Data-Driven Analysis of Database-Assisted Spectrum Access for Mobile Users

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***Abstract*—White space databases (WSDB) have relieved the mobile devices from the challenge of spectrum sensing at low signal levels by introducing *sensing-as-a-service* approach. On the other hand, the regulations for WSDB-based spectrum access have asserted very strict constraints for mobile secondary users (SU). According to the US regulations, a mobile SU must query the WSDB anew each time as it relocates 100 meters. This requirement is problematic for mobile users, since car moving at moderate speed will hardly have a chance to access the spectrum at all, because of average latency of a WSDB query. In this paper, we analyze the spatiotemporal changes in the TV white spaces (TVWS) to develop more insights on the current regulations and performance enhancements for mobile scenarios. More particularly, we simulate realistic usage of mobile devices and analyze spatiotemporal accessibility variations of TVWS using a large data set of observations. Using a publicly-available geolocation database, we monitor the TVWS spectrum for about 6 months for 9 routes in different locations across the US. We report on the change in number of free channels on a route, the variations in the availability of a particular channel over a time period, maximum permitted transmission powers, WSDB response time, and channel lease times. Studying spatiotemporal changes in TVWS, we find that current TVWS ecosystem is inherently static and displays minimal temporal variations. This observation supports the criticism that current regulations are very conservative especially for mobile usage and suggests that spectrum information caching would be efficient.**

I. Introduction

Transition to the Digital Television (DTV) has significantly reduced the amount of frequencies needed for TV transmissions. Vast spectrum bands that became available for opportunistic use after the transition are referred to as *digital dividend* or *Television White Spaces* (TVWS). The release of TVWS came at the right moment since frequencies allocated for mobile cellular networks and industrial, scientific and medical (ISM) band became highly overcrowded while demand for mobility and wireless communication keeps growing at an exponential rate [1]. The importance of efficient use of the spectrum is widely realized, e.g., [2], [3], as digital services have become crucial in our daily lives.

According to the spectrum allocation charts, all spectrum is already assigned. On the other hand, analysis on the actual usage shows that only a small fraction of allocated spectrum is actually in use [4]. The imbalance between spectrum congestion on the one hand and under-utilization of licensed frequencies on the other has given rise to dynamic spectrum access (DSA) model, where secondary users (SU) can access frequencies licensed to primary users (PU), as long as SUs do not harm PU communications.

Although spectrum sensing is an effective way to detect the presence of PUs, it increases the complexity of end user equipment [5]–[8] as guaranteeing operation without harmful interference to PUs is challenging and requires sensing of PU transmissions at very low signal levels. To secure the incumbents, regulators and industry turned towards the centralized solution in the form of online cloud service backed by geolocation database, called White Space Database (WSDB). WSDB stores transmitter characteristics of PUs such as location, power, and antenna properties. Before accessing spectrum, an SU sends request to the WSDB, which in turn applies radio wave propagation model to the stored PUs' data, e.g., TV transmitter locations and transmission powers. Next, WSDB calculates what frequencies the SU can use at its current location. SU's request message must contain location information and other transmitter characteristics, which are in practice represented as a device type parameter. Protocol to Access White Space Database (PAWS) [9], [10], standardized by IETF, provides the process of communication with a WSDB.

Database-assisted white space access has widely been adopted all over the world and the benefits of central management and reliable protection of incumbents seem to overweight shortcomings, such as prerequisites of secondary communication channel and geolocation capabilities. Yet, there are several concerns about the requirements imposed by the regulations on the SUs [3]. First, it is widely stated [5], [8], [11] that the techniques provided by the regulations to construct the WSDBs fall short of accurately identifying white space opportunities, which results in a significant loss in white spaces. Second, although not pronounced as widely, requirements for mobile SUs seem to be overly conservative. A mobile white space device (MWSD)'s access to an available TVWS channel is restricted by the temporal and spatial validity of the WSDB information. That is, an MWSD must re-query the WSDB every 100 meters it changes its location from the last query location [3]. Because of the latency in communication, WSDB access at this time scale is especially problematic for fast moving users, such as cars or flying drones. For example, if a car moving at 80 km/h ($\approx$ 22 m/s) waits for the WSDB response 2 seconds, it is almost half way to the next query point, and at best it has less than three seconds left to access the TVWS. In other words, the WSDB querying overhead results in $\approx \frac{2}{100/22} = 44\%$ loss in spectrum opportunity. Additionally, frequent WSDB access will naturally have an adverse effect on battery life of the mobile device and will put stress on the database provider to serve a massive number of requests from mobile TVWS users.

