Urban WiFi Characterization via Mobile Crowdsensing

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***Abstract*—We present a mobile crowdsensing approach for urban WiFi characterization that leverages commodity smartphones and the natural mobility of people. Specifically, we report measurement results obtained for Edinburgh, a representative European city, on detecting the presence of deployed WiFi APs via the mobile crowdsensing approach. They show that few channels in 2.4GHz are heavily used; in contrast, there is hardly any activity in the 5GHz band even though relatively it has a greater number of available channels. Spatial analysis of spectrum usage reveals that mutual interference among nearby APs operating in the same channel can be a serious problem with around 10 APs contending with each other in many locations. We find that the characteristics of WiFi deployments at city-scale are similar to that of WiFi deployments in public spaces of different indoor environments. We validate our approach in comparison with wardriving, and also show that our findings generally match with previous studies based on other measurement approaches. As an application of the mobile crowdsensing based urban WiFi monitoring, we outline a cloud based WiFi router configuration service for better interference management with global awareness in urban areas.**

I. Introduction

Significant interest in mobile phone sensing in recent years can be attributed to several factors, including: their ubiquitous nature; rapid evolution toward smartphones with several built-in sensors; carried by humans, making them natural to be used for "mobile" sensing; and the possibility of leveraging the cloud via several available connectivity options for computing power, storage and "centralization". Not surprisingly then, mobile phone sensing applications have been realized or envisioned in diverse domains (e.g., transportation, social networking, health monitoring) [1], [2]. When a group/community of participants (a *crowd*) is engaged with suitable incentives, mobile phone sensing becomes even more compelling for continual and fine-grained spatio-temporal monitoring of the phenomenon of interest in a *cost-effective* manner. Indeed, as Xiao et al. note in [3], the focus of mobile sensing research and applications is shifting towards *mobile crowdsensing*, which is defined as "individuals with sensing and computing devices collectively share data and extract information to measure and map phenomena of common interest" [4]. Several mobile crowdsensing applications have been developed and deployed (e.g., [5], [6]) and it remains a very active area of research.

We consider the application of the mobile crowdsensing paradigm to wireless network monitoring. Besides the many sensors, modern mobile phones feature several wireless network interfaces as connectivity options (e.g., cellular, WiFi, Bluetooth, NFC). Discussions of mobile phone sensing have been mostly centered around the use of built-in sensors and/or specialized add-on sensors (e.g., GasMobile [5], CellScope[1], NETRA[2]) with connectivity options serving as a means for data sharing (see [2], for example). We expand this commonly held view to treat network interfaces also as sensors. GPS, which is an integral part of all smartphones today, presents an example of a network interface that sits at the boundary of these two views — GPS is seen as a location sensor for mobile phone sensing applications whereas it is actually a RF communication system in which GPS receiver on a phone uses signals transmitted from satellites for localization. Technical specifications of some smartphones do acknowledge this view. See [7], for example. A more obvious example is the use of cellular interface on smartphones for crowdsourcing based active/passive measurement of mobile networks as in [8], [9]. As yet another example, in a recent work [10], we developed a system that exploits the WiFi interface on smartphones for low-cost and automated monitoring of WiFi networks in indoor environments like enterprises and public buildings (e.g., shopping malls).

In this paper, we focus on mobile crowdsensing based characterization of WiFi deployment and configuration in urban areas at a city level using the WiFi interface on smartphones as a measurement sensor. Specifically, we report results from a mobile crowdsensing based WiFi measurement study conducted in Edinburgh, leveraging participants with mobile phones traveling on public transport buses. Our findings and contributions are as follows:

- WiFi spectrum usage is quite unevenly distributed across 2.4GHz and 5GHz unlicensed bands as well as among various channels within the 2.4GHz (section IV.A).
- Many WiFi access points (APs) contend on the same channel with around 10 other APs (and their clients) in the nearby vicinity, thereby potentially experience severe interference. This is a result of the common practice of uncoordinated and non-adaptive channel assignment to home WiFi routers which are often left to use preset factory configuration settings for channel etc. (section IV.B).
- We also look into the distribution of open APs, which could be leveraged for vehicular WiFi access [11].

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[1] http://cellscope.berkeley.edu/
[2] http://web.media.mit.edu/~pamplona/NETRA/

We observe that the availability of open APs along contiguous road segments is limited to few parts near the city center (section IV.C).

- We find that observations about WiFi deployments in public areas of several different indoor environments match that of WiFi deployment characteristics at city-scale (section IV.D).
- We validate our measurement approach by comparing it against a carefully done wardriving study and obtain similar qualitative results (section IV.E).
- Our results from urban WiFi characterization based on mobile crowdsensing are in agreement with other previous studies following different measurement approaches (section V).
- We outline a cloud based WiFi spectrum management service for WiFi APs in urban areas (e.g., home wireless routers) that can make use of results from mobile crowdsensing based urban WiFi monitoring for better interference management (section VI).

Compared to the fixed infrastructure approach (e.g., Argos [12]), which relies on static deployment of WiFi monitoring sniffers, and the common practice of using wardriving [13], our mobile crowdsensing approach offers the promise of fine-grained and continual WiFi monitoring on a city-scale at low cost with comparable results to other approaches (section II).

