Analyzing Usage Conflict Situations in Localized Spectrum Sharing Scenarios: An Agent-Based Modeling and Machine Learning Approach

by

Pedro J. Bustamante

B.S. in E.E., Universidad del Azuay, Cuenca, Ecuador, 2010

MST, University of Pittsburgh, Pittsburgh, PA, 2016

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This dissertation was presented

by

Pedro J. Bustamante

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and approved by

Dr. Martin B. H. Weiss, School of Computing and Information, University of Pittsburgh

Dr. Prashant Krishnamurthy, School of Computing and Information, University of Pittsburgh

Dr. Joseph Yurko, School of Computing and Information, University of Pittsburgh

Dr. Edward Oughton, Geography and Geoinformation Science, George Mason University

Dissertation Director: Dr. Martin B. H. Weiss, School of Computing and Information, University of Pittsburgh

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Pedro J. Bustamante, PhD

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As spectrum sharing matures, different approaches have been proposed for a more efficient allocation, assignment, and usage of spectrum resources. These approaches include cognitive radios, multi-level user definitions, radio environment maps, among others. However, spectrum usage conflicts (e.g., "harmful" interference) remain a common challenge in spectrum sharing schemes. In particular, in conflict situations where it is necessary to take actions to ensure the sound operations of sharing agreements. A typical example of a usage conflict is where incumbents' tolerable levels of interference (i.e., interference thresholds) are surpassed. In this work, we present a new method to examine and study spectrum usage conflicts. A fundamental goal of this project is to capture local resource usage patterns to provide more realistic estimates of interference. For this purpose, we have defined two spectrum and network-specific characteristics that directly impact the local interference assessment: resource access strategy and governance framework. Thus, we are able to test the viability in spectrum sharing situations of distributed or decentralized governance systems, including polycentric and self-governance. In addition, we are able to design, model, and test a multi-tier spectrum sharing scheme that provides stakeholders with more flexible resource access opportunities.

To perform this dynamic and localized study of spectrum usage and conflicts, we rely on Agent-Based Modeling (ABM) as our main analysis instrument. A crucial component for capturing local resource usage patterns is to provide agents with local information about their spectrum situation. Thus, the environment of the models presented in this dissertation are given by the REM's Interference Cartography (IC) map. Additionally, the agents' definitions and actions are the results of the interaction of the technical aspects of resource access and management, stakeholder interactions, and the underlying usage patterns as defined in the Common Pool Resource (CPR) literature. Finally, to capture local resource usage patterns and, consequently, provide more realistic estimates of conflict situations, we enhance the classical rule-based ABM approach by using Machine Learning (ML) techniques. Via ML algorithms, we refine the internal models of agents in an ABM. Thus, the agents' internal models allow them to choose more suitable responses to changes in the environment.

keywords spectrum sharing, governance mechanisms, machine learning, agent-based modeling, citizen broadband radio service, telecommunications regulation, common pool resources, polycentric governance, self-governance.

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Preface

I would like to dedicate this dissertation to my entire family for teaching me that science is the cornerstone of knowledge. First, I want to thank my wife, Marcela, for all the patience, encouragement, support, and love throughout this process, this dissertation is as much yours as it is mine. I also want to thank my parents for their infinite love and support not only in this last part but throughout my learning journey. Likewise, I want to thank my brother for being a constant source of inspiration. I want to dedicate this work in a special manner to my little boy Oliver, who with his sweetness and joy is my constant source of energy and hope. Finally, I have to thank my furry little co-worker Toby for being my constant companion through long working hours.

I would like to thank my advisor, Dr. Martin Weiss, for being the most amazing mentor. His guidance in all the aspects of my Ph.D. journey has been fundamental in this process, as he showed me that research goes beyond the technical aspect of it. I am sincerely grateful to the members of my dissertation committee Dr. Prashant Krishnamurthy, Dr. Joseph Yurko, and Dr. Edward Oughton. Their guidance and support were crucial for the completion of this work.

1.0 Introduction

Spectrum sharing and pooling for increasing utilization, capacity, and availability of wireless network resources have been considered by researchers, regulators, and industry over the last decade. The main goal has been to find and develop mechanisms that allow a more efficient allocation, assignment, and usage of spectrum resources. The typical example of spectrum sharing considers portions of Radio Frequency (RF) spectrum licensed to an incumbent or Primary User (PU) who uses the spectrum band in limited space, time, and frequency. Spectrum can thus be licensed to other users, commonly known as Secondary Users (SUs) or new entrants when it is otherwise unused. SUs pledge to maintain a time-varying exclusion zone that will not cause interference to the incumbent. In some sharing agreements, SUs may pool their resources to serve their customers. In the process, they should not cause interference to each other. Sharing schemes could include additional participants who can use the spectrum on an unlicensed basis. These users should not cause spectrum usage conflicts that impact the normal operations of any other user in the sharing agreement (i.e., PU and other SUs).

A crucial issue in spectrum sharing is the emergence of usage conflicts, such as those caused by unacceptable interference levels (i.e., "harmful" interference) in the incumbent's service area. To deal with this problem, multiple solutions have been extensively discussed in the spectrum management and policy literature. These approaches include the creation of static exclusion and coordination zones around the Primary User (PU) (e.g., the spectrum agreement of the 1695-1710MHz band), the development of devices with spectrum sensing and awareness capabilities (e.g., Cognitive Radios (CR)), the creation of multi-level or multi-tier systems (e.g., the Citizens Broadband Radio Service (CBRS)), among others [2].

A common problem with most interference mitigation approaches is that they are envisioned as global "one-size-fits-all" solutions. Nevertheless, as the Common Pool Resources (CPRs) literature has extensively shown, multi-level, bottom-up, and localized solutions can provide valuable, successful, and sustainable solutions to management problems arising in cooperative settings such as spectrum sharing [3]. This approach requires us to account for different spectrum and network-specific characteristics that impact our ability to assess conflict in sharing scenarios.

There has been limited implementation of spectrum sharing agreements in the "real-world". Several reasons have led to this situation. First, ensuring that interference to federal and commercial high-tiered users remains under acceptable levels has led to rules based on worst-case scenarios (e.g., large static exclusion zones), which limits spectrum sharing opportunities. Second, there is an absence of (secondary) spectrum markets to facilitate the exchange, trading, or sharing of the spectrum to increase incentives for new entrants. Finally, complying with the requirements of sensing and updating database records of spectrum availability is cumbersome and expensive. The lack of widespread spectrum sharing systems has led to limited access to "real-world" data from operators and regulators. In addition, many of the sharing schemes discussed by regulators are proposals; thus, experimental data is not yet available.

In this work, we examine and study spectrum usage conflicts[1] while considering local resource usage patterns. The goal is to provide a more realistic prediction of usage conflict events in spectrum sharing settings. We have selected two spectrum and network-specific characteristics to capture local sharing agreements and assess conflict situations: resource access strategy and governance framework. By focusing on these characteristics, we aim to provide a richer perspective of what spectrum usage entails and how conflicts may arise at a local level. To study spectrum usage conflicts dynamically, we utilize Agent-Based Modeling (ABM). We explore the interactions among participants who are willing to adopt a specific access strategy, and who will adapt to a particular governance framework.

[1] Note that throughout this work we analyze the coexistence among active users, not between active and passive participants. An analysis of the active-passive spectrum sharing use is outside the scope of this dissertation.

2.0 Background and literature review

Spectrum sharing has been considered one of the most promising approaches for an efficient allocation, assignment, and utilization of spectrum bands. Many sharing schemes have been proposed in academic, government, and industry settings [4]. One of the main concerns regarding sharing schemes is the minimization or mitigation of spectrum usage conflicts (e.g., "harmful" interference to incumbents or specific new entrants[1]). At the same time, spectrum sharing should maximize the utility or incentives to new entrants. Throughout the literature, many approaches have been proposed to deal with spectrum usage conflicts and incentives for new entrants, such as exclusion and coordination zones [5, 6, 7], multi-tiered systems [8, 9, 10], secondary spectrum markets [11, 12, 13], spectrum sensing and awareness [14, 15, 16], among others. Even though these approaches have been successful in different circumstances, they are usually envisioned as global "one-size-fits-all" solutions. It is also important to note that these interference mitigation methods tend to focus on specific aspects of spectrum sharing. For instance, they may concentrate on the technical aspects of the resource definition (see for example [17, 5, 6]), the details concerning the assignment of resources (see for example [12, 7]), the development of specific technologies (see for example [18, 19, 14, 15]), or user hierarchies and rules governing such structures (see for example [20, 13, 11]). To the best of our knowledge, there are no examples that combine different spectrum and network-specific characteristics to assess the overall impact of conflict situations in spectrum sharing scenarios. We expect such an approach to provide a more holistic study of spectrum sharing, including mechanisms to deal with usage conflict situations.

[1] Harmful interference can also be experienced by new entrants or Secondary Users (SUs) depending on the nature of their sharing contract.

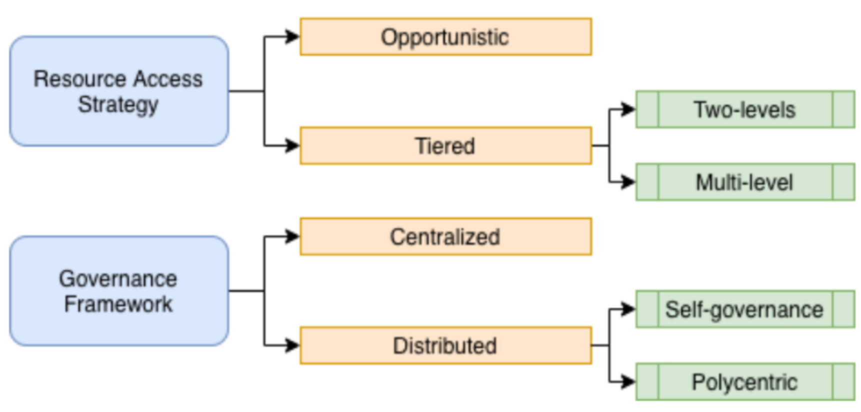

Figure 1: Spectrum and network-specific characteristics to study potential conflict situations in spectrum sharing scenarios

2.1 Spectrum and network-specific characteristics

The research path that we explore in this dissertation aims to study opportunities for localized spectrum sharing initiatives and regulation. For this purpose, we define two spectrum and network-specific characteristics to estimate potential conflict circumstances in resource usage: **resource access strategy**, and **governance framework** (see Figure 1). In this section, we provide background information on the mentioned above aspects of interference assessment in spectrum sharing. It is also important to note that the literature that has been explored in each of these topics has significantly contributed to the definition of the core problem of this dissertation and has shed light on the avenues that we consider convenient to explore.

2.1.1 Resource access strategy

The first step in understanding localized spectrum sharing agreements is to examine how different users access such resources. In the literature, the most common spectrum access strategies are opportunistic access and tiered-access [12, 21].

2.1.1.1 Opportunistic access The opportunistic access strategy is also known as Opportunistic Spectrum Sharing (OSS). In OSS, unlicensed users (i.e., new entrants) opportunistically access the licensed spectrum on a non-interference basis to licensed users (i.e., incumbents) [14]. Three common characteristics define opportunistic access to wireless resources. First, radios can sense or survey the environment to identify transmission opportunities (i.e., find coverage "holes" or "cavities"). Second, the system considers that all new entrants have equivalent rights (i.e., similar access/use priority). Finally, there is no mandated coordination between PUs and SUs to share the available resources. Hence, secondary users must independently identify transmission opportunities. The primary examples of this type of access strategy are Cognitive Radios (CRs) and Cognitive Radio Networks (CRNs) [16, 19].

Cognitive Radios (CRs) were proposed as the driver to implement opportunistic sharing. The main idea is to create devices (i.e., RF equipment) that can sense the spectrum and adapt their usage behavior accordingly [22]. In other words, cognitive radios sense the spectral habitat over a wide range of frequency bands to, opportunistically, meet their communication requirements [23]. Note that CRs are secondary users of the spectrum assigned to a primary user. Hence, the main condition for these radios is to avoid causing interference to the incumbents in their vicinity. Contrary, primary users are not required to adapt their infrastructure or usage behavior to account for the presence of CRs [24].