Our goal is to understand whether such requirements for WSDB re-query are indeed strict and envision a solution to ease the TVWS access for mobile scenarios. To this end, we investigate how much TVWS actually varies for mobile users while they follow their routes. Our contributions are two-fold:

- We provide an in-depth analysis of TVWS access, such as spatiotemporal variability, by gathering spectrum observations over a period of six months from a publicly-available WSDB, i.e., Google Spectrum Database. To our knowledge, ours is the first data-driven analysis of database-assisted TVWS use for mobile scenarios.
- As our investigation shows low variability, we argue that *spectrum caching* can mitigate the burden on mobile devices and make TVWS usage more appealing and less battery-hungry for mobile users.

The rest of this article is organized as follows. Section II overviews the current regulations defined for MWSDs. Section III introduces the methodology followed in our research and describes the experimental setup. Section IV provides an analysis of the collected spectrum data while Section V discusses the implications of our observations and future work. Section VI introduces the related work, while Section VII summarizes the paper.

II. Overview of Regulations for Mobile TVWS Users

While TVWS regulations are country-specific, we concentrate in this paper on the US regulations for two reasons. First, it is the first country to approve database-assisted spectrum access, and hence the regulations have long been the subject of wide discussion by various stakeholders. Second, the WSDB data we used for our research only covers US territory.[1]

Federal Communications Commission (FCC), the regulatory body for TVWS regulations in the US, approved usage of TVWS by unlicensed devices in 2008 [12], requiring that TV-band devices would consult FCC-approved WSDB for available channels. An additional requirement was that devices must sense the spectrum with an interval of 60 seconds to detect wireless microphones or other legacy devices. FCC defined sensing as optional in 2010 [13], making TVWS usage easier. The latest regulations published in 2015 [14] aims at higher attainability of TVWS by relaxing many previous requirements; ±50 meters geolocation accuracy required for all devices is relaxed at the expense of higher minimum separation distances, up to 10W transmission power is permitted for stationary devices, to name a few.

[1]Please see https://www.google.com/get/spectrumdatabase/ for more information.

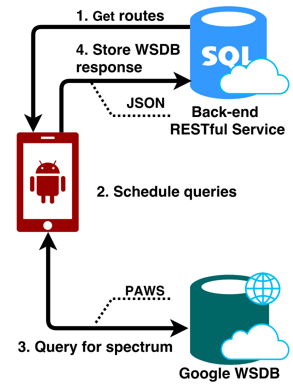

Fig. 1. System overview

FCC defines white space devices as fixed and mobile. The latter consists of Mode I and Mode II sub-categories according to their geolocation capabilities. Mode II devices are equipped with localization hardware and can consult the WSDB directly for spectrum information by providing their location data, whereas Mode I can only retrieve accessible channels via Mode II or fixed WSD. The maximum permitted power level for mobile devices are 100 mW (20 dBm). However, if there is a PU signal in the adjacent channel, then maximum power level reduces to 40 mW (16 dBm) for all mobile devices to avoid interference at the PUs. Another requirement for mobile devices is that whenever location changes at least 100 meters, MWSD must update its spectrum availability information by querying the WSDB again.

III. Methodology and System Setup

The purpose of our study is to investigate the usage of TVWS by mobile devices in realistic scenarios. More specifically, we have raised the following three questions.

(i) For realistic mobility scenarios, how much does the spectrum availability vary throughout the trajectory of a mobile device?,

(ii) How frequent there will be changes in spectrum environment along the route as the time pass by?, and

(iii) How much overhead does WSDB access entail?