II. Related Work

In this section, we discuss the fixed infrastructure and wardriving approaches that were previously employed for urban WiFi characterization and contrast them with our mobile crowdsensing approach.

Fixed Infrastructure. In this approach, a set of monitoring devices are positioned across the area of interest. Argos [12] is an urban WiFi monitoring system that exemplifies this approach. It is based on a deployment of stationary set of 2.4GHz sensors (sniffers); these sniffers are interconnected wirelessly as a mesh network operating on a separate 900MHz channel. The contribution of Argos lies in efficient mechanisms for coordinated channel sampling by multiple sensors and collection of monitoring traffic, both aimed to cope with the limited backhaul mesh capacity.

The study reported in [14] presents another example following this approach; here the measurement data is manually retrieved from monitoring equipment[3] deployed for a day at some chosen locations spanning different WiFi environments (houses, apartments, cafes and shopping centers).

From a characterization and monitoring perspective, the requirement for deployment of dedicated infrastructure makes this approach expensive, especially for fine-grained spatio-temporal mapping.

Wardriving [13]. This has been the most common approach taken for urban WiFi characterization. It typically involves group of wardrivers, each carrying a specialized laptop-class WiFi and GPS equipped device running wardriving software (e.g., inSSIDer [15]) and possibly with custom antenna, going around the city to locate existing WiFi APs. During this operation, wardriving software is often the only application running on the device [13]. There exist public databases like WiGLE [16] to aggregate data from wardriving campaigns. The approach underlying the study reported in [17], where measurements are collected while walking around in select London neighborhoods, can also be seen to fall under this category.

Typical use of wardriving data and the resultant mapping of WiFi APs is for localization (e.g., Skyhook, Place Lab), as a more reliable, faster and energy-efficient alternative to using GPS. [11] reports another use case for wardriving that is aimed at assessing the feasibility of vehicular Internet access via open WiFi APs; their companion website [18] shows a map of APs found from the wardriving exercise in the Boston area. Like typical wardriving studies, [11] also makes use of a custom hardware/software platform.

As the authors in [19] note, wardriving is an expensive and tedious operation. As such it maybe impractical for fine-grained and continual WiFi monitoring.

Mobile Crowdsensing. This is the approach we take. It bears similarity to wardriving but eases the burden on the participants and makes use of off-the-shelf smartphones with measurement software running in the background. Thus it has the potential to enable cost-effective, fine-grained and continual spatio-temporal wireless monitoring.

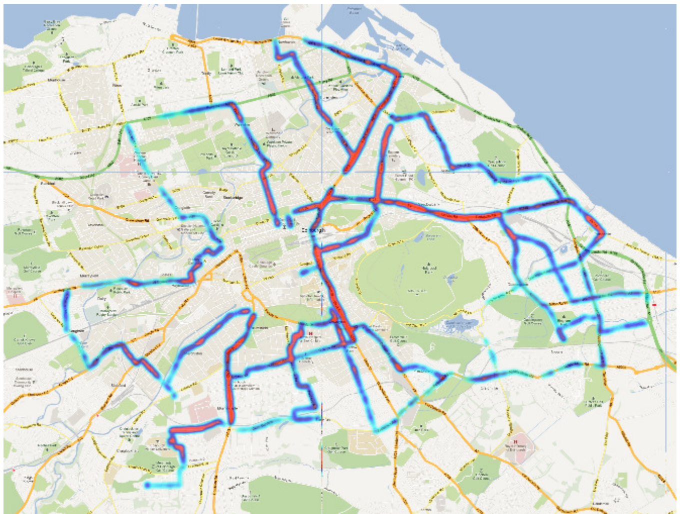
The use of crowdsensing for mobile cellular network measurement has received considerable attention. For example, the problem of useful yet scalable crowdsourcing based mobile network measurement is tackled in [8], [20] while OpenSignal [9] and Mobiperf [21] represent passive and active crowdsourced mobile network measurement systems with freely available mobile apps.

For WiFi, [22] is an existing work that uses mobile crowdsourced datasets. Specifically, it reports analysis and comparison of mobile Internet access performance between WiFi and cellular connections using `speedtest` mobile app based active performance measurements (download/upload speeds and latency). In contrast, our objective is to use mobile crowdsensing for characterization of urban WiFi deployments.

Pazl [10] aims at WiFi monitoring within indoor environments (enterprises, shopping malls) via mobile crowdsensing, and addresses the associated challenge of locating measurements via a hybrid localization mechanism that combines pedestrian dead reckoning with WiFi fingerprinting. Our primary target in this paper is instead on outdoor cityscale measurement where GPS based phone/measurement localization can be fairly reliable (see next section).

In [23], the authors propose a system to detect and track WiFi enabled smartphones using off-the-shelf AP hardware as monitoring stations, a converse to the problem that we consider which is to detect the presence of WiFi APs using commodity smartphones.

[3] A laptop with GPS receiver and two USB dongles – AirPcap Nx and WiSpy DBx.