Cognitive radios have three main functionalities: spectrum sensing (detects unused spectrum), spectrum management (selects the best available channel), and secondary spectrum sharing (coordinates the channel usage with other CRs) [25]. In the latter, cognitive radios form a coordination network, usually referred to as Cognitive Radio Network (CRN) [26, 16, 15]. This network allows them to coordinate the usage of spectrum holes or white spaces while sharing sensing and detection capabilities. In CRNs, Cognitive Radio Devices (CRDs) can configure different parameters on the fly (e.g., frequency band, transmit power, among others) based on the surrounding environment and consequently exploiting underutilized spectrum portions [27]

2.1.1.2 Tiered-access Is usually referred to as vertical spectrum sharing, where different users hold different spectrum usage rights (i.e., property rights) [28, 29]. The users who currently possess the spectrum usage rights (i.e., primary users or incumbents) will maintain higher priority rights to the spectrum band over the new entrants. In other words, different "hierarchical" or tier levels are defined within the sharing agreement to maintain the sound operations of the system (e.g., avoid spectrum usage conflicts).

Two-level access: Participants in the sharing agreement are divided into two tiers, namely primary and secondary users. This organization is considered the classic and original approach for spectrum sharing. In this scenario, an incumbent or primary user grants usage and access property rights to a new entrant or secondary user. The incumbent is located at the top of the hierarchical structure. Hence, it receives higher protection from the consequences of usage conflicts. On the other hand, secondary users are authorized to access the band, according to the conditions of the sharing contract, as long as they do not generate conflict situations [30].

An example of this type of resource access strategy is the 1695-1710MHz sharing scheme in the United States. This frequency band is part of the Advanced Wireless Services (AWS-3) defined by the Federal Communications Commission (FCC) and the National Telecommunications and Information Agency (NTIA) [31]. In this Federal-Commercial sharing framework, we have a two-tiered resource access strategy. The incumbents are the meteorological satellites of the National Oceanic and Atmospheric Administration (NOAA). The Secondary Users (SUs) are mobile phones (i.e., LTE Mobile Stations (MS)) [32, 33]. To protect PUs against usage conflicts, the FCC and NTIA proposed two static protection zones: 1) an Exclusion Zone (EZ), which is a restricted area where no new entrants are allowed to operate, and 2) a Coordination Zone (CZ), which extends beyond the EZ boundaries, and allows for new entrants' operations under predefined circumstances [31]. Based on the definitions of exclusion and coordination zones, several authors [5, 6, 7] have designed methods to specify the characteristics of this Federal–commercial sharing environment. In particular, authors have sought to develop methods for creating and sizing both restriction zones. Available approaches propose a more flexible scheme than the one suggested by the FCC/NTIA, as their main objective is to reduce the size of both zones, and increase the value and incentives for new entrants.

Multi-level access: Expanding on the two-tier spectrum access scheme, other sharing settings have been proposed for a more optimal assignment of spectrum resources. In particular, a multi-tiered system, where more than two levels (i.e., tiers) of users are defined [30, 34]. Note that this type of scheme involves a more complicated sharing agreement. For instance, additional coordination entities need to be included (e.g., Spectrum access coordinators) [35].

A well-known example of multi-tiered systems is proposed for the Citizens Broadband Radio Service (CBRS). This proposal is a three-tier spectrum sharing model created for the 3.5GHz band in the U.S. [36]. In this model, the Incumbent Access (IA) users represent the highest tier; hence, they receive the highest interference protection from other CBRS users and devices (CBRD). These PUs include federal shipborne and ground-based radar operations and fixed satellite service (FSS) earth stations in the 3550–3700 MHz band and, for a finite period, grandfathered terrestrial wireless operations in the 3650–3700 MHz band [28]. The non-incumbent users in the band are further divided into two tiers: the Priority Access License (PAL) and the General Authorized Access (GAA) users. In this multi-tier model, operations from the PAL users receive protection from GAA operations, while the lowest-tiered participants (i.e., GAA) do not receive any interference protection [37, 38].

2.1.2 Governance framework

The other primary component in our spectrum sharing analysis is the governance structure. In the literature, the most common governance structure in the allocation and assignment of spectrum resources is the centralized approach of "command-and-control" [39, 40, 41]. However, as discussed in the Common Pool Resources (CPRs) literature[2], "alternative" governance mechanisms are available to govern and manage such commons. Consequently, besides studying a **centralized** approach, we have selected two widely known distributed systems, specifically **self-governance** (i.e., self-governing, self-enforcement, etc.) and **poly-**

[2] Authors in [29, 42, 43, 1, 17] have concluded that the exploitation of radio spectrum bands for wireless transmissions can be defined as an example of a Common Pool Resource (see Section 2.4).

centric governance as relevant governance frameworks for our analysis.

2.1.2.1 Centralized governance One crucial assumption in centralized schemes is that individuals are not capable of reaching credible ex-ante commitments, especially when there are substantial ex-post "temptations" to break such agreements [44]. Hence, as Hobbes proposed, there is a need for a "coercive power, to compel men equally to the performance of their covenants, by the terror of some punishment, greater than the benefit they expect by the breach of their covenant". As argued in his famous "Leviathan", we need the presence of a "powerful" entity to maintain equilibrium in the system [45]. This assumption has led to the belief that without government (at least as a principal actor) there is no law to prevent the strong from plundering the weak, to stop the presence and proliferation of "free-riders", and the dishonest taking advantage of the honest. Furthermore, Hobbes' critical assumption was that "without government there cannot be governance" [46].

A widely used definition of "government" dates back to 1919, where Webber defined it as a "territorial monopoly on the legitimate use of coercion" [47]. This definition has many common characteristics with the notion of the centralized "command-and-control" system. These assumptions have also been used for developing regulation and enforcement policies in several fields, including telecommunications. In command-and-control schemes, only governments[3] can require or prohibit specific actions or technologies, with possible fines, sanctions, or jail terms for punishing rule-breakers [48]. In other words, the decision power is concentrated (i.e., centralized) in a single institution, the government, while other participants have little or no control. Many authors in the literature agree that when sufficient resources are made available for monitoring and enforcement, such an approach can be successful [48, 46, 49]. However, if there is a lack of resources, these approaches become ineffective, not to mention that these mechanisms have also proved to be economically inefficient in many circumstances [48, 50].

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[3] Usually through government agencies such as the FCC or the NTIA.

2.1.2.2 Distributed or decentralized The governance literature of Common Pool Resources (CPRs) has studied many governance systems where appropriators have repeatedly shown their capacity to organize themselves, create rules, monitor others and themselves, and successfully enforce the agreed-upon rules. These organizations have been able to create self-organized and self-controlled institutions without reference to central authorities (i.e., governmental institutions), at least in principal roles. Further, the institutions that have emerged have been sustained over long periods without the participation of any external agency [51]. Two prominent examples of distributed or decentralized governance systems are polycentric governance [52, 53, 54] and self-governance [55, 46, 56, 57].

Self-governance: One example of "distributed" mechanisms is a government-less or self-governance approach. Note that self-governing or private-governing institutions do not refer to the complete absence of law; instead, they refer to the lack of a formal government or state dictating and enforcing the law. The main characteristic behind this idea is that agents, who find themselves in government-less situations or choose to eschew government, develop their own and privately-created law [56].

In centralized governance approaches, it is assumed that some participants tend to break the ex-ante agreements. Hence, there is a need for a powerful entity (e.g., central government) for keeping such agreements. Consequently, the natural question in private-governing arrangements is: how a privately-created law is enforced? A short answer to this question is "discipline of continuous dealing". As Axelrod argues [58], the idea behind this principle is simple, "[i]f you do not behave today, I will take repressive actions". These actions include stopping the interaction with you tomorrow, telling others not to interact with you, reducing your future privileges, etc. Consequently, if you value the future interaction with a given user and their social network, you will not break ex-ante agreements [59, 46, 60].

Polycentric governance: Has its roots in the concepts introduced by Vincent Ostrom for self-organizing systems. A polycentric system is "1) composed of many autonomous units formally independent of one another, 2) choosing to act in ways that take into account other participants, and 3) through processes of cooperation, competition, and conflict resolution" [52, 61]. Polycentric systems are characterized by multiple heterogeneous authorities at different levels, where each unit exercises considerable independence to make norms and rules within a specific domain or jurisdiction (e.g., a family, a firm, a local government, a state or province, a federal government, etc.)[4] [62]. One of the main goals of polycentric systems is that problems associated with non-compliance (e.g., breaking ex-ante agreements) and power inequalities can be better addressed [49]. The literature on polycentrism also shows that adopting a polycentric governance structure can have considerable advantages due to their mechanisms of mutual monitoring, learning, and adaptation over time to local resource conditions [63, 53, 62].

A shift towards polycentric approaches can be advantageous in localized spectrum sharing schemes. First, instead of relying on a single type or level of governance, polycentrism incentivizes the involvement of resource users and managers at different scales. For instance, local knowledge can inform the design of diverse, context-specific rules, while larger organizations and the government can enhance the capacity to deal with regional problems and support the necessary conditions to prevent and sanction non-compliance with rules [63]. Besides, the probability of a national failure could be significantly reduced, while some management units might fail others could become successful and innovative. Thus, the costs of failure associated with a centralized governance system are compensated by successes at smaller scales [52, 49].

2.2 Usage conflicts in spectrum sharing

A fundamental goal of this dissertation is to study conflicts that arise in spectrum-sharing agreements. In this work, we refer to spectrum usage conflicts or spectrum sharing problems as situations where actions need to be taken, by one or more stakeholders, to ensure the sound operations of the system. System operations include the protection of the Primary User (PU) or incumbent, and the access of Secondary Users (SU) or new entrants to the available spectrum units. In the different stages of this dissertation, we focus on situations where incumbents' tolerable levels of interference (i.e., interference thresholds)

[4] Note that some systems can also have institutions with overlapping jurisdictions.

are surpassed[5]. These conflict situations might result from a combination of factors that may be related to stakeholders' behaviors, as well as their resource usage patterns. In other words, scenarios that result from the interaction of different resource access strategies and governance frameworks.

2.2.1 Types of conflict events

In this work, we frame conflict events according to Table 1. This particular classification allows us to distinguish motives for different events. This process simplifies the forensics and user identification in future enforcement and adjudication processes [64].

In *Type I* events, we assume that all parties (e.g., incumbents and new entrants) are cooperative. The parties in the agreement are doing their best to avoid conflict situations, no attempt is made to obfuscate transmissions or to evade compliance, and to guarantee the sound operations of the system. Therefore, we assert that conflict situations of *Type I* are more amenable to different governance and enforcement systems. *Type I* conflict events might occur due to aggregation of similar devices, propagation anomalies, location errors, interference cartography errors, etc.

We assume that non-cooperative actors, who are responsible for *Type II* events, do not follow the general guidelines and rules of the system. These agents tend to evade detection, evade compliance, and engage in a technological "arms race" with other stakeholders (e.g., incumbents, regulators, etc.). Consequently, *Type II* events are likely to be highly unique on a case-by-case basis, a situation that is not easily amenable for automated systems.

Type III events may be considered a subset of *Type I* events[6]. Nonetheless, the potential liability for the caused conflict situations may rest elsewhere. This type of event might also be sufficiently unique as some can be widespread or very local depending on the source of the problem.

Finally, we have *Type IV* conflict events. These are also rather unique situations. One example is parties trying to exploit loopholes in the regulation of the agreements for their

[5] In some scenarios, this definition also applies to higher-ranked users or participants.

[6] Parties are still complying with the rules of the system.

