Technology Adoption in Spectrum Sharing: Estimating the Impact on Incumbents in the 3.5GHz Band

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Abstract

In spectrum sharing, incumbents are concerned about interference to their operations caused by spectrum entrants. Technical approaches, such as cognitive radios, spectrum databases, etc. have been developed in an attempt to minimize this interference. Whether the interference is co-channel or adjacent-channel, the power level of the interfering signal depends on the number of entrant radios and their spatial relationship to the incumbent operations.

In this paper, we report on a modelling approach that is based on technology adoption literature and uses a tool that was developed for epidemiology to empirically estimate received signal power in a particular geographic location for a particular sharing framework (CBRS). Using this tool, we can estimate the received signal strength a particular points in space (US Naval base, in particular) under different technology adoption profiles, and allow these to change over time.

1 Introduction

The FCC has made the 3550-3700 MHz Citizens Broadband Radio Service (CBRS) spectrum available for shared use. Access to this band is managed by a Spectrum Access System (SAS), a database that specifies if users can access the spectrum, and other sensors to prevent harmful interference to incumbents. One of the principal incumbent users of the band are ship-borne radars for the U.S. Navy. The interference that incumbents may face corresponds to the aggregate signal energy (Received Signal Strength, or RSS) at the radar antenna from Priority Access License (PAL) and General Authorized Access (GAA) users in this band (see Figures 1 and 2)[1]. This RSS is a function of the number and locations of PAL and GAA radios in operation at the time of measurement. This, in turn, is a function of the adoption of CBRS radios by the population of the areas surrounding the base. Hence,

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[1] A thorough description of these entities is provided in subsection 2.1

estimating the interference requires us to model the *adoption* of this technology in space and time, and the associated signal propagation that causes interference[2]. In particular, we use the FRED modeling tool[3] to simulate technology adoption in areas where the 3.5 GHz framework could be adopted.

FRED is an agent-based modeling platform that was developed for modeling public health dynamics. We rely on agent-based modeling (ABM) because data from widespread implementations in the CBRS band are not yet available for analysis. With ABM, we can build and analyze synthetic systems. FRED has detailed demographic data at the census block level for the entire US, making it possible to create adoption models based on income, location, and population density. Further, we can tune parameters to slow or speed-up the adoption of CBRS technology.

In this work, we model technology adoption following the characteristics of disease propagation in time and space. These disease propagation framework is provided by the FRED platform. With this framework, we are able to produce specific location estimates of radio deployments (according to the underlying demographic data), and combine those estimates with well-known propagation models. In this way, we can leverage different types of parameters to characterize interference.

In summary, our objective is to take into account demographic characteristics of the potential users of shared spectrum. This is a new dimension for studies of spectrum sharing because it goes beyond considering only the characteristics of Service Providers (SPs) accessing spectrum in a given band. Our analysis considers the characteristics of the underlying users, their demographics, behavior, and willingness to adopt new technologies (e.g., devices in the CBRS band). These factors may provide us with insights on the rate of adoption of a given system, and how that impacts the usage/sharing boundaries established by regulation.

Relying on such a modeling approach further allows us to test different scenarios and determine which scenarios would require active intervention from policy-makers. At the same time, this modeling framework may allow us to develop more informed decisions on whether existing rules for sharing should be more rigorous or flexible.

The rest of this paper is organized as follows: In section 2, we provide background concepts and works which have been useful for developing our model. Section 3 explains the methology of our work, and section 4 shows the analysis and explanation of the results we have obtained. Finally, section 5 presents our conclusions and future work directions.

2 Background and Related Work

We begin this section by providing a conceptual context for our work. We consider it important to introduce the ideas behind diffusion of innovation; and how this relates to our topic of interest.

Innovation diffusion has been an important research topic in the social sciences since the 1940s. According to Rogers in [1], "[d]iffusion is the process by which an innovation is communicated through certain channels over time among the members of a social system.