(a)

	Min	Median	Mean	Max
Location Error (m)	4	8	9.6	1095

(b)

Total number of measurements (scans)	147488
Distinct measurement locations	11225
Distinct APs detected	13800
Distinct open access APs detected	2977

(c)

Fig. 1. (a) Mobile crowdsensing based WiFi AP scanning measurements shown as a heatmap; (b) Location error statistics for the collected measurement dataset; (c) Filtered measurement dataset summary.

III. Methodology

Our mobile crowdsensing based urban WiFi characterization study is done using Android phones, specifically Samsung Galaxy S III [7] phones which feature a 802.11a/b/g/n radio that can operate in both 2.4GHz and 5GHz unlicensed bands. We rely solely on passive scanning based measurement, listening to AP beacons. The information available at the user level with the Android API for passive scans is limited to: SSID, BSSID, channel, RSSI and the security scheme in use. For the measurements, we use the freely available RF Signal Tracker app [24], which keeps passively scanning for WiFi access points (APs) in the background every three seconds or on passing 5 meters; it locally stores the result of each scan tagged with GPS location and timestamp on the phone in a CSV file. As this app does not log location errors and is not open source, we have a developed an auxiliary app that runs alongside and records location errors. Measurement data from phones is subsequently transferred to a back-end server where custom python scripts are used to import the data into a database, which then is used for further querying, analysis and mapping of data.

As mentioned at the outset, our urban WiFi characterization focuses on the city of Edinburgh, which is a typical European city [25] — smaller in size and densely populated, especially in the center. For proof-of-concept and wider spatial coverage with fewer participants in a short measurement period, we focus on a measurement scenario where participants are travelling on public transport vehicles. Specifically, our measurement results are obtained from phones carried by participants during the times they travel at low to moderate speeds on buses in the city operated by a local bus company called Lothian Buses [26]. In this sense, it follows a participatory sensing approach along the lines of earlier urban air/noise pollution monitoring studies [5], [6]. Measurements reported in this paper correspond to traveling over 31 buses over a 15 hour period in total. Note that in principle crowdsourcing based measurement can be done in a fully opportunistic manner, covering all modes of movement including walking, standing, etc. The limits we place are for above mentioned reasons. Also note that there is an assumption underlying our study that visible APs from next-door neighbors can also be seen from the street and vice versa.

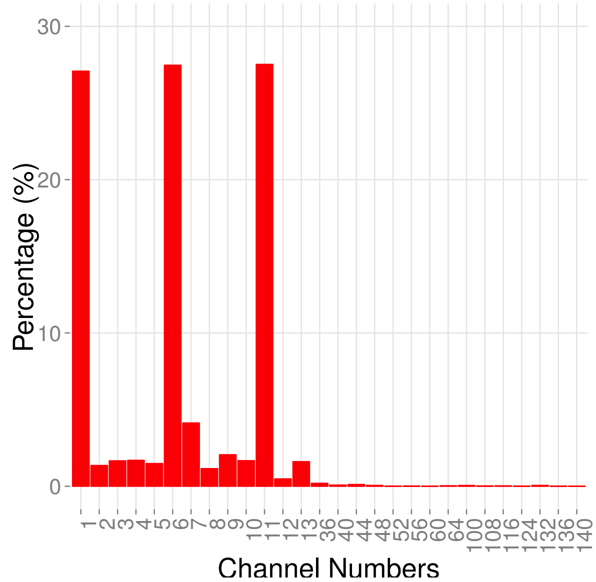


Fig. 2. Relative usage of different channels across 2.4GHz and 5GHz bands by the detected APs.

Fig. 1(a) shows the total set of measurements as a heatmap. Red areas in the map indicate places where there is a high density of APs as well as those places with multiple measurements due to overlapping road segments between different bus routes. Fig. 1(b) lists the location error statistics across all measurements in our dataset. We observe that while the maximum error can be over 1Km reflecting locations that do not get a GPS fix, the error is under 50m in 95% of the cases. To obtain reliable spatial distribution of APs on the map, we filtered out the 5% of the measurements with location errors greater than 50m. Fig. 1(c) presents a summary of the resultant dataset. From closer inspection, we observe that majority of the APs correspond to home WiFi networks interspersed with the rest (e.g., WiFi hotspots).

IV. Results

A. Spectrum Usage

We begin by looking at the channel usage of WiFi APs in our dataset. Fig. 2 shows the relative usage of different channels across 2.4GHz and 5GHz bands. Clearly, the channel

