car segmentation.

Segment	Busy	Non-Busy	Both	Total
Rare (≤ 10 days)	0.4%	0.9%	0.9%	2.2%
Common (10+ days)	1.3%	59.0%	37.5%	97.8%
Rare (≤ 30 days)	0.7%	5.0%	4.2%	9.9%
Common (30+ days)	1.0%	54.9%	34.2%	90.1%

typically appear during network busy hours or not. This kind of car *segmentation* can guide various traffic management solutions.

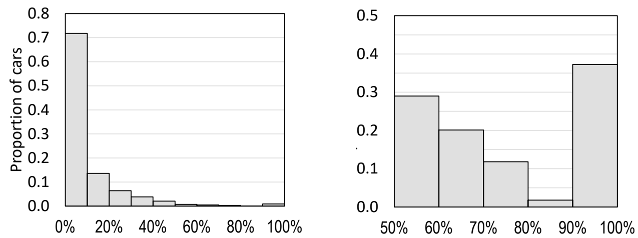
To be able to define *common* and *rare* we need either some intuitive definition, a specific use case definition, or we can derive it from data. To derive from data, we can use the number of days over the study period that cars were connected, as shown by the histogram in Figure 6. It appears that 10 days is the point under which a sharp drop off exists, and past 30 days is where increasing trend begins. If we use simple definitions that rare means 10 days or less in one use case and 30 in another, we can segment the car population as in Table 2. We consider a car to typically connect in busy (non-busy) hour if 65% or more (35% or less) of its time on the network is in cells with average $U_{PRB} > 80\%$ for those 15-minute bins. Otherwise, cars' connected time is more balanced in both busy and non-busy hours.

To produce Table 2, we combined three types of data, (i) usage patterns of all cars as exemplified in Figure 5, (ii) classification of each cell as busy or non-busy for each 15-minute bin, exemplified by *average* curves in Figure 1, and (iii) classification of a car as common or rare as per Figure 6.

An example use of this type of segmentation is in the context of FOTA updates. In some managed FOTA scenario, rare cars would be prioritized over the limited FOTA campaign window, and common cars would be perhaps randomized or scheduled depending on the typical time they connect. In particular, cars that typically appear during busy hours will likely need special treatment to avoid impacting the network and other users during large downloads.

While general temporal pattern of cars' connections offers important insights, we further seek to assess the potential impact by considering the *typical network conditions* that cars encounter on their journeys. In particular, understanding how much cars typically connect to busy cells could further refine the management decisions. For example, allowing a large FOTA download in an already loaded cell (e.g. $U_{PRB} > 80\%$) might be considered pouring oil onto the fire.

To assess this type of impact, we plot the deciles of time that each car spends connected to the busy radio cells in Figure 7. It turns out that cars do not spend most of their connected time in highly loaded cells. However, a small number of cars, about 2.4%,



(a) Percentage of time spent in busy cells. (b) At least 50% of time in busy cells.

Figure 7: Network conditions that cars encounter.

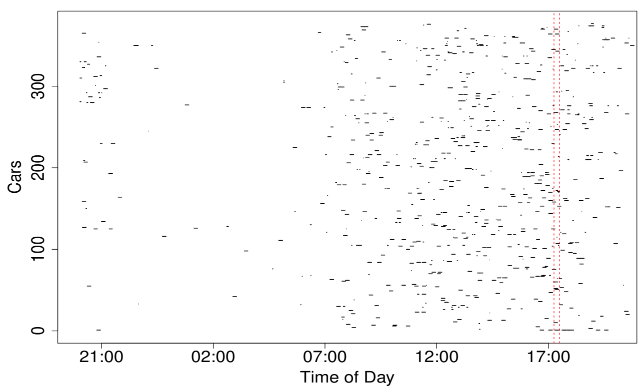


Figure 8: Concurrent cars in one cell over 24 hours.

spend more than 50% of their connected time on busy radios, with about 1% or 10,000 cars spending all their time on busy radios.

Combining car behavior with network data directs us towards types of policies to use for different segments of cars, depending whether they need FOTA update, regular user traffic, or infotainment services.

4.4 Temporal behavior at micro level

We now shift from the macro level of looking at the whole network to the micro level, where we can study the connected car behavior per radio cell and per car.

Since cars are expected to drive distances spanning multiple cells and base stations, we are interested in the duration of each connection to a cell. This will provide insights into the length of impact per cell. As an example, Figure 8 visualizes unique cars' radio-level connections. There were 377 cars connected to this cell over 24 hours and their individual connections are shown as horizontal lines, one per car. We can see several typical car behaviors: (i) connections are short, (ii) connections are rare overnight, (iii) concurrency is high regardless of each connection being short. The 15-minute time bin with the most concurrent cars, 16, is marked.