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[2] While some devices already operate using LTE in part of these bands in other countries, it is unclear how adoption will be in the US.

[3] `https://fred.publichealth.pitt.edu/`

It is a special type of communication, in that the messages are concerned with new ideas." Rogers also points out that the *newness* of ideas involves a degree of uncertainty [1], hence the likelihood that a given individual will adopt new technology will have to do with their willingness to take risks [2]. The uncertainty associated with new technologies may stem from lack of knowledge about the actual value of the technology as well as how to extract value from it. This uncertainty, in several cases may result in users failing to adopt the technology [3].

Further, authors have pointed out that relationships among people have an important impact on the success/failure of technology adoption. For instance, Valente explores this issue via network analysis [4], and more specifically in terms of social network thresholds. These threshold models tell us that individuals engage in different behaviors based on the proportion of people, in their social system or environment, who also engage in the same behaviors [2].

It is important to note that early analysis of innovation diffusion points to the similarity between the pattern of the spread of a new technique or idea, and the pattern describing the spread of infections through populations. This allowed researchers to describe innovation diffusion as an *S-shape* given that "the rate of spread starts off slowly, accelerates through the mid range of the graph, and then slows down and levels-off" [5]. An additional point to note from early work, is that most work relies on the homogeneity of users. This homogeneity implies that all users are in contact with each other, and that users are *identical* to each other [6].

Following the description of diffusion and its comparability with the spread of disease, we have identified works that focus on areas that are somewhat similar to our area of interest. In [7], the authors utilize agent-based modeling to study the adoption of new drugs in the market. The authors rely on the relationships among physicians in a hospital environment in Galicia, Spain. The study focuses in the imitative behaviors that physicians may adopt, in terms of the treatments prescribed to their patients. The analysis shows that small, and cohesive groups are substantially more influential than larger groups due to their higher coordination potential. Additionally, in this study, proximity among physicians helps diffuse the use of new drugs, as well as the reputation of certain physicians i.e., physicians considered authorities in their field tend to have a higher influence on their peers, hence becoming influential factors in the diffusion process.

Within an Information Technology (IT) context, Rice et al., in [8] have explored the factors leading to the adoption of an electronic messaging system in a government office. Along the same lines, James in [9] studies the adoption trend of IT in under-developed countries. He points out that the *S-shaped curve* used to describe the diffusion process is applicable for developed countries. However, it does not do a good job at describing the situation of underdeveloped areas, where adoption is subject to other social factors. Interestingly, the author finds that adoption is quite low for most types of technologies, except for the adoption of mobile phones. The leapfrogging characteristics of this technology have significantly changed its adoption, making it, in some cases, higher for underdeveloped countries than for their developed counterparts.

From this conceptual analysis, we find that the underlying characteristics and behaviors of people influence their likelihood of adopting a given technology. In the context of our work, the 3.5 GHz band represents a new way to access resources, or an innovation in spectrum

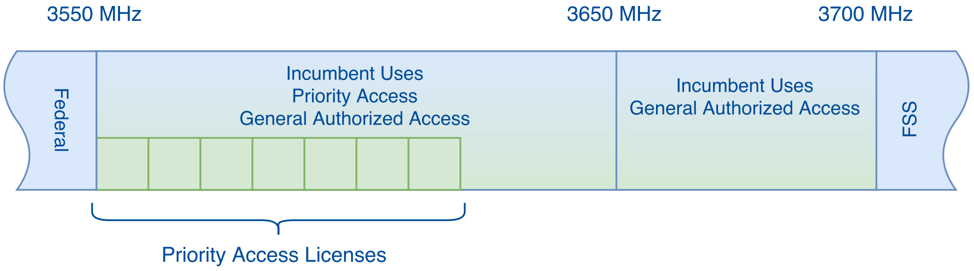


Figure 1: Frequency sharing options in the 3.5 GHz band

sharing. The expressly identified similarity between the spread of innovation and the spread of disease, supports our idea of utilizing the FRED model as an exploratory step in this type of analysis. To the best of our knowledge, we present the first work that combines technology adoption with the shared use of spectrum, particularly in the 3.5 GHz band.