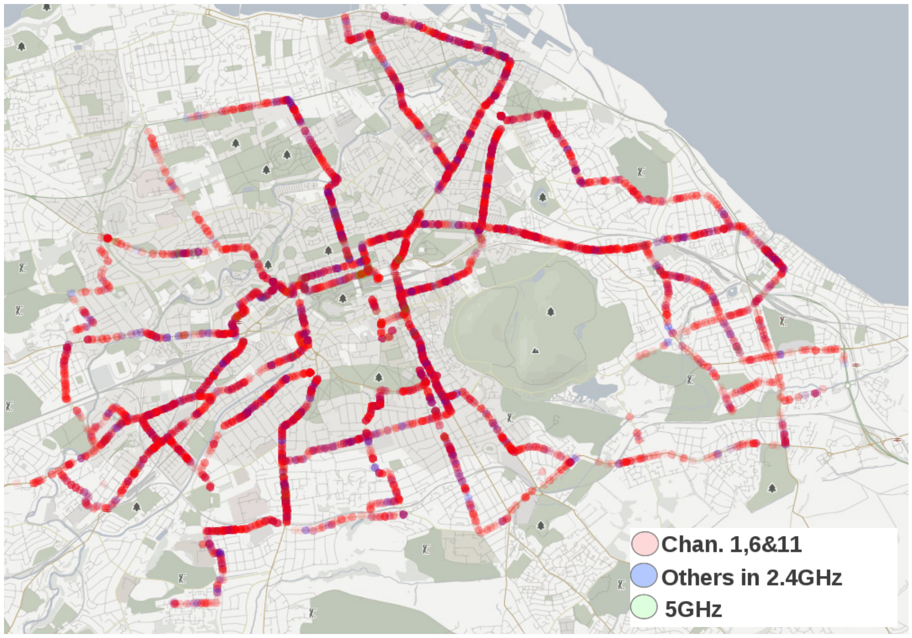


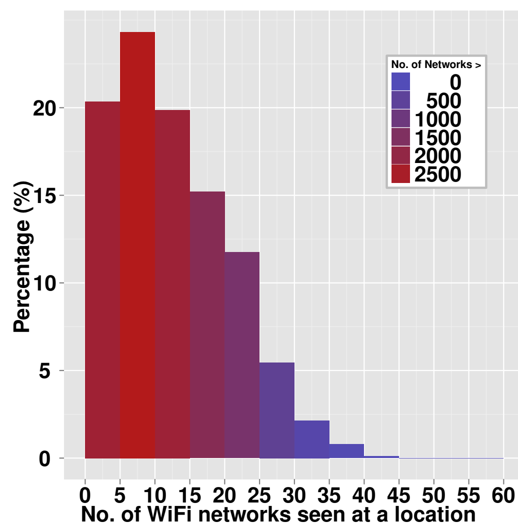
Fig. 3. Map of distinct APs detected.

usage is quite uneven, dominated by channels 1, 6 and 11 in the 2.4GHz band. We attribute this primarily to users leaving their APs to use factory settings, which commonly focus on channels 1, 6 and 11 given that they are non-overlapping. Among the rest of the channels, channel 7 is the next most common channel which we find is due to the fact that WiFi APs corresponding to one of the ISPs (identified based on their SSID) are always set to use channel 7. The very little perceived use of 5GHz channels may be partly due to the relatively poor propagation characteristics at 5GHz and our measurement from outdoors while APs are almost always located indoors. Nevertheless, we do not expect our conclusion on the unevenness of channel usage to change qualitatively given results discussed later in this section on the nature of WiFi deployments seen in different indoor environments and laptop-based wardriving measurements.
We explore this observed non-uniform channel use further in the next subsection, particularly looking at spatial variation in spectrum usage and its implication for potential interference levels.

B. Spatial Distribution of Spectrum Usage

Fig. 3 shows the map of detected APs, colored differently depending on the set of channels used. Besides confirming the channel usage pattern from Fig. 2, the red patches on the map highlight the closeness between APs using one of three popular channels (1, 6 and 11), thereby the potential for high interference. Fig. 4(a) provides a quantitative equivalent of the map in Fig. 3 and shows that more than half of the locations "see" more than 10 APs. Statistics in Fig. 4(b) confirm the same.

Since Fig. 4(a) and Fig. 4(b) correspond to the spatial distribution of AP density *over all channels*, they do not directly represent levels of interference in any one channel. This information is shown in Fig. 5 for the three mostly commonly used channels (1, 6 and 11). The striking aspect

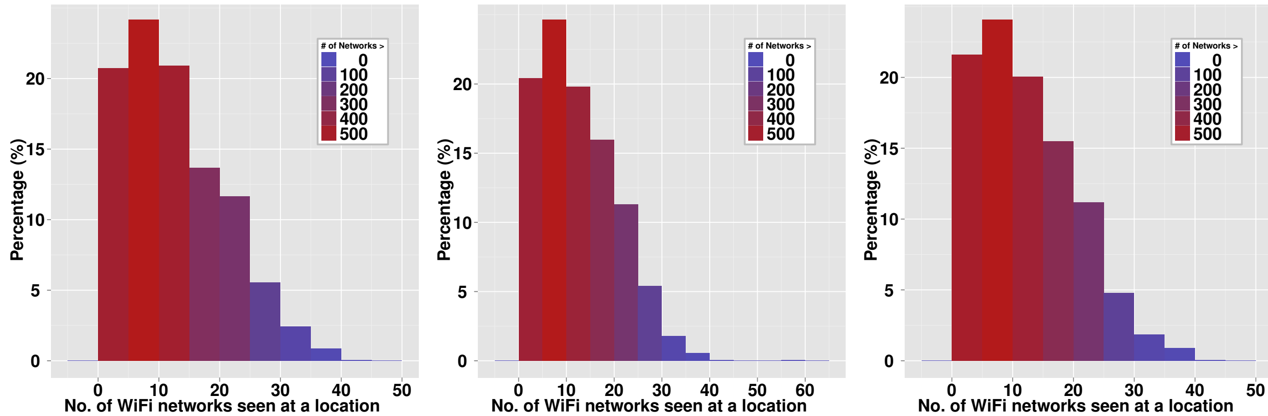


(a)

	# APs
Minimum	1
1st Quartile	6
Median	12
Mean	13.4
3rd Quartile	19
Maximum	59

(b)

Fig. 4. (a) AP density spatial distribution; (b) AP density statistics across all measurement locations.