Across the network and connections, Figure 9 shows that cell sessions are generally short, with the median of 105 seconds and 73rd percentile at 600 seconds. The mean connection duration is 625 seconds for the full, and 238 seconds for the truncated sessions, respectively. However, a significant number of sessions are very short. Even with relatively short time spent in each cell, it is still possible to encounter high concentration of cars in the same cell (Figure 8). Intuitively, this would occur in highway traffic during commute times, at shopping malls, or event parking lots.

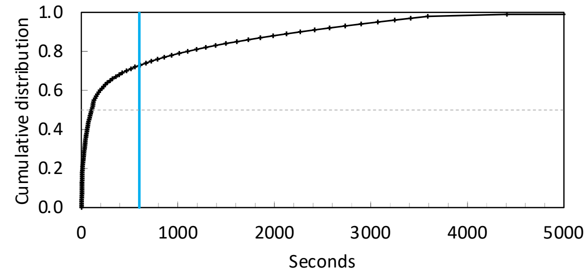


Figure 9: Duration of cars' connections per radio cell.

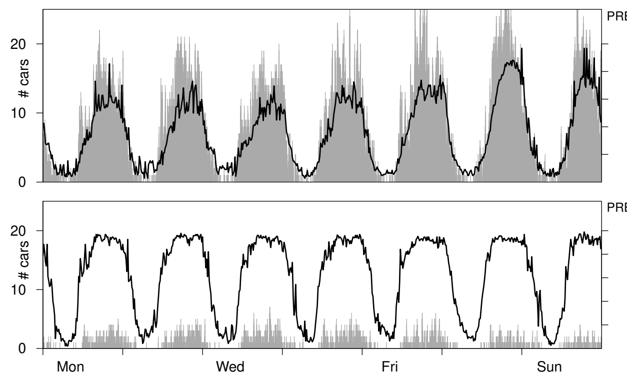


Figure 10: Concurrent cars on two sample radios.

Short connections suggest a potentially small amount of data that can be transferred through each cell prior to handover and point to judicious use of policies, e.g. on seamless vs. lossless handover, to mitigate data loss [11].

We show two examples of concurrent cars over one week in Figure 10. We declare cars concurrent if their connections straddle a 15-minute time bin of the day. We select time bins longer than typical connections because we expect that the highest impact will come from large downloads that may both extend the cars' own connection time and other users' connections, simply due to bandwidth sharing.

In these examples, the number of concurrent cars has the same diurnal pattern as the cell load, which is represented by the average U_{PRB} for each 15-minute time bin. In the top plot, we see a moderately loaded cell (solid line) that becomes more busy over the weekend, but consistently sees between 10 and 25 connected cars (impulses) during its busy hours. The bottom plot shows a different combination, a cell that is busy for the most of the day, but sees a few connected cars. It is important to take into account that both scenarios can lead to undesirable consequences.

We applied an exploratory clustering process to understand such behavior at network scale. We picked all cells such that the average PRB utilization during one week (96 15-min timebins) is larger than or equal to 70%. Such cells are very busy cells where FOTA downloads could have high impact. For each of these radios, we create a 96-sized vector that contains the number of cars whose aggregated sessions (§3) straddle a 15-minute time bin of the day. Within these vectors, we applied the classic k-means algorithm which returned two clusters as seen in Figure 11.

In general, the number of concurrent cars follows the same diurnal pattern of the cell load, which is represented by the average U_{PRB} for each 15-minute time bin. Both clusters are very similar in

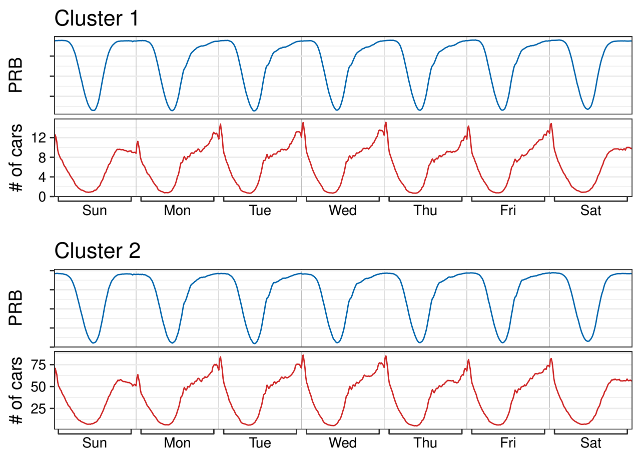


Figure 11: Concurrent cars on all busy radios.