2.1 CBRS Regulatory Background

On April 17, 2015, the Federal Communications Commission (FCC) adopted a Report and Order and Second Further Notice of Proposed Rule-making (see [10]), which established shared broadband use of the 3550 - 3700 MHz band. This band is referred to as *3.5 GHz band*, and comprises the Citizens Broadband Radio Service (CBRS).

As explained by the FCC in [11], "[t]he Citizens Broadband Radio Service is governed by a three-tiered spectrum authorization framework to accommodate a variety of commercial uses on a shared basis with incumbent federal and non-federal users of the band. Access and operations will be managed by a dynamic spectrum access system, conceptually similar to the databases used to manage Television White Spaces devices". The three tiers that have been proposed are: Incumbent, Priority and General Authorized Access.

One of the goals behind this three-tiered implementation is to take into account local supply and demand conditions for resource assignment. In this manner, under high competitive rivalry conditions, auctions can be used to resolve conflicts among mutually exclusive applications in particular areas. On the other hand, under low competitive rivalry conditions, a setting similar to *unlicensed access* is adopted, so as to provide a low-cost entry point for potential users [10]. In figure 1, we can observe (shared) licensing options for different portions of the 3.5 GHz band.

2.1.1 Access Tiers

As previously mentioned, the three access tiers considered in this sharing framework are: Incumbent Access, Priority Access and General Authorized Access (GAA). In what follows, we provide a brief description of what operation in these tiers entails. A summary of operations in each tier can be found in Figure 2.

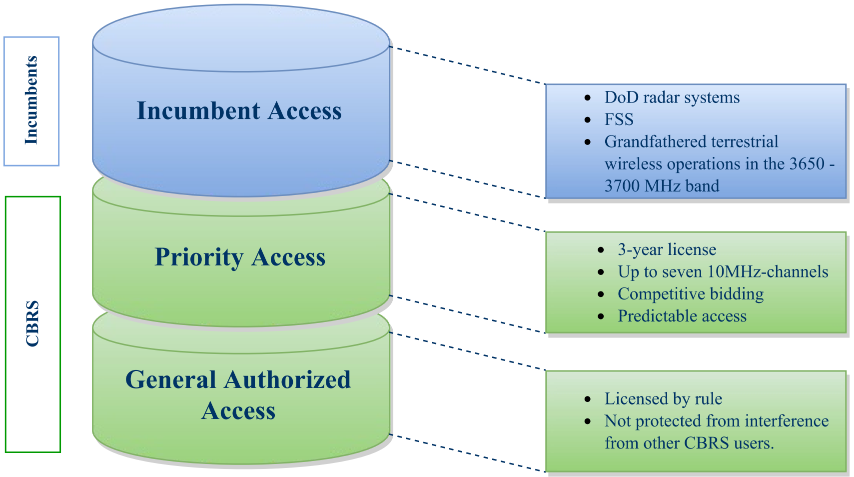


Figure 2: Description of allowable operations in the access tiers for the 3.5 GHz band

Incumbent Access

This access tier comprises authorized federal and grandfathered fixed satellite service (FSS) uses that currently operate in the 3.5 GHz band. Incumbent users should be protected from harmful interference from other users in the band i.e, Priority Access and General Authorized Access users.

Priority Access

Users in this tier are granted access to spectrum via *Priority Access Licenses (PALs)* obtained through competitive bidding within the 3550 - 3650 MHz portion of the band. PALs are defined as “non-renewable authorization[s] to use a 10 megahertz channel in a single census tract for three-years”. A maximum of seven PALs can be assigned in a given census tract, and one single applicant may be granted up to four PALs. Applicants are able to obtain a PAL for two consecutive terms, in any given license area, during the first auction. Note that Priority Acces users or licensees receive interference protection from operations by General Authorized Access users [10].