(a) Channel 1 (b) Channel 6 (c) Channel 11

Fig. 5. Per channel spatial distribution of AP densities.

is that the spatial distributions of AP density for each of these channels are similar to the aggregate distribution spanning all channels shown in Fig. 4(a). Hence we can actually infer that in over half of the locations we are likely to find more than 10 APs on any of the three heavily used channels. The same result is illustrated in Fig. 6 on a map. It shows the locations with 10 or more APs configured to use the most common channel at that location with the size of each circle representing the number of APs at a location — larger the size of the circle, more the number of APs that could potentially interfere with each other (or their associated clients).

C. Open Access Points

Here we look into the question of "open" APs which could be exploited for public and vehicular wireless Internet access in cities. In our measurement dataset, we find that open APs constitute around 20% of the total number of APs detected (2977 vs. 13800). And a large fraction of these open APs (nearly 76%) are served by a single ISP — British Telecom (BT), making it plausible to view them all to be part of a single administrative domain from a vehicular client perspective for seamless roaming. This argument is made stronger by the fact that BT in the UK has a partnership with the Fon WiFi community network [27], making every BT broadband customer automatically a member of the Fon network. However, the spatial distribution of open APs along roads (Fig. 7) suggests that the presence of contiguous set of APs with overlapping coverage areas is limited to few areas in the very center of the city, limiting the possibility of seamless vehicular WiFi Internet connectivity via open APs.

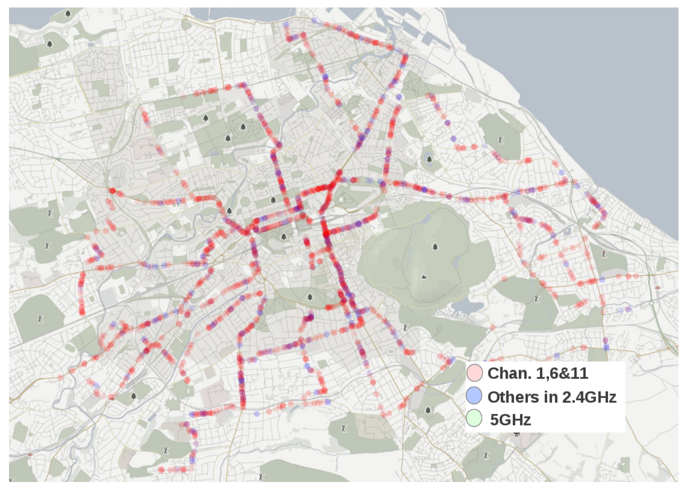


Fig. 7. Map of open APs detected.

D. Comparison with Indoor Environments

We study the characteristics of public WiFi deployments in indoor environments as a way to increase the confidence in our findings from outdoor measurements concerning the nature of urban WiFi networks. For this purpose, we developed a custom mobile application called IndoorScanner based on Funf [28]. The need for a different measurement app for indoors is motivated by the fact that GPS does not reliably work indoors and given that RF Signal Tracker app used for our outdoor measurements relies on GPS for locating measurements. In contrast, IndoorScanner requires the user to select the measurement location on a digital map of the indoor environment (e.g., floor map, building layout) in a manner similar to traditional site survey procedure for WiFi fingerprinting based localization systems. Note that these indoor measurements were one off and gathered by a single user, hence we did not need to employ Pazl [10] for this purpose.

We consider several different indoor environments located in different parts of the city for this study. These include: three different shopping centers, a large hospital, a supermarket, and a small shop. We carefully measure in public places inside these environments looking for the presence of WiFi networks. As shown in Fig. 8(a), WiFi use in indoor environments happens largely in the 2.4GHz band just as seen from outdoor measurements (cf. Fig. 2). Fig. 8(b) shows that maximum number of APs at a location using the same channel can be as high as 37, which is similar to what is obtained from outdoor measurements (cf. Fig. 5).