Type	Description
I	All sharing parties are making best efforts to comply with the rules and consequently avoid conflict situations. Conflict usage events occur due to factors that are generally unavoidable
II	Some sharing parties are not willing to comply with the rules. In other words, "rogue" actors making no attempt to comply with the sharing agreements
III	Conflict situations are the result of technical hardware and/or software faults
IV	Conflict events are the result of errors in regulatory design, where all sharing parties are in technical compliance

Table 1: A topology of conflict events in spectrum sharing scenarios [1].

benefit. Similar to *Type III* events, the liability for the conflict situations rests outside of the participating parties (e.g., the interfering and interfered actors).

It is necessary to point out that conflict situations are present in the uplink and downlink communication directions. In the uplink, the direction of the communication is between mobile stations and base stations. On the other hand, downlink communications occur between static stations and mobile devices. In this work, we focus on conflict situations occurring in the downlink; particularly, conflict situations around the receivers' communications equipment.

2.2.2 Interference mitigation

The literature on Dynamic Spectrum Access (DSA) systems has heavily focused on interference sensing and mitigation. Particularly, interference mitigation for members of higher protection tiers (e.g., the incumbent of the band) [5, 6, 7, 65, 66]. To analyze different interference mitigation approaches, we can study two well-known Federal-commercial sharing agreements in the U.S., the 1695-1710MHz band and the Citizens Broadband Radio Service (CBRS). These systems have implemented different policies when dealing with interference mitigation, which are significant examples of spectrum interference mitigation approaches that are currently available.

First, the 1695-1710MHz band is part of the Advanced Wireless Services (AWS-3) defined by the FCC and the NTIA. The incumbents or Primary Users (PU) are the Meteorological Satellites of the National Oceanic and Atmospheric Administration (NOAA) [32]. Mobile LTE handsets (MS) are the Secondary Users (SU) or new entrants.

The first approach to mitigate interference in the band was introduced by the telecommunications regulators (i.e., the FCC and NTIA). Their goal was to protect the incumbents or PUs against "harmful" interference. This interference is assumed to be the product of the operations of other users in the band (e.g., new entrants) [67]. Hence, the FCC and NTIA proposed two static protection zones to mitigate possible interference events: 1) an Exclusion Zone (EZ), which is a restricted area where no new entrants are allowed to operate, and 2) a Coordination Zone (CZ), which extends beyond the EZ boundaries, and allows for new entrants' operations under predefined circumstances [31].

Based on these zone definitions, many authors have explored different options to maximize incentives to the secondary users while protecting the incumbents [6, 5, 7]. In this light, authors have developed and analyzed tools and mechanisms to model the aggregate interference caused by SUs to identify spatial spectrum sharing opportunities and increase the incentives to new entrants [6]. The goal of these systems is to estimate the maximum interference that can be generated within a coordination zone. For instance, authors argue that it is necessary to monitor the integrity of the signals of interest (i.e., signals generated by the SUs) around the PU and the overall spectrum environment to detect the presence of interference signals. To do this, the system must perform four basic monitoring functions: detect, classify, and identify the source of interference, as well as, notify wireless carriers of said interference[7] [68].

The Citizens Broadband Radio Service (CBRS) is a three-tiered access and authorization framework, which also accommodates federal and non-federal use of the band. Regulators adopted a different approach to deal with the presence of conflict situations (e.g., interference). First, access and operations are set to be managed by an automated frequency

[7] Monitoring will continue for the government operator to verify that the wireless carriers have mitigated the interference.

coordinator, known as a Spectrum Access System (SAS). To measure spectrum usage the SAS may incorporate information from an Environmental Sensing Capability (ESC)[8] system. A SAS coordinate operations among users of the three tiers of authorization in the 3.5 GHz band [69].

Sharing in the CBRS band is the newest Federal-commercial spectrum sharing agreement, hence, it considers a more dynamic approach regarding interference mitigation. It includes a local or regional entity in charge of measurement and coordination activities. Nonetheless, the rules about conflict identification and mitigation are still dictated by a centralized institution (i.e., the regulators) and conceived as a "one-size-fits-all" solution [70].

These examples of spectrum sharing best summarize the current efforts of conflict mitigation in spectrum sharing scenarios. To the best of our knowledge, they do not focus on the development of spectrum sharing strategies that adapt to local conditions. In what follows, we provide an overview of the research that has been done around Radio Environment Maps (REMs), Common Pool Resources (CPRs), adding learning capabilities to Agent-Based Modeling (ABM), and how Machine Learning (ML) techniques have been utilized in spectrum management. We believe this literature provides a very suitable framework to create valid spectrum sharing models and examine and analyze spectrum usage conflicts. Further, the concepts and techniques from this literature help us to capture local usage patterns and their corresponding governance characteristics (see Figure 2).

2.3 Radio Environment Maps (REMs)

In the literature, we find that one of the first steps in developing more efficient approaches for the allocation and assignment of spectrum resources was the development of Cognitive Radios (CR) [71, 72, 73]. A crucial goal was for these RF-devices to leverage the presence of TV White Spaces (TVWS)[9] to fulfill their communication requirements. Due to

[8] A sensor network that detects transmissions from the Department of Defense radar systems and transmits that information to the SAS. Both SASs and ESCs must be approved by the FCC before they operate.

[9]

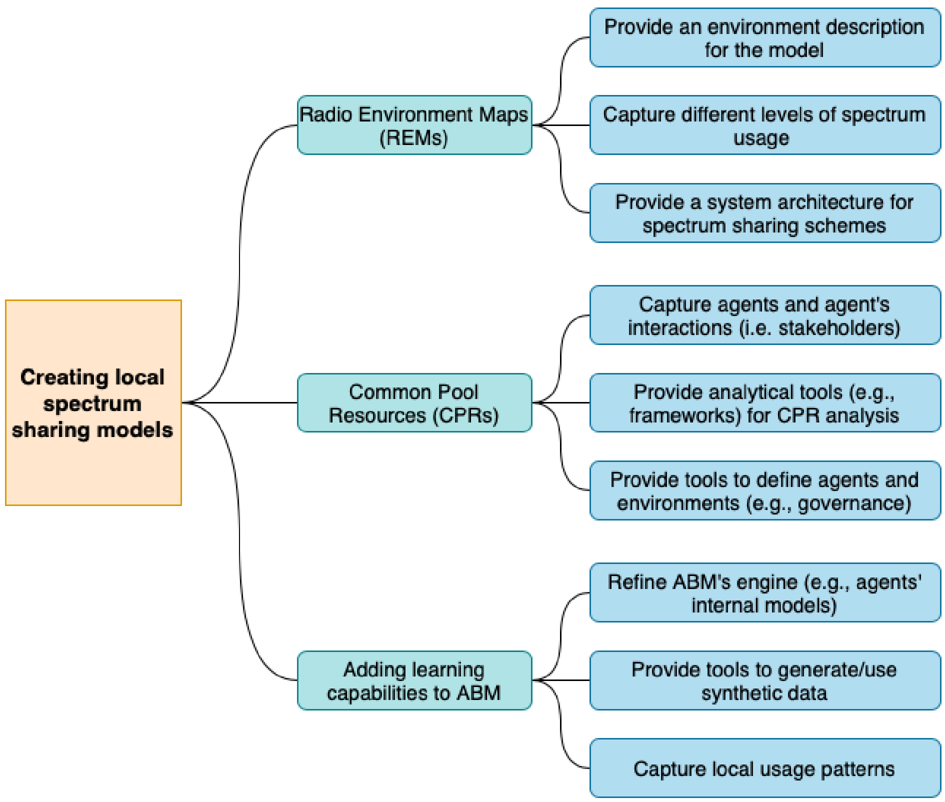

Figure 2: Literature review for creating and analyzing local spectrum sharing models

concerns raised by the PUs (i.e., broadcasting stations), regulators established overly conservative rules for TV White Space Devices (WSD) (e.g., the detection of a primary signal at -114 dBm). Such regulations drastically reduced the availability of white spaces. For instance, as shown in [71], a reduction by a factor of three heavily limited the widespread usability of CRs.

Due to the sensing restrictions adopted by different regulatory bodies, accessing a centralized spectrum database (i.e., TV Databases (TVDB) or White Space Databases (WSDB)), which stores the available spectrum based on geographical coordinates, was considered a promising solution for opportunistic spectrum access [74, 75, 76]. In this geolocation-based spectrum access scheme, based on their current longitude and latitude, RF-capable devices query the database for the available frequencies. In the particular case of TVWS, the transmission activities of the primary users (e.g., TV stations) are quasi-static, where their transmitters are, indeed, static. Hence, a TVDB could successfully meet the requirements for TVWS secondary communications [77].

Many authors agree that one of the biggest challenges of geolocation databases is their limitation to provide enough information for "real" Dynamic Spectrum Access (DSA) networks [77, 78, 79, 16]. A step further from geolocation databases is the development of Radio Environment Maps (REMs). REM stores live multi-domain information of entities in the network as well as the history of data of the environment (e.g., geographical information, policy and regulation data, services, radio transmissions, among others). The REM is essentially a comprehensive spatio-temporal database and an abstraction of "real-world" scenarios. It contains static environmental information (e.g., geographic data) and dynamic data (e.g., SU's location). The goal is to support cognitive functionality for radios with different levels of "intelligence" while being transparent to the specific radio access technology to be deployed [79]. The most significant difference between REMs and geolocation databases is that REMs generate spectrum maps by processing the data collected from multiple sources (e.g., Measurement Capable Devices (MCDs) and regulatory bodies). Consequently, they can easily adapt to dynamic operating environments, whereas database-based approaches

Defined as the available frequencies (in the broadcasting television bands), at a given location and time, used for secondary transmissions.

store quasi-static information. Radio Environment Maps are also viewed as an extension of the Available Resource Map (ARM), which is a "real-time" map of all radio activities in the cognitive network for radio applications in Unlicensed Wide Area Networks (UWANs) [80, 18].

As depicted in Figure 3, Radio Environment Maps have been explored from many perspectives. In this work, we focus on the construction of REM models, the corresponding data model, and their architecture. In the following sections, we provide additional details about each of these components of a Radio Environment Map.

2.3.1 Methods for the construction of REMs

To detect, identify, and use available spectrum opportunities, secondary users need spatial information of the "state" of the spectrum environment. This state mainly involves wireless signal information. Particularly, the SU needs to know whether there are primary/other secondary receivers (transmitters) and how much interference these receivers (transmitters) can tolerate. A fundamental layer in REMs is Interference Cartography (IC), which refers to a map that displays the signal characteristics (e.g., Signal-to-Noise Ratio (SNR) or Received Signal Strength (RSS)) at different frequency bands over an area or region of interest (i.e., map) [81, 82, 77].