General Authorized Access (GAA)

Access to this tier follows the *licensed-by-rule* scheme, which allows for “open, flexible access to the band for the widest possible group of potential users” [11]. GAA users can utilize any portion of the 3550 - 3700 MHz band that has not been assigned to users belonging to a higher tier (i.e., Incumbent and Priority Access). Additionally, GAA users are allowed to “operate opportunistically on unused Priority Access channels”[11]. Since GAA devices are not protected from interference, “in a given region, multiple GAA devices belonging to different or the same entity (owner) can be assigned the same channel”[12].

2.1.2 Spectrum Access System

The Spectrum Access System (SAS) is the entity in charge of enabling the operations in this three-tiered sharing framework. The SAS is considered an "advanced, highly automated frequency coordinator across the band"[10]. It is in charge of protecting higher priority users and optimizing frequency use so that maximum capacity can be achieved while ensuring sound coexistence for GAA and Priority Access users. Additional functions of the SAS include "real-time assessment of spectrum availability, adjustment of exclusion zones, interference protection, operational privacy, enforcement of regulatory policies, and other interference mitigation and coexistence techniques"[13].

2.1.3 Potential Providers

According to [10], the following entities are providers who would benefit from resources in the 3.5 GHz band:

- Carriers that seek to deploy small cells on a GAA basis (i.e., opportunistically)
- Real state owners interested in deploying neutral host systems in high-traffic venues. This would permit "cost-effective network sharing among multiple wireless providers and their customers"[10].
- Manufacturers, utilities and other large industries interested in constructing "private broadband networks to automate processes that require some measure of interference protection and yet are not appropriately outsourced to a commercial cellular network"[10].
- Networks for smart grid, rural broadband, small cell backhaul, and other point-to-multipoint services.

3 Methodology

3.1 Building a CBRS agent-based model

Our overall goal in this project is to develop a modeling platform for the study of resource (spectrum) sharing mechanisms and the impact they may have in existing services. In this way, we aim at investigating realistic patterns of interference to incumbent access users. Most investigations focus on the aggregate interference produced by devices operating in a given band, taking into account signal propagation, geographic configurations, antenna characteristics, among others. In this particular study, we are interested in delving deeper into what amounts to *unbearable* levels of interference. Indeed, we focus on the fact that increased levels of transmissions stem from widespread adoption of a given service/technology that relies on the band in question (i.e., 3.5GHz). In this study, we analyze the *diffusion of innovation*, taking into account the demographics of a given area. This type of information allows us to more accurately model users and, more importantly, the probabilities with which they would adopt/reject a given technology; hence estimating the likelihood of them causing harmful interference.

3.2 Modeling Tool

The Public Health Dynamics Laboratory, at the University of Pittsburgh, has developed the Framework for Reconstructing Epidemiological Dynamics, FRED [14]. This is an agent-based modeling tool that has been used for modeling the spread of different diseases, such as measles, flu, etc. across populations with different demographic characteristics. FRED contains a rich array of demographic data, from multiple areas across the United States. Even though the primary applications of FRED are related to public health issues, we think that there is an important parallel to be drawn between how conditions spread, to how innovation and the use of technology spreads. Both, in fact, can be modeled in terms of risk factors, proximity and interaction among agents, demographic characteristics, among others. In this way, our objective is to leverage the capabilities of FRED to model existing and upcoming spectrum sharing proposals. This would permit us to explore how likely it is for users (of a given area or census tract) to adopt services that rely on a technology, and whether we would reach adoption levels that would pose risks to incumbents.

3.3 Model Description

We model the diffusion of innovation through a widely used model of epidemics, known as the SIR model. The SIR model represents the spread of a disease through a population in three phases – *Susceptible*, *Infected*, and *Recovered*. FRED utilizes this model by running custom-defined "conditions" that spread through synthetic populations. In order to simulate the adoption of CBRS by the general public with the SIR model, we need to specify the appropriate parameters to represent the diffusion of innovation as an infectious propagation.