To address these questions, we devised a system as depicted in Fig. 1 that uses Google WSDB and emulates mobile node's movement as they would occur in the US. To represent realistic scenarios, we created several trajectories as listed in Table I representing a diverse set of mobile users; tourists, people going from suburbs to the city center for work, recreational cyclists, business travellers, and so on. To cover different environments, we chose geographic locations for our routes from both densely and sparsely populated regions.

The system consists of two entities: mobile application emulating Mode II device and a back-end service. The workflow proceeds as follows: when the mobile application is initiated, it contacts the back-end service and fetches the routes information. Each route has a starting time and associated set of locations, where the mobile application queries WSDB for the available spectrum. There is explicitly specified delay between points to emulate the realistic speed of movement for different pragmatic scenarios. After the retrieval of trajectory data, the mobile application schedules querying times for each point, and subsequently sends requests at those times to WSDB using HTTP based PAWS protocol [9], [10]. WSDB responses are stored in the back-end database for further analysis. We implemented back-end as a RESTful service on Microsoft Azure platform, using JSON for data transfer.

Running querying application on actual mobile device gave us the possibility to measure the time required by a modern cellular gadget to obtain spectrum availability information. We used two mobile devices in our experiments: one smartphone GT-I8160 (Samsung Galaxy Ace 2) and a tablet GT-P3100 (Samsung Galaxy Tab 2 7.0). The version of Android on both devices is 4.1.2 (Jelly Bean).

A. Metrics

A WSDB response message has the following structure: first comes the validity period (*StartTime* and *StopTime* fields) for the entire message, we refer to this time interval as *spectrum lease time*. Second is the set of available frequency ranges (*startHz* and *stopHz* fields). Reported ranges are often wider than just one channel and end user has to deduce channel numbers itself. Maximum permitted power levels (*MaxPowerDBm* field) are specified for each frequency range. Special power level of -52.8 dBm is used as unavailability marker.

To quantify the spatial variability, we assess minimum and maximum number of free channels along the route with their power levels. As for temporal variability, we define a particular measure that we call the *probability of daily change*, denoted by P_{dc}. We calculate it on a route basis as a ratio of number of days with any kind of TVWS change along the route $D_{changes}$ to total number of days the route was observed D_{total}, i.e., $P_{dc} = \frac{D_{changes}}{D_{total}}$. The measure is harsh since it does not address specifically what changed and how much, but the main purpose is to derive the general indicator of how often changes occur.

Our measurement encompasses not only spectrum details but also the entailed WSDB access overhead, i.e., total latency. Total latency represents the elapsed time between the time a query is initiated by the mobile application and the time WSDB spectrum information is received by the mobile device. More formally, total latency is calculated as: $L_{tot} = L_{WSDB} + L_{nw} + L_{MWSD}$, where L_{WSDB} is the time a WSDB needs to calculate spectrum availability after it receives the spectrum request; L_{nw} is the round trip time of the network between the user and the WSDB; and L_{MWSD} is the time required by a mobile device to issue request and process response.

IV. Analysis of the Collected Spectrum Data

In this section, we present our observations on the collected spectrum data using the metrics defined in Sec. III-A.

A. Spectrum Availability

A brief look at the data in Table I reveals high supply of TVWS in sparsely populated regions, such as Alaska or Montana. In the major metropolitan areas, there is either no free spectrum, e.g. Santa Monica, or just one channel, like in Manhattan district. Despite that, in regional centers, like Bozeman or Billings the availability is high with 18 and 14 free channels respectively. Spatial variability is notable when a route encompasses densely populated areas, e.g. as moving from Santa Barbara to Los Angeles number of free channels reaches the maximum of 17 between two cities and goes to 0 in Los Angeles. However, the significant finding is the temporal perspective which shows a strong indication that TVWS availability changes very rarely as data in P_{dc} column shows. Most changes happened in mid-sized metropolitan areas like San Diego or Santa Barbara.