Interference cartography (IC) corresponds to a geolocalized combination and exploitation of radio measurements at the mobile-terminal level and network level. This wireless signal representation provides a complete view of the spectrum environment. IC aggregates data of interference (e.g., SNR) measured by entities of several different wireless networks with sensing capabilities (e.g., CRs, network operators, among others), combines this information with geolocalization data, applies signal processing techniques, and updates the information to provide a snapshot (i.e., map) of the spectrum environment. This process allows for efficient detection, analysis, and decision activities of secondary users [83]. In the literature, the most common architecture to construct the IC is to utilize a Measurement Collection Module (MCM), an IC Manager, and IC Database [83, 66, 78]. In some spectrum sharing scenarios, a fourth element is also included, namely a Network Spectrum Manager (NSM)

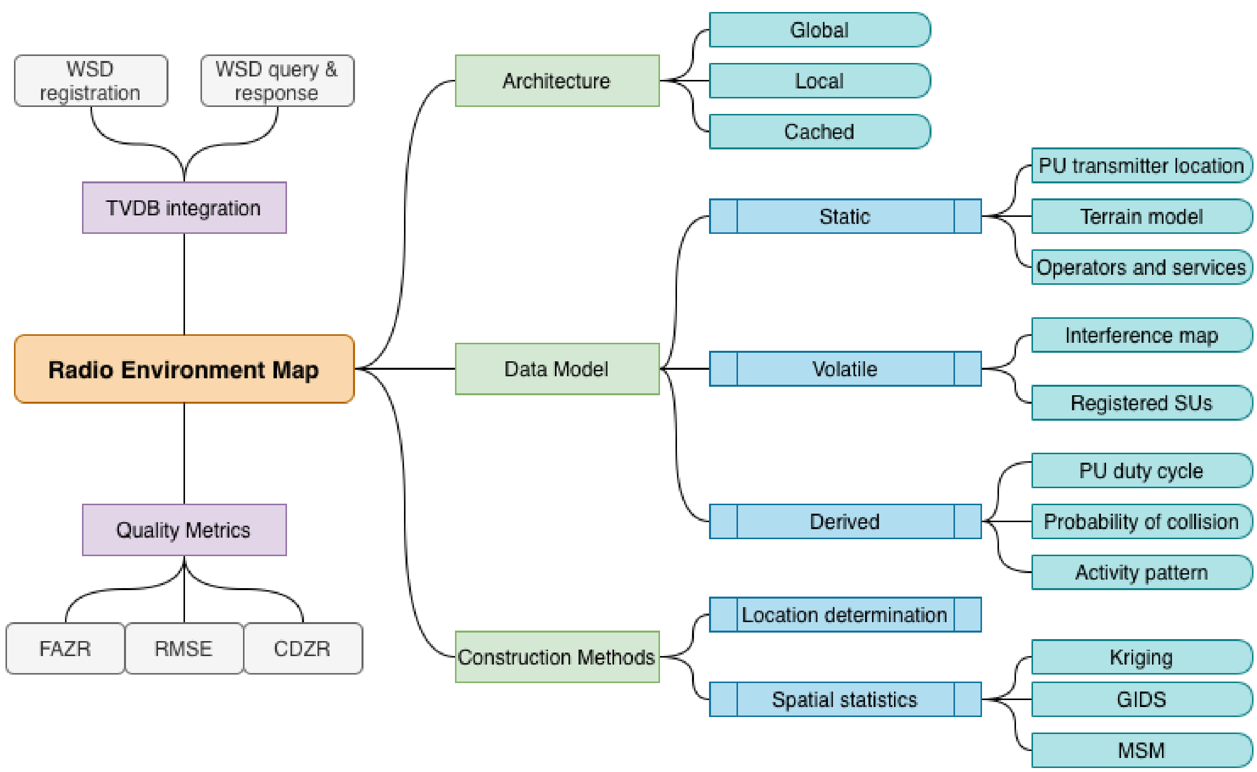

Figure 3: Main components of Radio Environment Maps (REMs)

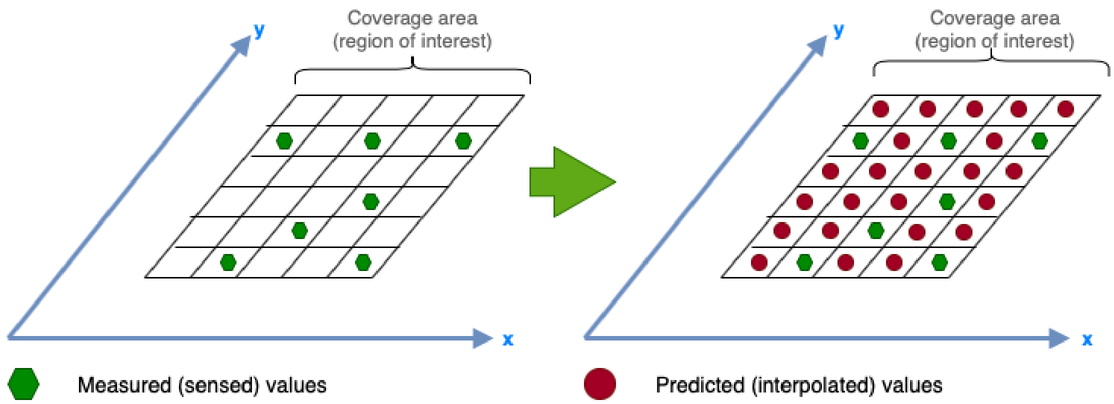

Figure 4: Interference cartography (IC) in Radio Environment Maps

[84]. The IC manager is responsible for the IC construction based on measurements collected by the MCM. The resulting IC is stored in the IC database and is used by the NSM for spectrum allocation and assignment.

If measured data is not available for a particular location within the region of interest, the REM fuses the available measurements to estimate the interference level at such positions. Thus, the main goal of the IC is that given a finite number of localized measurements, it is possible to deduce (i.e., interpolate) the missing values for the entire region of interest (see Figure 4). This process is usually known as REM construction or IC generation. The literature classifies REM construction techniques into two categories: spatial statistics-based or direct methods, and transmitter determination-based or indirect methods [85, 86, 87, 77, 83].

2.3.1.1 Interference cartography construction using spatial statistics (direct methods) Using spatial statistics and existing measurements at specific locations, an REM can estimate missing data at areas without measurements [82]. Spatial interpolation is a well-known procedure commonly used in Geographic Information Systems (GIS) [88]. Formally, spatial interpolation is a statistical procedure that estimates missing values at unobserved locations within a given area based on a set of available observations of a random field. This interpolation is mainly based on a primary principle in geography called the "spatial autocorrelation". This principle states that everything is related to everything else, but nearby things are more related than distant things [89]. In the literature, many methods based on spatial statistics have been suggested for the construction of REMs, as shown in Table 2.

2.3.1.2 Interference cartography construction using the transmitter location (indirect methods) The literature also uses the transmitter's location and well-known propagation models to construct IC maps within REMs. These techniques are known as transmitter location-based or indirect methods. Indirect IC methods start by estimating the location of transmitters based on the measurements from several sensors (e.g., Measurement Capable Devices (MCDs)). Once the transmitters' location has been estimated, by applying the transmitters' calculated parameters in a valid propagation model, the signal level at any location in the region of interest can be estimated.

In the literature, two main techniques have been proposed as valid options to estimate the location of a transmitter and, consequently, estimate the REM interference cartography: Received Signal Strength Difference (RSSD) and the Received Signal Strength (RSS) methods [78, 96, 87].

In RSSD, it is assumed that all the transmitters in the area have similar and known transmission power. Hence, the only remaining task to construct the IC is to estimate their location. For this purpose, the ratio of the signal powers (or their differences) observed at two different sensing locations is related to the ratios of the emitter-to-sensor distances. On the other hand, RSS combines analytical models with a statistical evaluation through measurements to create a practical model for the RSS at location i (see Equation 2.1) [25]. The values of path-loss constant lo, path-loss exponent α, and standard deviation σ all depend on the environment and propagation scenario. Further, all these variables can be experimentally computed from the measured data, using linear regression models. The goal is to minimize the difference between the measured and estimated path losses in terms of the mean-square error over a wide range of measurement locations and different separation

Method	Description
Kriging [90]	The key to the Kriging method is the determination of the weighting factor. The method dynamically determines the value of the variable according to an optimization criterion function in the interpolation process, so that the interpolation function is in the best condition.
Inverse Distance Weighted [91]	This method assumes that each input point has a local effect, and this effect is weakened as the distance increases. It is usually referred as linear interpolation since different types of lines are used to estimate missing values.
Nearest Neighbor [82]	This method is to find the k nearest neighbors of the unknown sample point and obtain the attribute of the unknown sample point by assigning the weight of the attribute of these neighbors.
Thin Plant Splines [82]	The surface of the control point is established by the sheet spline function and the slope of all points are minimized. That is, the minimum curvature surface fitting control point.
Discrete Smooth [92]	A network of interconnected networks is established between discretized data points. If the known node value on the network satisfies a certain constraint, the value on the unknown node can be obtained by solving the linear equation
Joint Tensor Completion [93]	Model the multi-dimensional spectrum data from the perspective of a spectrum tensor. Improve the low rank tensor completion algorithm, and evaluate it by comparing the improved spectrum tensor completion, the original one, and the spectrum matrix completion scheme
Modified Sherpard's Method (MSM) [94]	The IDW-based modified Shepard's method takes a different approach in solving the interpolation problem. MSM is local interpolant that makes no assumptions about the nature of the spectrum occupancy and treats the observational data as localized and known values of some unknown real multivariate function
Gradient plus Inverse Distance Squared (GIDS) [94]	Similarly to the MSM, it assumes that the underlying radio quantity of interest can be represented with multivariate real function. This technique introduces a third independent variable that represents the elevation of the observed values above the reference plane
Barnes Surface [95]	A Gaussian weighted averaging interpolation based on the least square fit and a Fourier integral representation. This approach act as a smoothing filter as well as an interpolator

Table 2: Spatial statistical (direct) methods for the construction of Radio Environment Maps

distances from the transmitter [96].

$$P_ri(d) = P_t - l_o - 10\alpha\log(d_i[m]) + X(0,\sigma) \tag{2.1}$$

Other techniques have also been proposed for the construction of REMs. For instance, Hu and Zhang [97] propose a novel framework for secure crowdsourced REM construction in the presence of false spectrum measurements. Hybrid models have also been suggested as viable solutions for the construction of IC maps. In [98], authors use a combination of the Nearest Neighbor (NN) algorithm to interpolate measurements into an image, which in the case of direct methods already forms the radio frequency component of the REM. Nevertheless, this image is further processed by selected image processing techniques to identify propagation and transmitter features. A different hybrid approach is proposed in [99], where the IC is constructed by a simple numerical propagation model. Then this original representation is corrected according to the available measurements and the Kriging interpolation.

The accuracy of REM construction techniques is usually evaluated through several location metrics. These metrics include the transmitter localization error and transmitter signal power error. To evaluate an REM from the perspective of lost opportunities and possible harm to the primary user, additional quality metrics are also part of the evaluation of the IC construction techniques. The most common evaluation metrics are Correct Detection Zone Ratio (CDZR) and False Alarm Zone Ratio (FAZR). Nevertheless, a deeper analysis of such methods lies outside the scope of this work.

2.3.2 REM architecture

Many authors classify Radio Environment Maps according to their purpose of operation (general and specific) [85, 78], their implementation (virtual and stand-alone) [77, 25], and, the most common classification in the literature, their location (local or global). In this work, we focus on the origin, extent, and purpose of the information of REMs. In this light, REMs are classified as global (centralized) and local (distributed) [79, 80] (see Figure 5).

A global REM is usually implemented, at least partially, as a network back-end system. Its principal function is to provide extensive processing capabilities. On the other hand, a

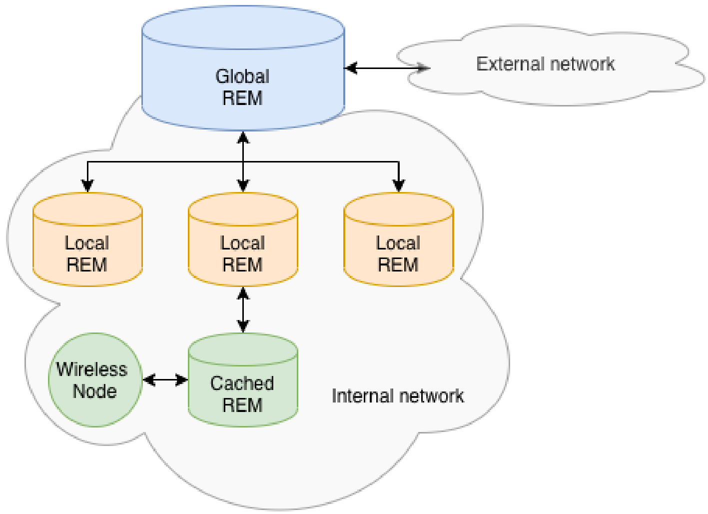

Figure 5: System architecture of a Radio Environment Map

local REM usually resides within the network of MCDs. The main goal of a local REM is to increase the responsiveness of the system and maintain a local "snapshot" of the sharing environment. Local REMs need to be synchronized with global REMs to update their experiences and information. Finally, each capable node (e.g., CR) can also keep its local REM (i.e., a cached-REM) based on information retrieved from its local REM and its measurements and experiences [100, 77]. This REM architecture is crucial in our work because it allows us to capture the interplay of different factors at different levels while considering local sharing scenarios.