3.3.1 Definition of the Condition

Technology adoption is modeled as an infection with a simple three-state condition: *SUSCEPTIBLE*, *EXPOSED*, and *ADOPTED*. Every agent is initialized in the *SUSCEPTIBLE* state, which means it has not adopted the technology yet. As the simulation progresses, initial agents are gradually exposed to CBRS technology, which advances them to the *EXPOSED* state. Then, as exposure increases, agents become "infected" by the technology, with a certain probability, which marks their shift to the *ADOPTED* state. We assume that an agent that adopts a technology does not revert back, or is "cured".

3.3.2 SIR Parameters

- *Propagation Model*: Diffusion of innovations is modeled as a proximity-based infection (as opposed to respiratory-based infections). Existing research depicts diffusion of innovation as the propagation of an effect through a social network [2]. The infection threshold of a susceptible agent is represented as a probability that increases with the number of adjacent infected agents. Thus, proximity-based transmission represents an appropriate mode of proliferation when utilizing the SIR model.

- *Susceptibility & Transmissibility*: Susceptibility and transmissibility are probabilities of transmission. In an SIR model, these parameters indicate the probability of an agent advancing to the next level of infection. A range of susceptibility and transmissibility probabilities (i.e., 0 to 1, with step size 0.1) is used to determine the effect of a given parameter in the model.

- *Duration of State*: FRED simulates a probabilistic change in an agent's state during their life cycle. We model the duration of the *EXPOSED* state as a lognormal distribution. The lognormal distribution of the duration is used to model state transitions that result from a variety of complex factors [14]. We tested different median and duration dispersion values for the lognormal distribution.

We run the simulation for varying periods, from 100 days to 1000 days in 100-day intervals.

3.3.3 Model Initialization

Before the simulation starts, 10 initial agents are randomly selected from the initial synthetic population to be the original CBRS General Access users (i.e., infected users). These agents serve as the initial infection points in the system.

3.3.4 Obtaining Aggregate Interference

The coordinates of General Access CBRS users are obtained after running our model using demographic information from the synthetic population of a given county. For every 0.5 mile by 0.5 mile grid within the county, the aggregate CBRS interference link budget from General Access coordinates to the grid is calculated. Calculation of the link budget follows the method suggested in [15].

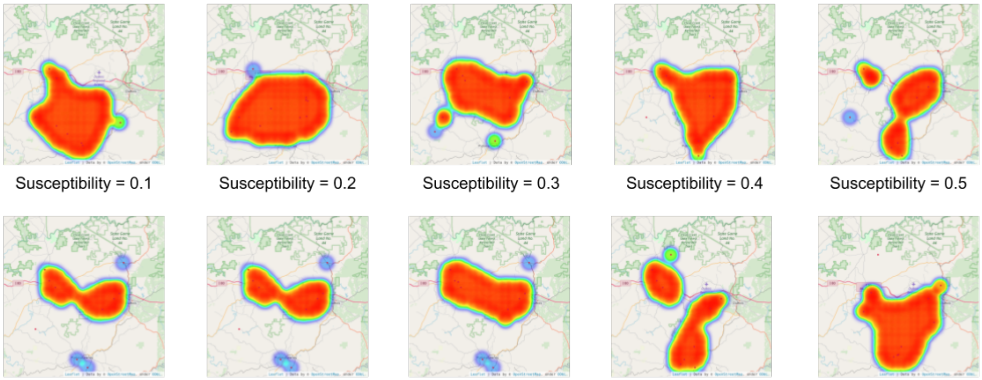
4 Model Analysis and Results

4.1 Simulation Results

4.1.1 Susceptibility

Figure 3 shows the effect of different values of susceptibility in our model. Masked regions in this figure correspond to regions where aggregate interference from users' CBRS equipment exceeds the interference fade margin of 40dB [16]. This value corresponds to the standard interference fade margin suggested by the National Telecommunications and Information Administration (NTIA). Real information of radio antennas of Incumbent Access users is not publicly available.