shape, but the number of concurrent cars on Cluster 2 is five times larger than in Cluster 1. Although Cluster 1 is four times larger than Cluster 2, the impact of those cars has undesirable consequences. *For example, any number of large downloads added to the loaded cell may deteriorate experience for everyone, same as having 20 or more cars attempt overlapping downloads.*

4.5 Spatial behavior

We next consider mobility of cars across the network. While cars' connections are expected to hand over across base stations, it turns out that the radio-level logs do not support such precise analysis. Since connected cars do not constantly send or receive, their connections timeout often. Therefore, cars often do not connect to every cell they traverse, unless there is an immediate request to transfer data. To assess a lower bound on number of cells and handovers, we account for handovers within sessions on the network during which the longest connection gap is 10 minutes.

We find that the most common handover is across base stations, which is the expected behavior. The median number of handovers is 2, 70th percentile is 4 and 90th percentile is 9. This suggests that for most large downloads by a connected car, the impact will span between 3 and 10 base stations. Other types of handovers are observed in negligible numbers, namely between radio technologies (3G/4G), between carriers of the same sector and between sectors of the same base station. This behavior might change once massive FOTA campaigns start. Similar implications apply as discussed for short connections per cell.

4.6 Frequency band usage

As cellular networks evolve, it is important to understand the capabilities of legacy devices. Connected cars stay "on the roads," meaning continue to be used, far longer than typical smartphones, often decades vs. years, respectively. As cellular technology evolves, some connected cars will not be able to catch up due to their legacy hardware. We study the current capabilities by breaking down cars' network usage per frequency band or carrier. Higher frequency bands allow for wider bandwidth in carriers, which translates to higher data throughput.

The cars under study connect to the network using 5 observed carriers, which we name Ci, where $i = 1, 2, \ldots 5$. We first consider how many cars in total connected at least once to each carrier (Table 3). While this breakdown can be affected by availability of each carrier at particular base station that cars connect to, we actually confirm the expected behavior. Connected car modems of this OEM predominantly have the capability to use carriers C1-C4, and only a few C5 connections are registered.

Table 3: Carrier use of connected cars

Carrier	C1	C2	C3	C4	C5
Cars (%)	98.7%	89.2%	98.7%	80.8%	0.006%
Time(%)	18.6%	7.4%	51.9%	22.1%	0.000%

We next assess the current use of carriers as it indicates the maximum achievable performance of the connected car population as a whole. Table 3 also shows the breakdown of total connection time spent on each carrier. The key finding is that carriers C3 and C4 are used nearly 75% of the time, with almost no usage of C5.

While cars can connect to and use most available carriers today, this may change as new carriers are added in the future, which cars may not support. We see some evidence of that already.

4.7 Discussion

After analyzing spatial, temporal, and carrier usage of connected cars, we find that connected cars are a very complex type of device that is becoming mainstream in cellular networks. Specifically, we observe that cars actually have three sets of characteristics.

Similarities to smartphones include weekly and diurnal patterns of connecting to the network, high concurrency of connections across multiple cars, and predictability in behavior. These are in addition to known ability to generate traffic similar to smartphones using WiFi hotspots. These findings suggest that treating cars same as smartphones would work for some data services, but that different management approaches may be needed for FOTA updates.

Similarities to IoT devices include limited carrier use capability, connecting to a subset of the network cells (most IoT devices are not mobile and connect to the same cell or base station), short time on the network overall and per session. These imply the need for legacy support, that the overall impact of car population may not extend to the whole network on a day-to-day basis, and that handover policies are important for overall efficient use of resources.

Connected car-specific traits include connecting to different cells on different days, having commute-time pattern or no pattern, and inherent mobility. These characteristics call for possible per-car prediction models for efficient content delivery, and mobility management that will ensure efficiency and correct routing, while providing quality of experience in the face of frequent handovers and high speed.

5 CONCLUSION

We conduct a measurement study of a large population of connected cars in a production cellular network. Using radio-level connection data we derive usage and mobility behavior of cars and obtain insights that enable modeling and analysis of their impact in cellular networks. We find that cars share characteristics of both smartphones and IoT devices, but also exhibit some specific traits. Most importantly, we find that it is possible to classify cars by how often they appear on the network and whether their network presence would occur during busy or non-busy hours.

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