2.3.2.1 REM spectrum situation The literature of DSA systems also classifies REMs as spectrum situation or radio environmental knowledge structures [85, 77]. Spectrum situation REMs are mainly composed of three aspects: spectrum sensing, spectrum situation generation, and spectrum situation application (see Figure 6).

Spectrum sensing is primarily responsible for obtaining the current state of the spectrum space (i.e., measurements) from each MCD node. This information includes the spectral

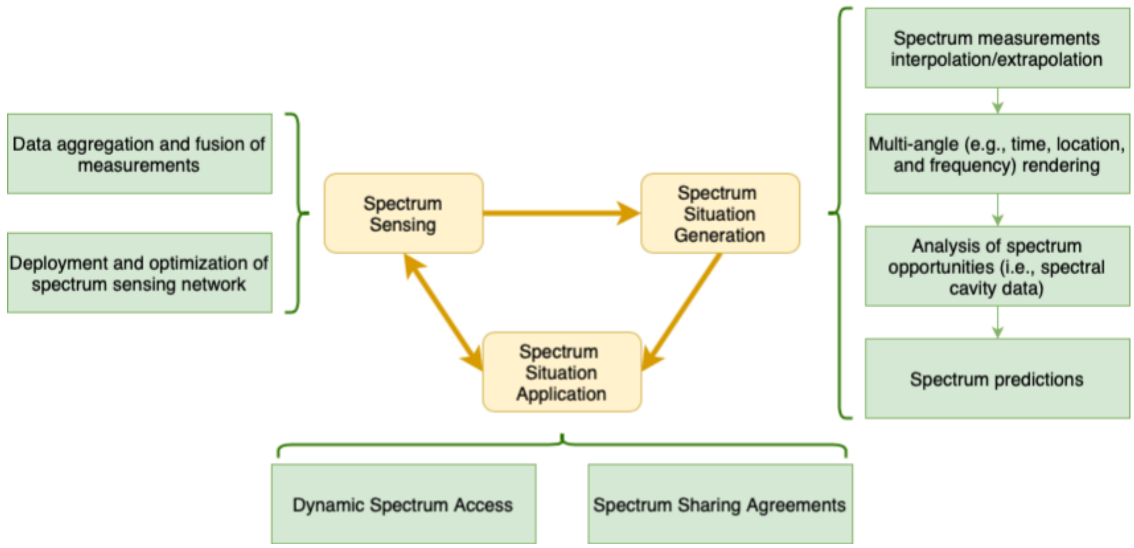

Figure 6: Spectrum situation in Radio Environment Maps

cavity information (i.e., spectrum holes)[10], spectral radiated power, spectrum modulation mode, and spectrum access protocol (i.e., strategy).

In spectrum generation, the main goal is to analyze and predict the comprehensive situation and future development trends based on spectrum sensing. An essential step in this aspect is the creation of the Interference Cartography (IC). Once the REM builds a spectrum representation, the data is presented at multiple angles.

Finally, in the spectrum application, the observation and analysis of the spectrum situation are carried out. The goal is to achieve a dynamic allocation of spectrum resources, improve spectrum utilization, and guide the actions of the different participants involved in the sharing agreement.

[10] A spectrum cavity (i.e., hole) can be obtained in the frequency domain, time domain, airspace domain, angle domain, code domain, among others. Leading to a multi-dimensional information scheme [85].

2.3.3 REM data model

Since REMs are abstractions of "real-world" spectrum situations, they are composed of several types of data. Most authors agree that the main pieces of information in any given REM are radio elements, spectrum environment, and radio sense [77, 85, 101, 100, 98]. Radio elements are information related to all devices. For instance, telecommunications operators in a region, transceiver properties, location, and mobility status. This information does not change frequently and is considered to be "static" data. Next, the environment data encloses the secondary users in a network and their usage information, interference field data, geographic properties, and terrain model. This information is highly dynamic and, hence, it is classified as "volatile" data. Finally, the radio sense is the information about the operation of the networks. For example, the provided services, policies, regulations, etc. This data is considered to be "derived" data since it can be interpolated from the static and volatile pieces of information.

2.3.4 Application of REMs in spectrum management

The original goal of REMs was to support the development of Cognitive Radio Networks (CRNs) [79, 85]. REMs allow simple devices without advanced cognitive functions to be perceived and operated efficiently. Consequently, the original application scenario for REMs was the TV White Spectrum/Spaces (TVWS) [85]. Nevertheless, the spectrum management literature shows that REMs can be easily adapted for their implementation in other wireless settings, as we explore in the following sections.

2.3.4.1 REM architectures for spectrum sharing in the radar bands Paisana et al. [84] analyze how REMs can be utilized in radar bands to enhance the awareness about operation environments of network entities. REMs also help in determining spectrum usage and propagation patterns to establish different requirements for protecting radar systems and mitigate interference between incumbents and secondary users.

Radar bands have been a successful candidate for sharing between wireless operators and radar systems[11]. These bands are used in a wide variety of applications, including astronomy, mapping, military, weather, and law enforcement. Thus, different radar systems imply different technologies, modes of operation, and interference protection criteria [102]. A network architecture based on REMs can work as an enabler for unified spectrum selection and aggregation tasks across these different types of systems.

The REM structure proposed for spectrum sharing opportunities in radar bands is depicted in Figure 7. For illustration purposes, there is a wireless network (e.g., LTE-A) located in a zone that has four different radar systems' sites in its vicinity[12]. Similarly to other REM architectures based on the spectrum situation concept (see Section 2.3.2.1), the REM-based architecture proposed by Paisana et al. is composed of: an Information and Measurement Resource Module (IMRM), a Database Module (DM), and a Spectrum Manager (SM).

Information and Measurement Resource Module (IMRM): Contains two sources of information, namely the radar systems and the network of Measurement Capable Devices (MCDs). The input for the radar systems consists of static information (e.g., location, scan pattern type, rotation period, transmit power, antenna maximum gain, etc.) and dynamic data (e.g., any scheduled change in the rotation speed of radar systems). On the other hand, the data collected from the MCD network includes the measured radar signal strength, time of arrival, measurement location, and waveform features.

Database Module (DM): Stores and lists the channels that are available in each area. Additionally, for each available channel, the DM stores the rules for its access, in particular, whether more advanced access schemes like temporal sharing are allowed.

Spectrum Manager (SM): Interacts with both sides of the sharing agreement (i.e., incumbents and new entrants). On one side, it interacts with communication network entities (e.g., Access Points (APs) and/or Base Stations (BSs)) to collect information about transmission characteristics. On the other side, the SM collects instructions generated by the DM. The goal is to combine the information received to notify the network entities of transmission opportunities. When a radar channel is selected by an SU then the SM provides

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11 Radars currently occupy a significant portion of the radio spectrum below 6 GHz.

12 The radar sites are labeled as *R1*, *R2*, *R3*, and *R4*, respectively.

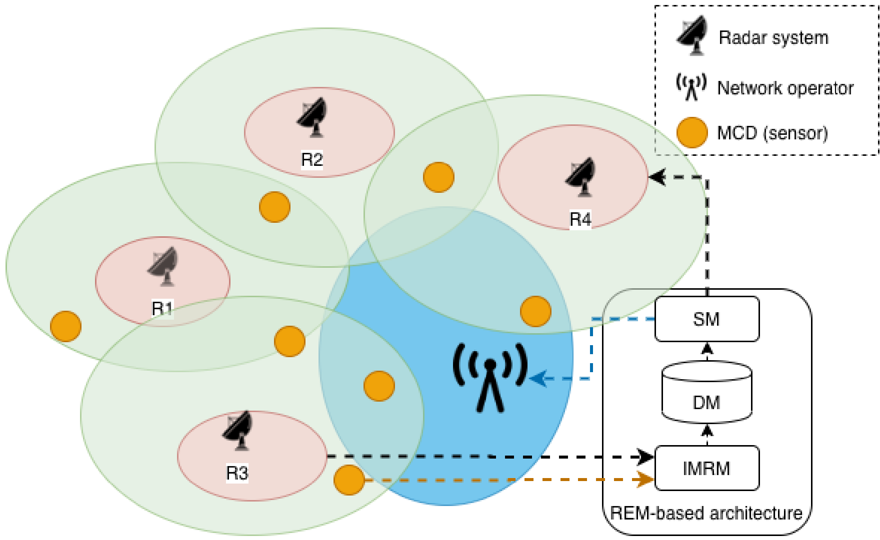

Figure 7: REM-based architecture for spectrum sharing scenarios in Radar bands

rules of sharing (e.g., resource access strategy and governance framework) for the selected channel. In the presence of conflict situations, the SM acts as a "mediator" or "coordinator" in charge of mitigating such situations.

2.3.4.2 REM for dynamic broadband access in urban areas

In [103], the authors use the results of extensive indoor and outdoor measurement campaigns[13] of several digital TV channels for the deployment of REM-based systems. The goal of the system is to provide broadband access in urban areas using the available spectrum resources.

The REM is used for the deployment of heterogeneous networks (e.g., overlapping of small cells). The objective is that information (e.g., available spectrum resources) can be obtained through the different elements of an REM. The authors propose the deployment of a local REM, whose coverage area is in the order of hundreds of meters, to serve as the indoor REM database. A global REM is also part of the system architecture. This global entity covers a much larger area and act as a centralized unit of data aggregation and decision-making. The focus of this global REM is outdoor databases, which can include

[13] Measurements taken in Poznan, Poland, and Barcelona, Spain.

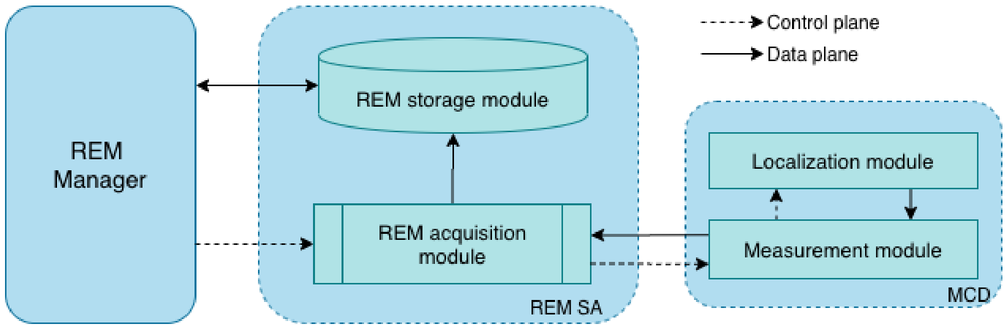

Figure 8: Functional REM architecture for its application in cellular networks

urban, suburban, and rural areas.

2.3.4.3 Application of REMs in mobile networks We conclude this section by exploring how Radio Environment Maps (REMs) add value to cellular (i.e., mobile) networks. In [104, 105], we find examples of how REMs provide solutions for planning tools and Radio Resource Management (RRM) techniques in traditional mobile networks.

An REM can be thought of as a knowledge source used to dynamically store information related to the radio environment of wireless systems and devices. In this way, a layered REM architecture can be a key component in helping cellular networks at different levels and different RRM tasks. In this scenario, an REM is composed of three parts (see Figure 8): Measurement Capable Devices (MCDs), an REM data storage and acquisition module (REM SA), and an REM manager. MCDs are network entities (e.g., CRs or user equipment) that are capable of measuring the radio environment at different locations. The REM SA has two functions. The data acquisition module accounts for all communication with the various MCDs. It sends measurement instructions to MCDs, collects measurement reports, and stores these in the storage module. Finally, the REM manager generates and maintains the REMs. It decides which measurements are performed by which nodes and when.