To better interpret the results from Figure 3, Figure 4 shows numerical values, which indicate that interference becomes more severe as susceptibility of the population approaches extreme values. A maximum aggregate interference from user equipment is observed when susceptibility was set to 0.2 (with 29.06% of the tested region experiencing aggregate interference above the predefined threshold), while minimal aggregate interference was experienced when susceptibility was set to 0.6 and 0.7 (with 11.35% of the tested region experiencing interference above the predefined threshold).



Susceptibility = 0.1 Susceptibility = 0.2 Susceptibility = 0.3 Susceptibility = 0.4 Susceptibility = 0.5

Susceptibility = 0.6 Susceptibility = 0.7 Susceptibility = 0.8 Susceptibility = 0.9 Susceptibility = 1.0

Figure 3: Effect of susceptibility on CBRS interference

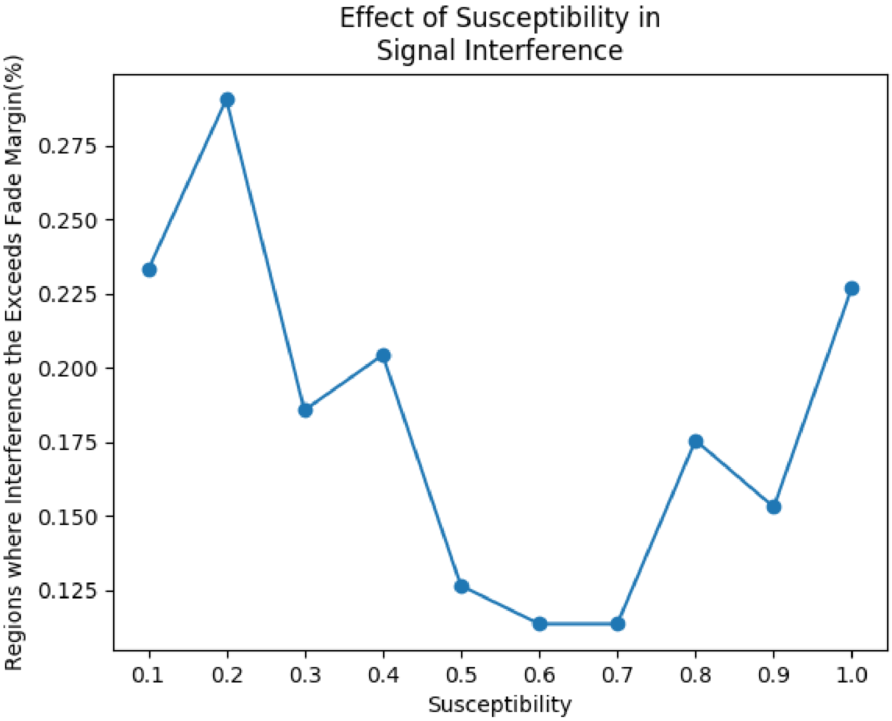


Figure 4: Exclusion zone percentage for each value of susceptibility

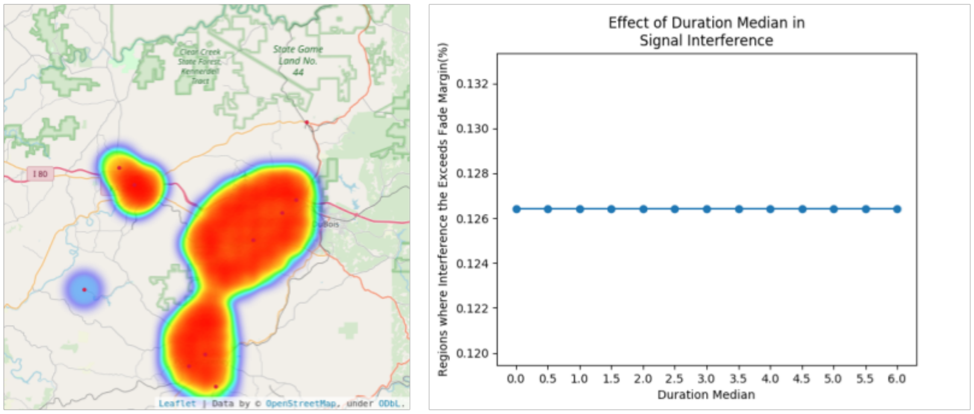


Figure 5: Effect of distribution median on CBRS interference

4.1.2 Duration of State - Duration Median

The effect of duration median that characterizes the duration distribution of the *EXPOSED* state (with susceptibility fixed at 0.4, and duration dispersion at 1.5) can be seen in Figure 5. Simulations show that tuning parameters that relate to characteristics of the *EXPOSED* state does not influence the overall adoption. For all values of duration median, 12.64% of the simulated geographic region was subject to the interference threshold defined in 4.1.1. Effects of the duration median were tested with varying degrees of susceptibility (from 0.1 to 1.0) and duration dispersion (from 0 to 6.0). Different values for susceptibility and duration dispersion did not change the minimal influence of the duration median.

4.1.3 Duration of State - Duration Dispersion

The effect of duration dispersion that characterizes the duration distribution of the *EXPOSED* state (with susceptibility fixed at 0.4, and duration median at 3.0) can be seen in Figure 6. Again, we see that the lognormal distribution parameters of the *EXPOSED* state do not impact overall adoption of CBRS. The resulting exclusion zones in Figures 5 and 6 are the same. For all values of duration dispersion, 12.64% of the simulated geographic region was subject to interference threshold defined in 4.1.1. Similar to duration median, effects of duration dispersion was tested with varying degrees of susceptibility (from 0.1 to 1.0) and duration median (from 0 to 6.0). Different values for susceptibility and duration median also did not change the minimal influence of duration dispersion.

4.1.4 Length of Simulation

The effect of simulation length can be seen in Figure 7 (with susceptibility fixed at 0.4, duration median at 3.0, and duration dispersion at 1.5). Our simulation was conducted with varying lengths, from 100 days to 1000 days, in steps of 100 days. Similar to the lognormal distribution parameters of the *EXPOSED* state, length of simulation does not impact overall adoption of CBRS. 100 days of simulation were enough to propagate the innovation throughout the synthetic population. For all simulation lengths, 22.71% of the tested region