E. Comparison with Wardriving and Device Effect

To validate the mobile crowdsensing approach taken in this paper, we compared it against a laptop based wardriving

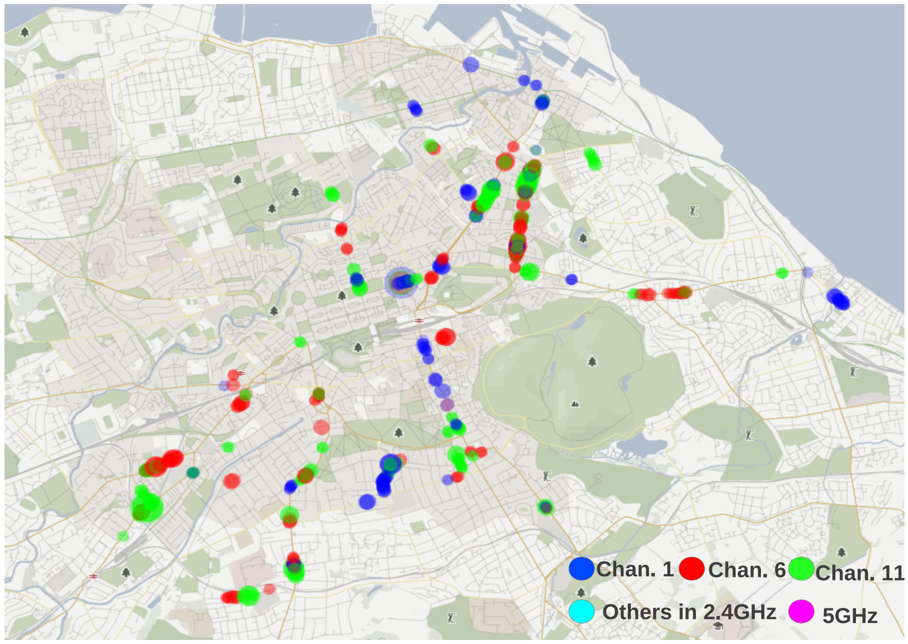
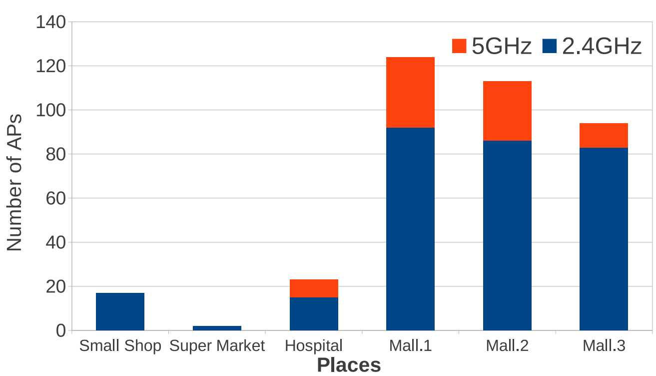
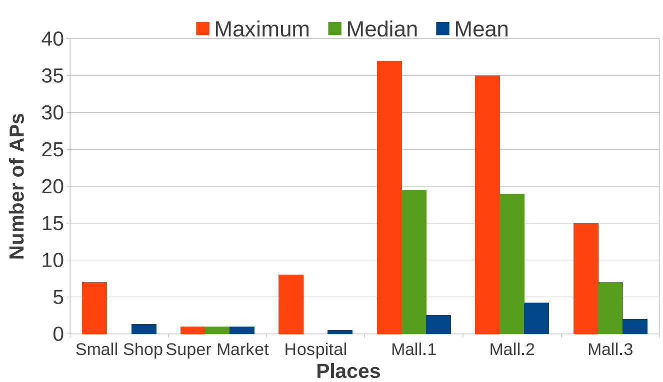


Fig. 6. Map illustrating likely high interference locations (with more than 10 mutually interfering APs).



(a) Spectrum usage



(b) Max AP density per channel

Fig. 8. WiFi scanning measurement results from different indoor environments.

study. Specifically the validation experiment was carried out over a Edinburgh University shuttle bus that connects two university campuses (one in the city center and the other in south Edinburgh), 2.7Kms apart. For the wardriving part of the experiment, we used a customized Lenovo T420 laptop with GPS and running only inSSIDer WiFi scanning software [15]. Two different smartphones, Samsung Galaxy S III and Google Nexus One, both running the RF Signal Tracker app in the background were used for mobile crowdsensing. Note that all other measurement results reported in this paper were obtained with Samsung Galaxy S III phones while Google Nexus One phone is used in this experiment to understand the device effect.

During the journey, 429 APs were detected by inSSIDer with the laptop while Galaxy S3 and Nexus One could detect 384 and 404 APs respectively. This shows that commodity smartphone based mobile crowdsensing approach can detect nearly all ($> 90\%$) APs that can be seen by the wardriving laptop. This is remarkable considering that laptops are equipped with better antennas and radios with higher receive sensitivities, a fact confirmed by higher RSSI values obtained with laptop in the experiment (Fig. 9). RSSI values for the two phones indicate device diversity (in terms of radio, antenna and platform design) and partly explain differences in the number of networks detected between them. Note that some of the differences in scanning results between the three cases stem from differences in channel hopping sequence and duration between different devices and software, which are outside our control in all 3 cases compared. Overall, the results from this experiment demonstrate that mobile crowdsensing with commodity smartphones can yield similar results to those obtained via carefully conducted wardriving campaigns.