REMs can be utilized on "LTE automatic neighbor relation". Accurate identification of base stations' neighbors is vital for the proper operation of RRM procedures like mobility and interference management [106]. By placing REM coverage maps with different temporal and spatial characteristics at different hierarchical layers, it is possible to obtain and maintain more precise, up-to-date, and reliable neighboring information.

Layered REMs are also useful to introduce new technologies in cellular networks. Operators typically introduce a new Radio Access Technology (RAT) in their network through a process commonly known as refarming[14]. Usually, the coexistence of the two technologies is handled by leaving enough spectrum guard bands, which inevitably wastes resources. Layered REMs can be used to automatically find and set relevant parameters (frequency reuse factor, guard band interval, etc.) in these specific areas. With precise interference information on each location coming from the REM, the guard band can be adjusted in an optimum way to prevent interference and minimize the waste of spectrum resources.

A REM-based radio resource management technique can be used to calculate interference and energy consumption in heterogeneous networks (HetNet). After allocating spectrum, the interference and energy consumption of the network can be estimated. It is essential to estimate the interference on each User Equipment (UE) to satisfy the UE's requirements. REMs can provide information about signal-to-interference plus noise ratio (SNIR) at a particular location (e.g., UE's location) [105]. Therefore, REMs can be utilized for these estimations instead of other traditional techniques. This can supply the service provider with additional tools to ease the RRM procedures.

Finally, REMs can be implemented to reduce the number of drive tests. In general, network operators are required to conduct drive tests to collect performance metrics that guide network deployment and operation. The main goal of drive tests is to detect where coverage holes are located, new sites may be deployed, power configurations may be optimized, or antenna tilts and azimuth may be changed [108]. The inclusion of REMs can increase the reporting rate or reduce the logging rate to minimize the impact on the terminal memory in drive tests. In addition, the intelligence embedded in the layered REM allows for efficient distribution of drive test data storage at different hierarchical levels of the system architecture.

[14] A gradual migration introducing the new RAT in the existing frequency band in a predefined area [107].

		Subtractability	
		Low	**High**
Exclusion	**Difficult**	Public Goods	Common Pool Resources
	Easy	Toll Goods	Private Goods

Table 3: A general classification of goods

2.4 Spectrum as a Common Pool Resource

The commons is a general term used to refer to a shared resource in which each competing stakeholder (e.g., fishermen) has an equal interest in a given resource (e.g., fisheries) [109]. Because the term is often conflated with "open-access commons", researchers in this area typically refer to Common Pool Resource (CPR) as systems that can have a variety of access permissions [110]. CPRs are natural or man-made resources shared among different users. These resources are defined by two main features: i) they are sufficiently large so that it is costly to exclude potential beneficiaries from using them, and ii) they are characterized by a high degree of subtractability or rivalry of consumption (see Table 3) [111, 112]. We can find a wide range of examples of goods defined as commons, which have been widely explored in the CPR literature: fisheries, forests, innovations, online communities, hacker communities, among others [113, 114, 115, 116, 48, 117]. A less widely-known example of a CPR system is the exploitation of electromagnetic spectrum bands for wireless communications.

Placing spectrum within the CPR context, spectrum bands have a subtractability feature, given that if a user transmits using an allocated band, its transmissions add to the noise level for all other users in the same band. Based on the Shannon-Hartley theorem, an increase in noise[15] decreases the available channel capacity to other signals transmitted in the same band [119, 120]. Inevitably, the band may reach a point in which it becomes unsuitable for any additional wireless communications in the same frequency, space, and/or time (i.e., a

[15] As Dytso et al. argue, this noise is a Gaussian interference input acting as a "foe" of other signals [118].

spectrum band). As to the excludability characteristic of CPRs, it is relatively difficult to exclude an arbitrary user from most regions of the radio-electric spectrum. Technologies that exploit spectrum bands have made it difficult, complex, and costly to do so. For example, it would be a complex and costly task to exclude any given user from transmitting and receiving wireless signals using a Bluetooth and/or Wi-Fi transceiver [121]. Pirate radio is yet another example of the difficulty of exclusion. Furthermore, cellular jammers and GPS jammers are readily (though illegally) available [122, 123]. Consequently, based on the common good features defined by Elinor Ostrom [51, 112, 49], many authors have agreed that the exploitation of radio-electric spectrum bands for wireless transmissions is consistent with the definition of a CPR [43, 1, 29, 42]. This definition allows us to leverage the multiple resource access strategies and governance frameworks that have been vastly developed and studied in the CPR literature.

2.4.1 Resource access strategies in CPRs

Resource access strategies are highly heterogeneous components in the literature of CPRs. The access strategy is correlated with the governance framework and the community structure in place.

Irrigation systems are one of the canonical examples of CPR management [124]. In most cases, irrigation systems are either managed by users' associations or self-governed agreements. In the first case, the community forms an association in charge of the management of the irrigation systems. These associations are in charge of, for instance, the allocation rules and water rights. They also regulate monitoring tasks to ensure that "water quotas" are met by the different members. On the other hand, in self-governing schemes, neighbors negotiate property rights over water resources (e.g., access to underground water sources)[16].

In the case of fisheries [125], similar access strategies are defined. In most cases, local associations determine the resource availability before assigning harvesting rights to fishermen. Based on the available resources, a resource access strategy is determined in the

[16] The system creates an association to solve usage conflict situations. Nevertheless, the association has little control over the formation of the private agreements.

community association. For this purpose, different strategies are defined based on the location, time, and fishing capabilities of the different members. For instance, small boats are granted harvesting rights to locations closer to the shore, where traditionally fewer resources are available; but boat access is easier. The community also dictates the rules and strategies for monitoring fishing activities.

In the case of the innovation commons [114] and hackerspace communities [116], we found two different types of resources. First, we have physical resources (e.g., construction tools, samples, among others) and virtual resources (e.g., information, knowledge, among others). In these commons, the communities or institutions have developed similar agreements for the usage of physical tools as we found in other CPR management systems[17] [126]. On the other hand, for intangible or virtual resources, the communities have developed different mechanisms for their utilization. As an example, both create a "pool of resources" regarding the knowledge and expertise of their members. In this way, a member can contact another member for help with a particular project while helping other users in the space.

2.4.2 Governance frameworks in CPRs

A commonly discussed feature regarding CPR systems is, without a doubt, the government schemes that have emerged in the regulation and control of this type of goods. We observe different approaches for both governance structures and enforcement systems, going from formal institutions in command-and-control to self-reporting and self-policing [52]. However, as Ostrom explained, defining governance structures in CPRs is not a straightforward task [126]. To achieve a "smooth" governance process we need: 1) resources and their uses to be constantly monitored, 2) rates of changes in the resources to be limited, 3) to maintain close face-to-face communications and dense social networks, 4) outsiders to be excluded at relatively low costs, and 5) users should agree to constant monitoring and enforcement of the rules [48]. As we explore in the following sections, we find a significant number of successful governance schemes within the CPR literature [127].

[17] For instance, in the hackerspace community, the members detail the rules for leaving personal tools in the space. These rules specify that tools must be labeled with the owner's name and contact information, and must be placed in an area agreed to by the community.

Baland and Platteau [128] found that through layered adaptations of governance mechanisms not only do small-scale CPR users enjoy legally guaranteed access rights to the resources but also that, through their local organizations, they are in charge of establishing regulations for the internal distribution of these rights. Additionally, users are responsible for the control of various types of resource access strategies. Formal government structures (e.g., prefectures) are in charge of laying down a general framework of basic principles and fundamental rules to be implemented at the community level. Note that these rules are set after adjustments have been made to local needs and conditions through locally complementary or supplementary measures. External agencies (e.g., governmental entities) assist the community in sanctioning processes. This clearly shows that multiple levels (i.e., layers) of government can be overlapped to achieve more efficient governance of CPRs.

Wade and Ostrom [129, 130, 51] showed that nested levels of appropriation, provision, enforcement, and governance (i.e., polycentric governance) are a viable option for CPR management. For this purpose, community or corporate organizations are in charge of managing the common property. A key to the effectiveness of these organizations is that they are based on existing structures of authority.

The work by Peter Leeson [55, 56] shows that governance without the intervention of formal government forms, at least as principal actors, is also a possibility. In such systems, all appropriators of CPRs repeatedly show their capacity to organize themselves, create rules, monitor others and themselves, and successfully enforce the agreed-upon norms. Hence, these self-governed organizations can create self-organized and self-controlled institutions without the need to fully rely on central authorities (e.g., governmental entities). As explained by Ostrom in [51], self-governance institutions that have emerged have been sustained over long periods without the participation of any external agency (at least as principal actors). Thus, self-governance has become a viable mechanism to govern complex CPRs.

So far, we have explored the great flexibility in the CPR system definitions for the management and exploitation of common goods. Particularly, the distinct and successful methods to define, access, and govern a CPR. In this light, the analysis of spectrum sharing through the lenses of CPR management allows us to add such adaptability and usability to our local sharing agreements. Besides, the literature of CPRs offers a rich selection of frameworks for a deeper analysis and study of this type of goods, as we explore in the following sections.

2.4.3 Frameworks for the analysis of CPRs

The development and use of frameworks is the most general form of theoretical analysis. Hence, to analyze and study the different parts present in managing and governing CPRs many frameworks have been proposed. These frameworks are valid tools to identify the elements and their general relations within institutional[18] arrangements. They attempt to identify the universal elements that any theory relevant to the same kind of phenomena needs to include [132].

2.4.3.1 Institutional Analysis and Development (IAD) framework A common framework utilized for the analysis of institutional arrangements in CPRs is the Institutional Analysis and Development (IAD) framework [133]. The IAD framework is a multi-tier conceptual map that allows identifying the major types of variables that are present in different institutional arrangements (see Figure 9). The IAD framework assigns all relevant explanatory factors and variables to categories and locates these categories within a foundational structure of logical relationships. The IAD framework has its origins in a general systems approach to policy processes, where inputs are processed by policymakers into outputs.

Exogenous variables: Or inputs. Include the contextual factors such as the attributes of the community, environment conditions (i.e., nature of the good/biophysical conditions), and rules-in-use. These components encompass all aspects of the social, cultural, institutional, and physical environment that set the context where an action situation is situated.

Action situation: This is the "black box" where decisions and choices are made. It is the core element of the IAD Framework, in which individuals (acting on their own or as agents of organizations) observe information, select actions, engage in patterns of interaction, and realize outcomes from their interactions. The working components of an action situation

[18] As defined by North [131], institutions are "[t]he set of rules used by a set of individuals to organize repetitive activities that produce outcomes affecting those individuals and potentially affecting others." Based on this definition, we can see that CPRs are indeed institutions in themselves.

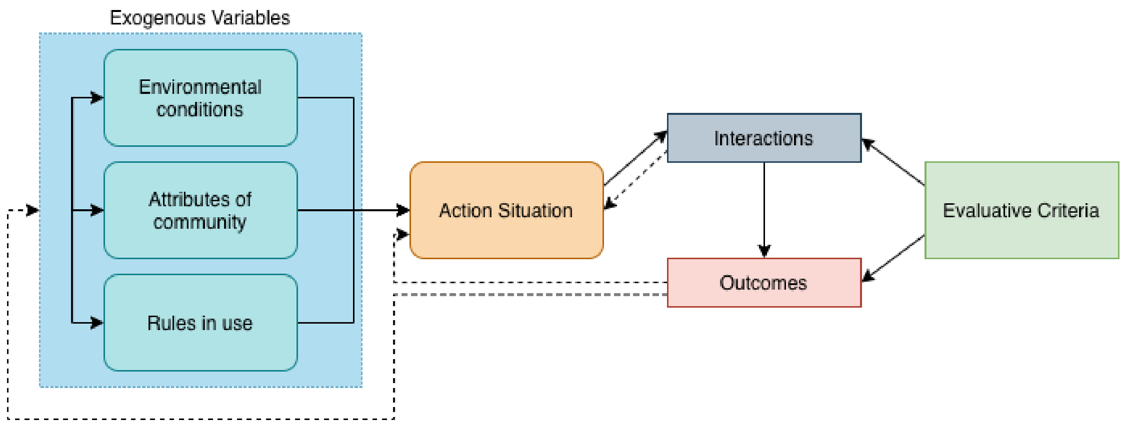

Figure 9: Basic components of the IAD framework

specify the nature of the relevant actors as well as the resources and options they face; thereby, it serves as a generalization of the "rules of a game". Within the action situation, the definitions of the participants, their positions, their actions, the information they possess, their links, and their benefits are determined (see Figure 10).