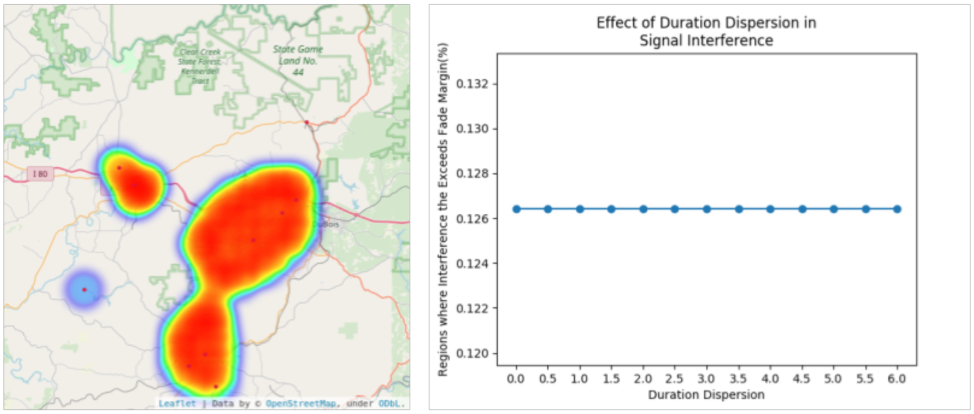


Figure 6: Effect of distribution dispersion on CBRS interference

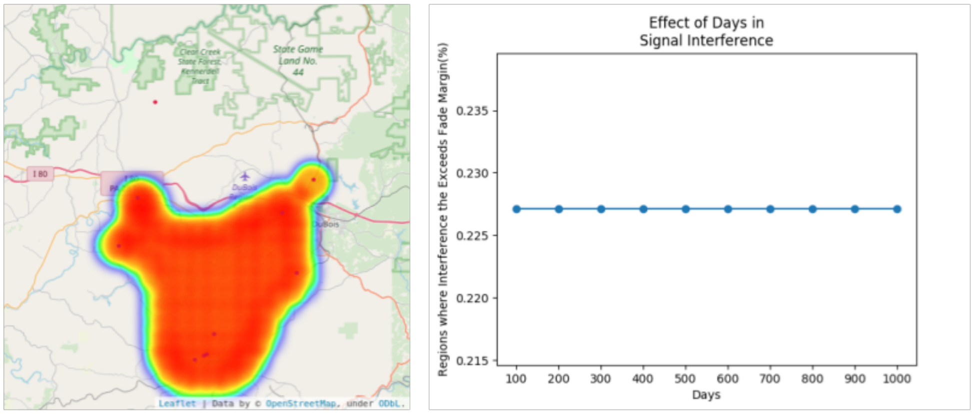


Figure 7: Effect of simulation length on CBRS interference

experienced aggregate interference above the threshold defined in 4.1.1. Further research is needed to determine whether more populated urban environments will also experience this break off in social propagation.

5 Conclusions and Future Work

In this work we have proposed an ABM approach to estimate technology adoption in the CBRS band. Our aim is to incorporate demographic factors into the diffusion of innovation in this three-tiered spectrum sharing scheme, and hence obtain more *realistic* measures of interference. This study is then an important step toward exploring opportunities for *localized* spectrum sharing initiatives and regulation. The particular ABM tool that we use is the FRED framework, which allows us to simulate innovation diffusion as a disease spread process. In this way, we have mapped different stages of innovation diffusion to the different steps in an epidemiological process.

To simulate public adoption of CBRS — and determine resulting exclusion zones – we utilized the simplest form of the SIR model. With a three-step condition scheme of

SUSCEPTIBLE-EXPOSED-ADOPTED, we identified four factors that could potentially affect the spread of CBRS: susceptibility, lognormal median, lognormal dispersion and length of simulation.

Our results show that, of the four factors, only susceptibility had a noticeable impact on diffusion of CBRS-related technologies through the population. Possibly counter-intuitively, increased susceptibility does not necessarily correspond to increased CBRS adoption. A possible explanation for this phenomenon could be found in the behavioral characteristics of the population in the experiment region. Societal differences in rural/urban environments, for example, might have greater impact on the spread of CBRS than factors like susceptibility. Such factors, however, are not designated as experiment parameters. Behavioral patterns of the synthetic population are recorded as static data from the United States Census. An advantage of the simulation method suggested in this paper is its applicability over said varying environments. Unlike conventional methods of determining exclusion zones, behavioral patterns of different regions of the US can be considered, simply by replacing the synthetic population data with that of another region.

This experiment may lead to the development of an alternative method to determine CBRS exclusion zones in a localized manner, using agent-based modeling. Updating the synthetic population from the upcoming population census in 2020 will yield more relevant results. Several potential use cases exist for this CBRS adoption prediction utilizing agent-based modeling. One such example is the planned CBRS automobile support system in Arizona [17]. Agent-based modeling can be applied to predict the system load, using behavioral simulations used in this experiment.

In this work, we have considered agents' proximity as a critical factor for innovation diffusion. In future work, we are interested in exploring additional social factors (e.g., social structures, hierarchies, networks, among others) which may influence the outcome. For the particular case of social networks, we plan to apply network science concepts to be able to translate these aspects into agents' characteristics in our model.

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