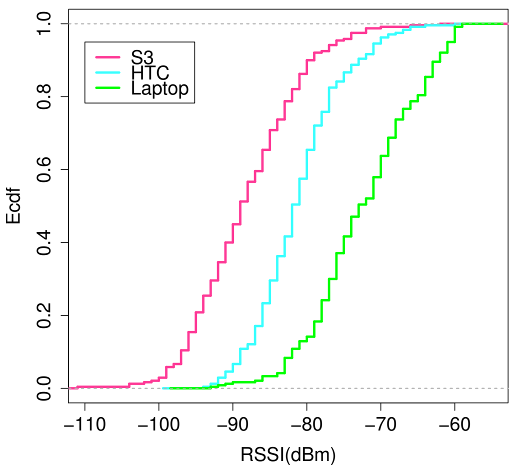


Fig. 9. Empirical CDF of maximum RSSI for common WiFi networks seen across different measurement devices.

V. Putting Our Findings Into Perspective

In this section, we compare our findings with other related studies on WiFi characterization and end-user performance assessment in the urban context.

Akella et al. [29] analyze several wardriving datasets and observe that up to 85 APs could be within close proximity of each other for an assumed interference range of 50m. They also find that more than 40% APs are configured to channel 6 in one of the datasets. Our results are qualitatively similar but obtained using a different, mobile crowdsensing, approach.

Two recent studies reported in [14] and [17], both commissioned by the UK communications regulator Ofcom, are closely related to our work in terms of the underlying goals to characterize WiFi usage in urban areas across unlicensed 2.4GHz and 5GHz bands and in different environments. Recall from our discussion in section II that these studies use different approaches from the mobile crowdsensing approach we take — [14] relies on a fixed measurement infrastructure, whereas [17] is wardriving based. Nevertheless, they report observations similar to our findings described in the previous section. We elaborate on some of these below for concreteness.

In [17], WiFi channel usage measurements across 2.4GHz and 5GHz via walk around surveys in central London neighborhoods show that majority of APs are configured to one of the three non-overlapping channels (1, 6, 11) in 2.4GHz band as shown in Fig. 10. This is precisely what we also found in Edinburgh although with a different measurement approach (cf. Fig. 2). An additional interesting observation made in [17] is that public WiFi hotspots are deploying their APs in 5GHz channels, which suggests the increased use of 5GHz band in future.

[14] studies the usage in 2.4GHz and 5GHz unlicensed bands and WiFi performance in different environments (houses, apartments, cafes and shopping centers) with the help of fixed installations of monitoring equipment at various selected locations. Similar to our study, it concludes that 2.4GHz band is more heavily occupied (10 times or more) than 5GHz band; it identifies this to be mostly due to WiFi transmissions in 2.4GHz and not because of other types of 2.4GHz usage such as Bluetooth, ZigBee and microwave ovens. It also has similar conclusions about rather high AP densities in some cases. Fig. 11 shows a sample of the results from [14] for reference.

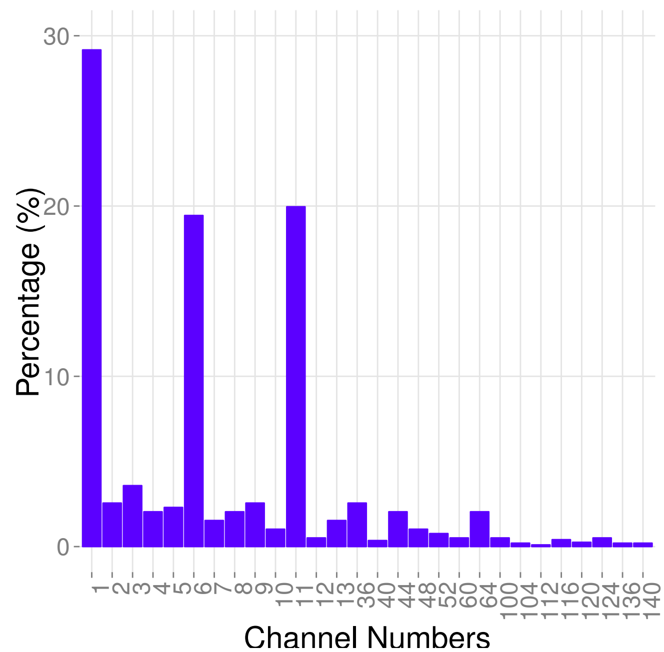


Fig. 10. No. of APs detected in different channels across 2.4GHz and 5GHz bands with walk around survey in central London [17].

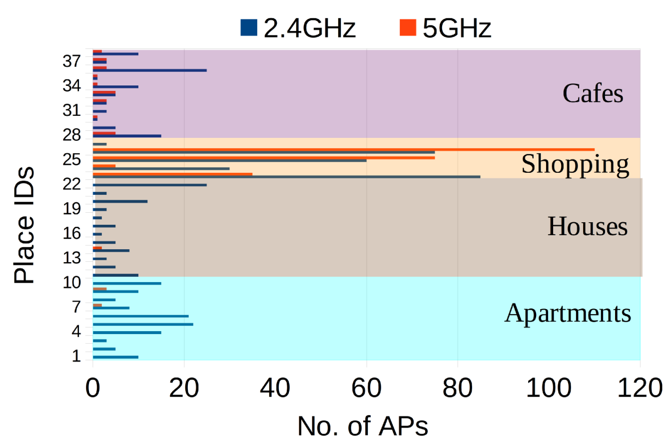


Fig. 11. AP densities across different environments as reported in [14] via fixed monitoring kit at different locations.