Outcomes: Are shaped by both the outputs of the action situation and by exogenous factors (i.e., inputs). They represent the results of the activities in the action situation given an environment defined by the exogenous variables.

Evaluative criteria Participants evaluate all the components of the process: actions, outputs, and outcomes. These evaluations may affect any stage of the system operation. Typical evaluation criteria include the efficiency in resource usage, equity in distributional outcomes and processes, legitimacy as seen by participants in decision processes, etc.

Interactions: Feedback and learning processes are triggered by actors' evaluation of actions and outcomes based on the information they can observe and process. Feedback may impact any component of the IAD framework, and different levels of learning loops may be used to distinguish more extensive processes of reconsideration.

2.4.3.2 Ecology of Games (EG) framework Governance structures enclose the internal definitions of Common Pool Resources (e.g., resource definition and resource access

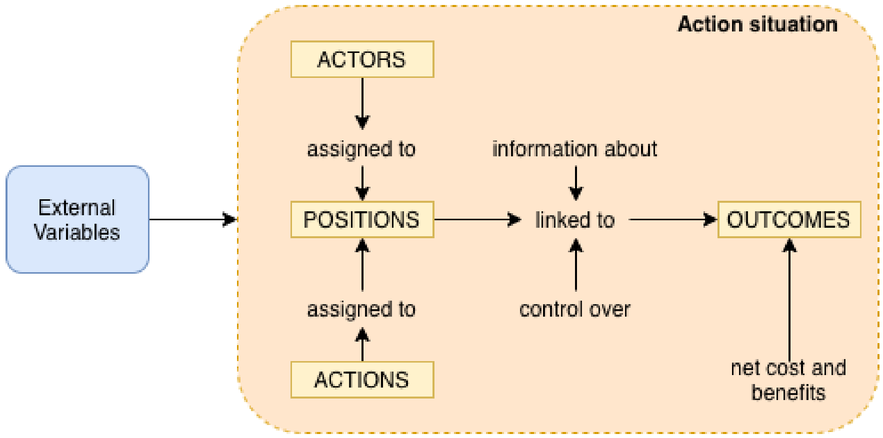

Figure 10: The internal structure of the *action situation* in the IAD framework

strategy). These structures are usually the result of multiple policy "games" operating simultaneously within a geographically defined policy "arena". A policy game consists of policy actors participating in a rule-governed collective decision-making process called a policy "institution". Finally, the combination of the policy institutions that exist at a particular time and place define the institutional arrangements of governance [134]. The Ecology of Games (EG) framework uses the same definitions of the IAD framework[19], but stresses the fact that multiple actors are involved with governing the authority of more than one institution. In other words, the EG framework adds a layer of analysis by combining overlapping jurisdictions. For this purpose, the policy outputs and outcomes are the functions of decisions made in multiple "games" over time in a given location [136].

The EG framework relies on six interrelated concepts for the construction of these policy interactions, specifically policy games, policy issues, policy actors, policy institutions, policy systems, and time [136]. Figure 11 illustrates the simplest multi-game setting featuring two policy actors (A and B), two policy institutions (X and Y), and two policy issues (*1* and *2*) taking place over a single policy system (S).

Policy games: Are defined by the constellation of policy actors, policy institutions,

[19] Institutional analysis defines institutions as the set of formal rules and informal norms that govern decision making, which could apply to the collective choice or operational rules regarding resource use [135].

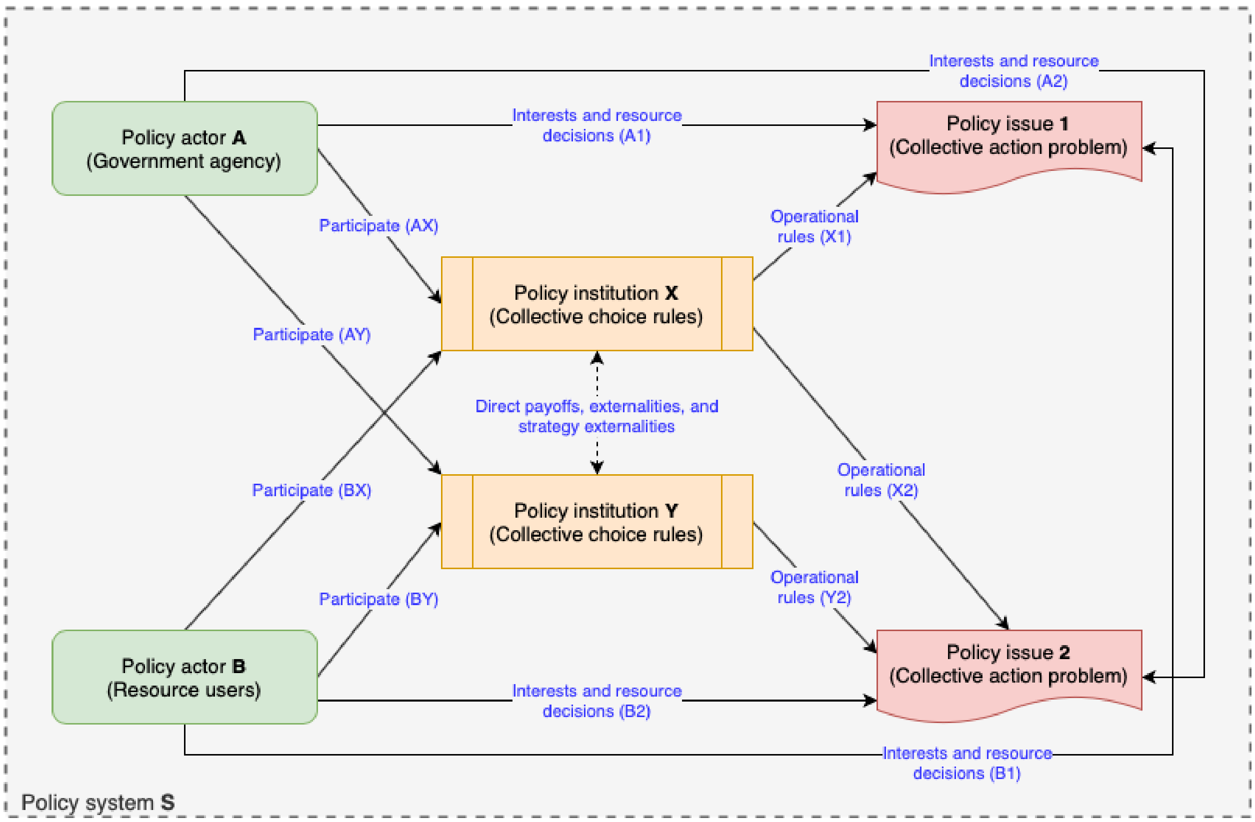

Figure 11: Ecology of Games framework - Simplest multi-game setting

and policy issues that are present in a geographically defined policy system. A game occurs when actors jointly participate and make decisions according to the collective choice rules of a specific policy institution. It is necessary to point out that a game is not equivalent to a policy institution[20].

Policy issues: Policy issues involve some type of collective action problem, such as water supply, water pollution, air pollution, traffic congestion, access to limited resources, etc. The strategic structure of the policy issues is the same as in traditional game theory[21]. The EG framework adds the complication that issues may be interconnected through biophysical, economic, or social processes. Hence, policy decisions regarding one problem may directly influence payoffs in other issues.

Policy outcomes: Are the results of the individuals' decisions regarding the use of resources involved with each policy issue. For example, the amount of non-point source pollution that flows into the watershed, fish harvested from a fishery, among others.

Policy institutions: Consist of sets of rules, norms, and strategies that structure how actors make collective decisions regarding the operational rules about particular policy issues (e.g., assignation of resources). Actors usually refer to policy institutions as "planning processes" or "policy venues" that shape the implementation of specific resource management activities. Each policy institution that exists within an EG framework provides an opportunity for different actors to interact and make collective decisions, and the resulting policy outputs have jurisdiction over some portion of the affected issues[22].

Policy actors: Are individuals (or groups of individuals) that have some interest or stake in the outcomes of decisions made in policy intuitions and the resulting operational rules. Examples of policy actors are resource users, political actors, interest groups, regulators, etc. Many policy actors also make specific resource use decisions, such as the appropriation of resources or the provision of public goods. Actors participate only in policy institutions with

[20] A sports metaphor can be helpful to differentiate both concepts. A football game only occurs when the players take the field, but football rules still exist even when the players are not participating.

[21] Payoffs are interdependent and equilibrium outcomes (if they exist) are often inefficient.

[22] Policy institutions typically have jurisdiction over multiple issues at a given time, and hence conversely policy issues are linked to multiple institutions [136].

jurisdiction over issues they care about. Policy actors also form networks with other actors in the same policy institution, policy game, and/or policy system.

Policy systems: Are geographically defined territories that encompass multiple policy issues (e.g., limited resource supply), multiple institutions (e.g., government regulations), and multiple actors (e.g., local, state, and federal government agencies). Policy systems can be defined at different scales (e.g., local, regional, statewide, national, and global.). The policy games that exist in a particular geographical territory constitutes a complex adaptive system that changes over time. Change can be endogenously driven by the actors as they participate in different institutions, try out different strategies, engage in policy learning, and even create and destroy institutions. Change can also be imposed exogenously according to the dynamics of the underlying resources.

2.4.3.3 ADICO Grammar of Institutions framework A salient feature of the study of CPRs is that they are categorized as independent institutions. This definition is key to leveraging the benefits of the ADICO framework (i.e., the ADICO Grammar of Institutions). This "grammar of institutions" is the perfect complement for the EG and IAD frameworks. It is an effort to develop a common framework for understanding strategies, norms, and rules as different types of institutional statements (see Table 4). These statements are governed by the following underlying grammatical structure [137, 138]:

- Attributes (A): The participants or actors to whom the institutional statement applies (i.e., the agents of the system).
- Deontic (D): The deontic operators or contents dictate the actions allowed to the agents, specifically obligated, permitted, and forbidden.
- Aim (I): Describes the action or outcomes to which the institutional statement applies (i.e., the actions related to the deontic operator for each agent).
- Condition (C): The set of parameters that define when and where a statement (i.e., rule, norm, or strategy) applies.
- Sanction (Or else) (O): The consequence of non-compliance with a given institutional assignment.

Statement	Components
Strategies	AIC only
Norms	AIC plus D
Rules	Full ADICO

Table 4: Structure of institutional statements using the *ADICO Grammar of Institutions* framework

2.4.4 Modeling CPRs

The literature regarding the study of CPRs has shown that it is possible to avoid Hardin's "Tragedy of the Commons" [109] in open access resources. Further, it has been proven that such "Tragedy" is a special case, not a general one. For this purpose, it is necessary to build a carefully-designed endogenous institution [126]. This process is neither a straightforward nor an easy task. The specific processes leading to institutional change are often difficult to study in the field due to a large number of factors potentially involved, and because such processes often occur on temporal scales beyond the scope of most research efforts. Laboratory experiments can offer a way out of the problem. Although experiments significantly contribute to the understanding of the dynamics of common-pool resource situations, the number of factors that can be reasonably tested in the laboratory is limited [112]. For instance, it is complex to design experiments involving long-term interactions among participants, create studies needing large samples of subjects, replicate "real-world" circumstances, among others.