TABLE I
SPECTRUM AVAILABILITY AND TEMPORAL VARIANCE

Route	Length, km	# of channels		Permitted power, dBm		P_{dc}
		Min	Max	Min	Max	
Montclair to Manhattan	24.6	1	1	16	16	0
Manhattan Tourist 1	2.1	0	1	0	16	0.0095
Manhattan Tourist 2	2.9	0	1	0	16	0.0048
Santa Monica Bicycle, Pacific Coast HWY	5.4	0	0	0	0	0
Sacramento, Route 128	43.5	3	6	16	20	0
Berkeley	72	0	1	0	16	0
Santa Barbara to LA, HWY 101	117.2	0	17	16	20	0.0122
LA to San Diego, Interstate 5	126	0	17	16	20	0.0552
Montana, Interstate 90	218	13	28	16	20	0.013
Alaska, George Parks HWY	30.3	27	28	16	20	0

Due to the space limitations, we present analysis only on the selected routes[2]. We start by the route that has the most temporal changes and goes from Los Angeles to San Diego. Fig. 2 shows the map of the route, which is 126 km long along the coastal line and has 14 points. The spectrum was observed from October 5th, 2015, to March 16th, 2016 on these locations. Point-1 is at the beginning of the route in Costa Mesa and point-14 is the last one, located in San Diego. Fig. 2 reveals details on temporal and spatial variations along the route, displaying number of available channels by each location. The temporal variations occurred at locations 9-14, where on certain dates accessibility of at most one channel changed. We see the dates when these changes happened on the horizontal axis of the right figure in Fig. 2. There were 9 such days out of 163 days of monitoring.

The second route we analyze is the *Manhattan tourist route* due to the pragmatical significance of the area. As Fig. 3 shows, a tourist starts the journey at the Modern Art Museum and continues by foot to Empire State Building, where approximately two hours are spent. After that, the walking tour ends at Carnegie Hall. As we can see from Fig. 3, only one channel is occasionally free, so reliable communication in the center of the New York city can not be established by the means of TVWS. Yet, the situation is slightly better than

[2] We plan to publish our data about all routes soon for the use of the research community.

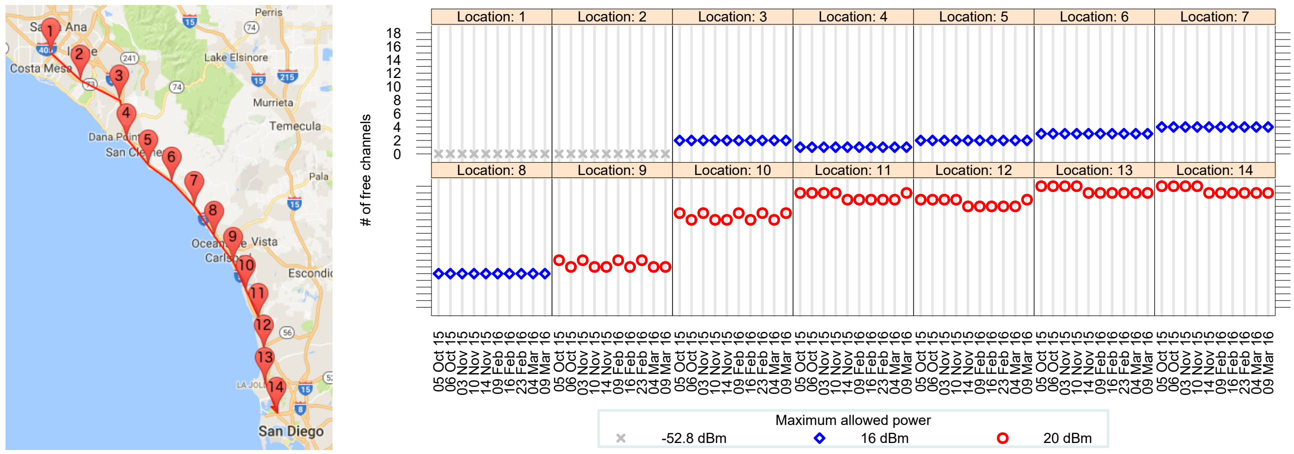

Fig. 2. Spectrum variability along San Diego route. All temporal changes occurred at locations 9-14 and as a result of change the number of free channels was either increased or decreased by one.