The above discussion attests to the validity and reliability of commodity smartphone based mobile crowdsensing approach for urban WiFi characterization and monitoring. It is even more remarkable that we are still able to obtain similar conclusions despite the inability to obtain lower level metrics such as channel utilization and number of MAC retransmissions with the current APIs on smartphones.

There also exist several studies that examine the negative impact of unplanned and uncoordinated urban WiFi deployments on end-user performance (e.g., [29], [30]), and those that investigate optimized AP configuration (channel, transmit power, etc.) and association mechanisms to mitigate such performance degradation (e.g., [31]). Given our observations concerning high density of APs in some locations, the analyses on the impact of high AP densities with unplanned WiFi deployments on end-user performance are particularly relevant. For example, the authors in [30] experimentally investigate the effect of AP density (equivalently, inter-cell interference) and client density on performance of different applications such as web and multimedia using the ORBIT testbed [32]. Their results show that increasing number of clients to 125+ in a single AP WiFi deployment scenario does not degrade the collision rate and throughput much, which is similar to what is reported in [33]. In contrast they find that in an unplanned multi-AP WiFi deployment scenario increasing the number of APs causes a significant increase in collision rate and consequent high drop in throughput; for example, aggregate throughput drops by 50% with only four interfering APs with the same overall number of clients as in a single AP scenario. Media streaming performance is also seen to take a big hit in the presence of inter-cell interference. For the voice over IP (VoIP) application, substantial performance degradation is seen in the multi-AP scenario with just three APs — average latency increases from 54ms in the single AP scenario to 304ms in the scenario with four uncoordinated APs; jitter also increases four-fold with the multi-AP scenario.

VI. Discussion

The findings from our measurement study and the foregoing discussion suggests that unplanned and uncoordinated home or hotspot WiFi networks in urban areas can potentially suffer from severe interference related performance degradation. This can be seen as a real world evidence to show that vast research on self-organization mechanisms for channel and transmit power allocation in unplanned WiFi deployments (e.g., [31]) has not actually materialized. We observe that the impediment for large-scale deployment of intelligent self-organization mechanisms in practice may not be technical but rather the lack of market incentives for their application. With this in mind, we outline an alternative approach that may find greater real world acceptance. The idea is for a mobile crowdsensing based urban WiFi monitoring system to continually feed spectrum usage measurements to a cloud based back-end, which takes the global awareness of spectrum usage and interference conditions to determine the best channel for each participating WiFi AP (home WiFi router). Such a spectrum management service could be subscription based and tied to the user's broadband service plan — the user's home WiFi AP can be reconfigured on the fly via the ISP, informed by the cloud based spectrum management service. Such managed and coordinated spectrum management approaches are emerging in other related domains such as efficient sharing of TV white space spectrum among secondary users (see [34], for example).

Another application scenario for mobile crowdsensing based urban WiFi monitoring is targeted toward outdoor small cell public WiFi based hotspots run by several different operators. The deployment of such hotspots is experiencing a high growth and is seen to complement LTE small cells in an overall solution to aid in better managing the steeply rising mobile data traffic[4]. The emerging passpoint technology to enable seamless roaming between public WiFi hotspots run by different operators will play a role in their widespread deployment and use, and in turn determine the need for coordinated interference management.

Concerning incentives for user participation in mobile crowdsensing based urban WiFi monitoring, real world evidence suggests that smartphone users have sufficient incentives to participate in crowdsourced mobile network measurement campaigns. For instance, in a 3G crowdsourcing measurement study [35] conducted by BBC in partnership with measurement firm Epitiro, nearly 45,000 volunteers installed the measurement app to participate within one month of announcement of the study. As another example, OpenSignal [9], another firm, with an app for crowdsourced mobile measurement has over 3 million people worldwide in over 200 countries collectively reported over 4 billion measurement samples till date. If such voluntary participation, offer of better connectivity or cheaper service while on the move may provide an incentive for mobile (smartphone/tablet) users to participate. We note that devising suitable incentives for mobile crowdsensing is a topic in itself and is currently receiving lot of attention in the research community.

VII. Conclusions

In this paper, we have shown the value of mobile crowdsensing approach for urban WiFi characterization and monitoring through a measurement study in the city of Edinburgh. Our results indicate that the uncoordinated and inefficient spectrum use is the source of potentially severe interference problems that might be seen in practice at locations with high AP densities. We have also found similarity between our outdoor city-scale WiFi measurement results and characteristics of WiFi deployments in several different indoor environments. We have validated our approach against a carefully conducted wardriving journey. Our results and findings are also in agreement with other previous urban WiFi characterization studies based on other measurement approaches. Finally we have outlined a cloud based spectrum management service that could leverage results from mobile crowdsensing based urban WiFi monitoring for more effective interference management in urban WiFi networks.

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