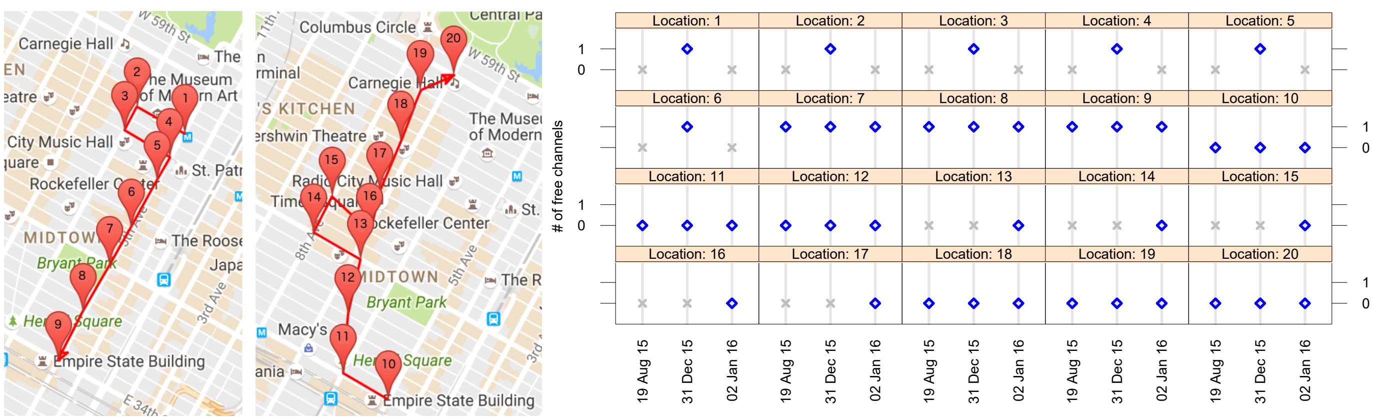

Fig. 3. Spectrum variability along Manhattan tourist route. Only one channel is occasionally available; maximum power is 16 dBm.

in Los Angeles, where no TVWS channel was free during the period of our observations.

In 210 days, there were only two changes: on December 31st, 2015 one channel at locations 1-6 became available; and on January 2nd, 2016 at locations 13-17 one channel became free; whereas in locations 1-6 the same channel lost its accessibility. These changes also reveal abrupt spatial variations, since there are only a few hundreds of meters between these locations.

B. Spectrum Lease Times

WSDB response contains two time values: one specifying the time from which SU can start using given channels, and the time when it has to stop. We call the interval between the start and stop time as *spectrum lease time*. As Fig. 4 shows, the shortest lease was only 30 minutes and the longest over two days. Most of the channels were leased for exactly 2880 minutes, i.e., two days. It is worth to note that regulations specify additional parameter, *maxPollingSecs*, that overrides lease time and is currently equal to 24 hours. The routes located in the Manhattan area got all shorter leases. It is difficult to articulate a particular reason from our data as it does not show any correlation between the population density and the lease period.

C. Total Latency

Fig. 5 displays the distributions of total latencies for the phone and the tablet. Both mobile devices handle the majority of the requests in less than two seconds. Our phone, GT-I8160, having 800 MHz dual-core processor with 768 MB RAM performed slightly worse than the tablet, GT-P3100, which has 1.0 GHz dual core processor with 1 GB RAM.

How this latency affects the spectrum utilization of a mobile user depends on the speed of the user. Assume that a user's speed is ν meters per second and the regulations mandate that user has to re-query the spectrum every Δd meters it changes its location from the last query point. Using the mean values of total latency calculated from our measurements (t_{wsdb}), we can calculate *fraction of TVWS loss* denoted by α as follows:

$$\alpha = \frac{t_{wsdb}}{\Delta d/\nu}. \quad (1)$$

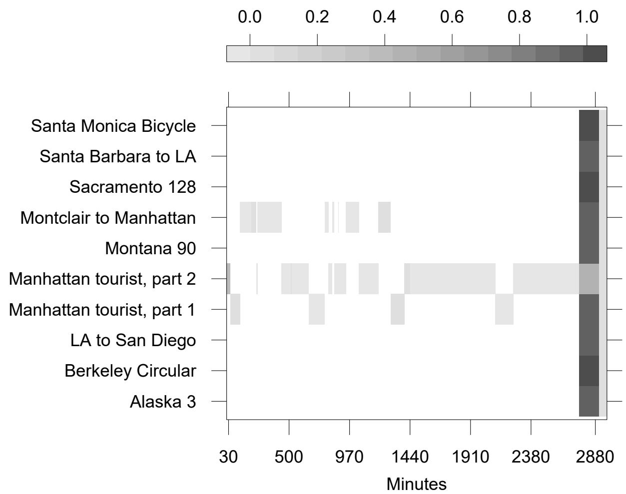

Fig. 4. Spectrum lease time distribution on each route.

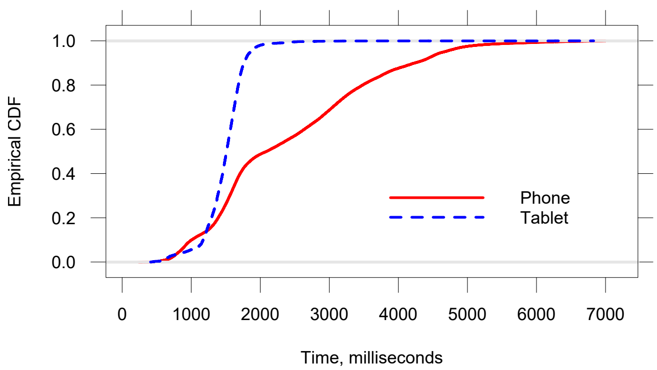

Fig. 5. Total latency to retrieve spectrum information.

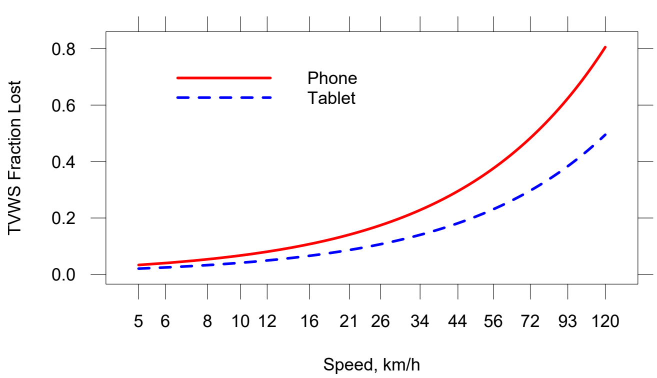

Fig. 6. Fraction of TVWS loss for mean latencies observed in Fig.5.

Setting $\Delta d = 100$ m, we plot the fraction of TVWS loss for our test devices in Fig. 6. As we observe in the figure, the loss of spectrum opportunity increases with increasing speed and might become significantly high for highly mobile users.

V. Discussion

The low temporal variability of TVWS suggests that caching can be an efficient option to facilitate mobile usage. The simplest form of caching would involve special behavior only of MWSD itself. The device can store the results of previous requests and proactively fetch spectrum availability data for those frequently visited locations, for which the lease is going to expire soon. Such a spectrum cache can operate on least frequently used (LFU) principle, meaning that locations which user does not visit often will be removed first. Additionally, the criterion for removal can be the speed of movement at the location, so that spectrum information for those locations where the user is moving fast stays in the cache to ensure smoothness of the communication.

The downside of the approach described above is that optimization is limited by the lease time or *maxPollingSecs* parameter, whichever happens to be smaller. The solution to reduce the number of queries further would be to extend spectrum lease times, and our data support that idea. The drawback is lower flexibility in spectrum management and need to plan carefully for future WSDB updates.

Another workaround that can decrease the size of messages and computational overhead, but not the number of queries, could be *versioning cache*. As the name implies, in such a system, WSDB and mobile device keep track of the version of their data. With each change in the WSDB information, WSDB increases its version. To evaluate the validity of its cache, MWSD requests the version of WSDB and compares it with its own. In case the cache is outdated, user device sends a spectrum request to the WSDB to retrieve the new channel list. The response of WSDB must also contain lease time so the client will know when to compare versions again. A further enhancement would be to partition WSDB into regions to avoid cache invalidations for locations where spectrum availability does not change frequently. The practical implementation requires enhancements to the PAWS protocol and modifications to the WSDB system.

For future work, we plan to evaluate the performance of the aforementioned caching solutions. Additionally, we will analyze the effect of relaxation of the regulations, especially the 100 meters rule. Since less strict regulations may result in collision with the PUs, it is crucial to identify fair operation regions where both the PUs are protected and opportunistic spectrum access does not entail too much overhead. Given modern mobile device capabilities, it is feasible to employ sophisticated machine learning techniques for optimization of caching and user movement prediction, so where is further room for enhancement of prefetching the spectrum data.

VI. Related Work

Ramjee et al. [3] present a criticism of FCC rulings, seeing unsuccessful regulatory decisions as main causes that TVWS is currently utilized mostly by stationary (fixed) devices intended for point-to-point backhaul communications. Despite spectrum congestion, no handheld or embedded TVWS-ready devices are yet available to the general consumer public. As highlighted in [3], major shortcomings of the regulations are as follows: (i) fixed propagation model leading to inaccuracies of WSDBs and causing spectrum starvation in densely populated areas; (ii) absence of indoor usage scenarios, where geolocational capabilities become unavailable; (iii) no SU coexistence support; (iv) stringent requirements for sensing-only devices. Our paper can be seen as a data-driven analysis of the arguments put forward in [3]. Motivated by similar concerns, we developed a system to monitor the spectrum availability over multiple locations for several months and analyzed the collected large data set with a focus on mobile scenarios.

Work related to TVWS mobile usage is quite scarce for now. Majid et. al. [15] proposes predictive optimization algorithm called *Nuna*. The algorithm deduces direction in which mobile device is moving and queries WSDB for locations laying ahead. *Nuna* assumes that the path is a straight line; thus the worst case is circular movement or continuous change of direction. The batch query technique defined in PAWS allows querying for multiple locations in a single request, minimizing the overhead. According to [15], the algorithm achieves up to 30% energy savings in realistic scenarios. Different than [15], we focus on how spectrum availability changes over the route of a mobile user to better interpret how database-assisted white space access performs for mobile scenarios.

The issues related to TVWS utilization efficiency have been in focus of research for a while. Chakraborty et al. emphasize the importance of accurate estimation of DTV station protection contours in the major metropolitan areas, where the gap between supply and demand is the largest [8]. According to results, about 75% of TVWS is lost in New Jersey and 40% in Long Island. The authors devise a model estimating the accuracy of WSDB and suggest augmenting WSDB with sensing in problematic areas. Other research in this area suggests several enhancements to the current solutions, e.g. using public transportation to increase the area of sensing [6], crowdsourced resources of sensory readings [5], using ambient sensing capabilities of mobile phones to sense the TV receiver locations rather than only using TV transmitter information for white space availability calculation [11], mathematical models for combining observations with propagation model results [16]. IEEE 1900.6b standard aims to develop schemes that facilitate spectrum databases to be supported by spectrum sensing for higher database accuracy [17]. Compared to aforementioned, we concentrate rather on nature of interactions between clients and WSDB in the context of inherent features of TVWS, than on potential improvements of WSDB technology itself.

VII. Conclusion

Motivated by the discussion on the current regulations being overly conservative, we collected TVWS availability data over a period of six months from a publicly available geolocation database to develop a better understanding on the current TVWS ecosystem by gaining insights from the data. More particularly, our goal was to see whether spectrum availability exhibits high variability both in temporal and spatial dimensions such that current rules for spectrum re-query for the mobile devices are indeed inevitable. To this end, we created several trajectories to mimic realistic scenarios for the mobile users. We also gathered data concerning the time required by a modern mobile device to issue a query to WSDB and process the response. The total latency was less than two seconds for most of the requests. The extensive WSDB querying did not have any noticeable adverse effect on everyday usage of the mobile phone. Gathered data has shown that on the one hand, the spatial variability of TVWS is high, on the other temporal variability is very low, suggesting the way for optimization in the form of caching and relaxation of the regulations, which require additional ivestigation.

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