For the analysis and study of CPRs, the creation and usage of computational models and simulation tools represent a valid alternative to both empirical and laboratory studies. The development and use of models involve making assumptions about a set of variables and parameters, based on a particular theory or framework, to derive predictions about the results of combining these variables. Different models (e.g., game-theory models, mathematically-based models, etc.) are used to explore systematically the consequences of these assumptions on a limited set of outcomes. But most importantly, multiple models are compatible with most theoretical frameworks [132]. For instance, authors in [138] develop an ABM simulation based on the principles of polycentrism using the IAD framework, while defining rules, norms, and strategies via the ADICO Grammar of Institutions method.

Many authors studying CPRs have successfully explored different issues through computational models and simulations. Given the nature of a CPR and the dynamics of its users' behaviors, Agent-Based Modeling (ABM) has become one of the most beneficial tools to study the dynamics of institutional developments in such systems [139, 138, 140, 141]. The main advantage of ABM methods is that they allow to design of virtual experiments using a more flexible set of conditions than what is feasible in the lab and to analyze their long-term dynamics more easily than what is possible in the field [142].

2.5 Agent-Based Modeling (ABM)

In general, the main objective of modeling is to allow the modeler to work with a representation of the "real world". Thus, a model is a "simplification of the real world and does not contain all of the details and inconsistencies that are present in it" [143].

Given that "real world" examples of spectrum sharing scenarios are limited or are currently being developed and implemented. There is limited access to data about their performance and overall working characteristics. In this light, modeling appears as a suitable tool for their representation, study, and analysis. However, these are not simple scenarios. They are characterized by multiple agents at multiple levels, and several and diverse external stakeholders (e.g., regulators). Because of this, it is necessary to utilize a modeling tool that permits us to capture the interaction among sharing participants and their approach toward the available resources. In this way, we believe Agent-Based Modeling (ABM) is an appropriate tool for modeling and analyzing spectrum sharing settings.

Several researchers, developers, and modelers consider Agent-Based Modeling (ABM) a philosophy more than a simulation tool or technique [144]. The main application of ABM and Agent-Based Modeling and Simulation (ABMS) is to model complex systems composed of (many) “agents”. These agents have behaviors (e.g., strategies, cost functions, among others) often described by rules and interactions with other agents. One of the fundamental advantages of ABMS is that agents are modeled individually and independently. However, the full effects of the diversity that exists among agents (and their attributes) can be observed as it gives rise to the behavior of the system as a whole [145]. In other words, ABMS allows the modeler to observe the macro-phenomena by defining (usually simple) rules at the more simple and basic unit, the agent. Additionally, patterns, structures, and complex behaviors of the system as a whole can often be observed in models created under the ABM philosophy.

Applications of ABMS are not concentrated in a particular field. Instead, we can find applications of ABM in a broad range of disciplines. For instance, we have examples of ABM in the stock market [146], prediction of disease transmission and epidemics [147], to model the immune system [148], to understand purchasing behaviors [149], to analyze resource allocation [150], among others. Agent-Based Modeling has also been utilized in the context of the spectrum and spectrum regulation. Some examples include the exploration of the conditions of spectrum trading markets [151], the study of spectrum secondary markets [152], the analysis of spectrum auctions [153], the study of wireless Internet of Things (IoT) networks [154], to analyze the diffusion of new technologies [155], to model fraud in telecommunications services [156], among others.

2.5.1 Structure of an Agent-Based Model

Usually, a model created under the Agent-based Modeling philosophy is composed of three main elements (see Figure 12[23]):

- A set of agents. These agents are independently and autonomously modeled with their attributes and behaviors.
- A set of agent relationships or interactions. Typically, an underlying topology defines how the agents are connected and, consequently, how the interactions might occur.

[23] Image taken from “Modeling civil violence: An agent-based computational approach” by Epstein [157]. In cellular automata, the Moore neighborhood is defined on a two-dimensional square lattice and is composed of a central cell and the eight cells that surround it [158].

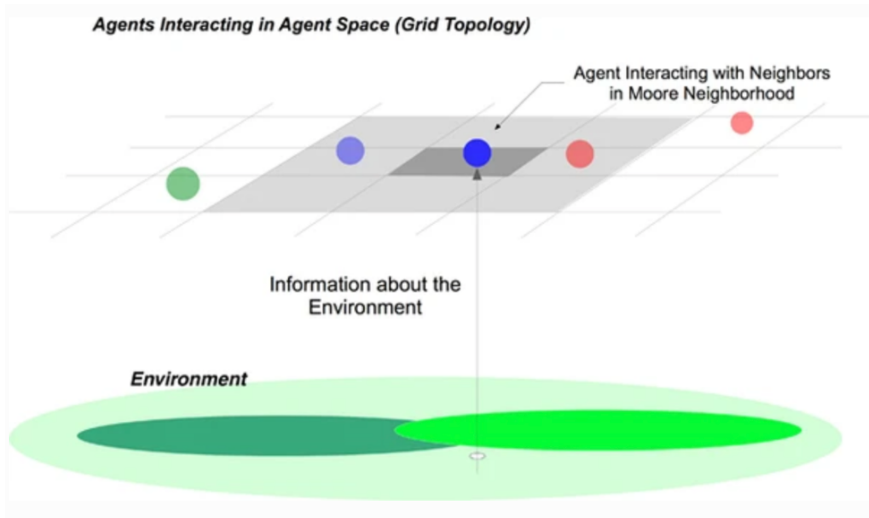

Figure 12: Basic structure of an Agent-Based Model

- The environment. This component refers to the agents' environment or physical "world" where the agents are placed and interact.

2.5.1.1 Agents In ABM, one of the most crucial characteristics of agents is their ability to act autonomously. For this purpose, agents are endowed with behaviors[24] that allow them to make independent decisions. Besides its independence, an agent is a self-contained, modular, uniquely identifiable, individual with attributes (e.g., cost function). Nevertheless, agents are not stand-alone entities. An agent is continuously interacting with other agents and the environment. In Figure 13, we can find the typical structure of an agent within an ABMS. In general, an agent is constructed by a set of attributes and a set of methods. The attributes of an agent can be static (e.g., unique identification) or dynamic (e.g., age). On the other hand, an agent method constitutes the different actions or strategies that an agent has in response to its interactions.

[24] Can be specified by anything from simple rules to abstract models, such as neural networks or genetic algorithms [149].

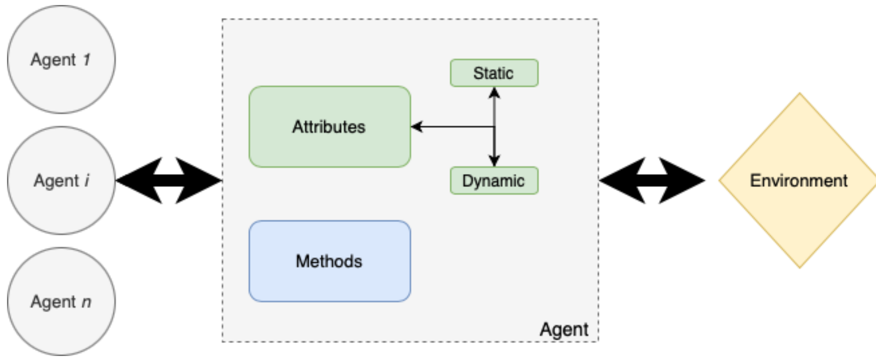

Figure 13: Basic structure of an *agent* in ABMS

2.5.1.2 Environment In general, the environment of an ABM model is defined as the "physical" space where agents are placed and interact [159]. However, the environment can also be defined as the "first-class abstraction that provides the surrounding conditions for agents to exist and that mediates both the interaction among agents and the access to resources" [160]. Thus, the environment is an independent block with its own set of responsibilities to provide the agents with the surrounding conditions to exist. The environment also mediates both the interaction among agents and the access to resources (i.e., interactions with the environment itself).

2.5.1.3 Interactions There are two types of interactions in ABM, namely agent-to-agent and agent-to-environment. Interactions are a key aspect in ABM, agents need to interact to solve problems or simply reach their goals. Further, interactions allow the coordination, cooperation, or competitions schemes that help the emergent phenomena to appear [161].

2.5.2 Adding learning capabilities to ABM

ABM's philosophy has proven to deliver valuable insights into complex problems such as the analysis and study of CPRs [162]. An important concern with ABM computational models is the fact that just a few models have been able to make use of an adaptive mechanism. This refers to the ability of a given agent to enhance its learning capabilities or even the potential of coming up with a new strategy of how to take action.

ABM models and simulations, in general, involve the following steps. First, manual development of an agent model, which in most cases is rule-based (i.e., follows simple behavior rules). Second, ad-hoc tuning of a large number of parameters about both, the agent behaviors and the overall model. Finally, validation of the model usually takes the form of qualitative expert assessment or it is based on the overall "fit" of the aggregate behavior it is trying to imitate [101]. This traditional construction of models, especially its rule definition, tends to limit the ability of the model to dynamically become a close abstraction of the "real-world" phenomena it is trying to emulate.

At the same time ABM research has been gathering momentum, so has Machine Learning (ML)[25]. If the ABM community can make use of the knowledge and research developed by the machine learning community, it would greatly facilitate the study of ML adaptation within ABM [163]. Machine learning can enhance ABMs' capabilities in two ways, namely endogenous modeling and exogenous modeling [164, 165, 166].

2.5.2.1 Machine learning endogenous modeling in ABM In general, endogenous modeling provides agents participating in the ABMS with machine learning techniques to improve their performance. First, machine learning techniques can be used to provide the individual agents a sort of intelligent behavior that analyzes data of past executions to learn from such experience and try to maximize some outcome. In other words, ML can be utilized to enhance the agents' learning capabilities. Machine learning techniques can also be utilized to tune some initial parameters (e.g., utility function) of the agents to reach some local maximum. In other words, fitting ML models to bootstrap the agents' behavior [165, 167].

Enhancing ABM agents' internal models: If we were to observe both ABM and ML from a bird's eye perspective, we can observe that both, the "ABM-cycle" and "ML-cycle", utilize fairly simple algorithmic structures to control their flow of operation. Roughly, these

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From the perspective of an area of artificial intelligence specifically concerned with the adaptation and building of internal models. Machine learning is the term used throughout this work. However, the models and techniques are also considered a part of Data Mining, Big Data, Knowledge Discovery, among others algorithms can be described in four phases: initialize the system, observe what is happening, refine the system, and take actions [163].

The "ABM-cycle" can be broken down into three main steps. First, initialize both the world and the agents. Second, the agents observe the world. Finally, each agent takes action based on the current observations and its internal model. After an action is taken, the agent goes back to observe the world. If a new step were to be incorporated between the agent's observation and action tasks, the ABM cycle can become adaptive. In this new step, each agent adapts their internal model or engine (see Figure 14 (a)).

The "ML-cycle" can be broken down into four main steps. First, create an initial internal model. Second, observe the world and take note of, for instance, the received rewards. Then, on the third step update the internal model. Finally, take an action based on the internal model and the current observations (see Figure 14 (b)).

It is necessary to point out that although both cycles are very similar, integration of the ML and ABM cycles could be done in many ways. In this dissertation, we use the cycle integration shown in Figure 14 (c) [163, 167].

When integrating ML and ABM in endogenous modeling, the goal is to create agents with the ability to compute independent strategies that evolve according to the environment in which they act [165]. Consequently, one question that must be answered during the construction of such models is whether the machine learning technique should be supervised or unsupervised [163]. In the case of supervised methods, an external "teacher" determines whether any action taken was correct or incorrect. Additionally, supervised learning requires explicit knowledge of what actions provoked what rewards (i.e., a mapping of inputs and outputs) [168]. On the other hand, in unsupervised learning techniques, agents take actions and occasionally gain rewards but there is not necessarily a chain of causation from any action to reward. Unsupervised learning does not require explicit knowledge of what actions provoked rewards but, instead, simply builds a model of how the world behaves [169].

Even after the family of techniques has been decided upon, there are still many specific algorithms that are more or less useful, and must be carefully considered. To model the agent's internal models, we can use some methods derived from the studies on artificial intelligence, such as Artificial Neural Networks (ANN) and evolutionary algorithms. ANN

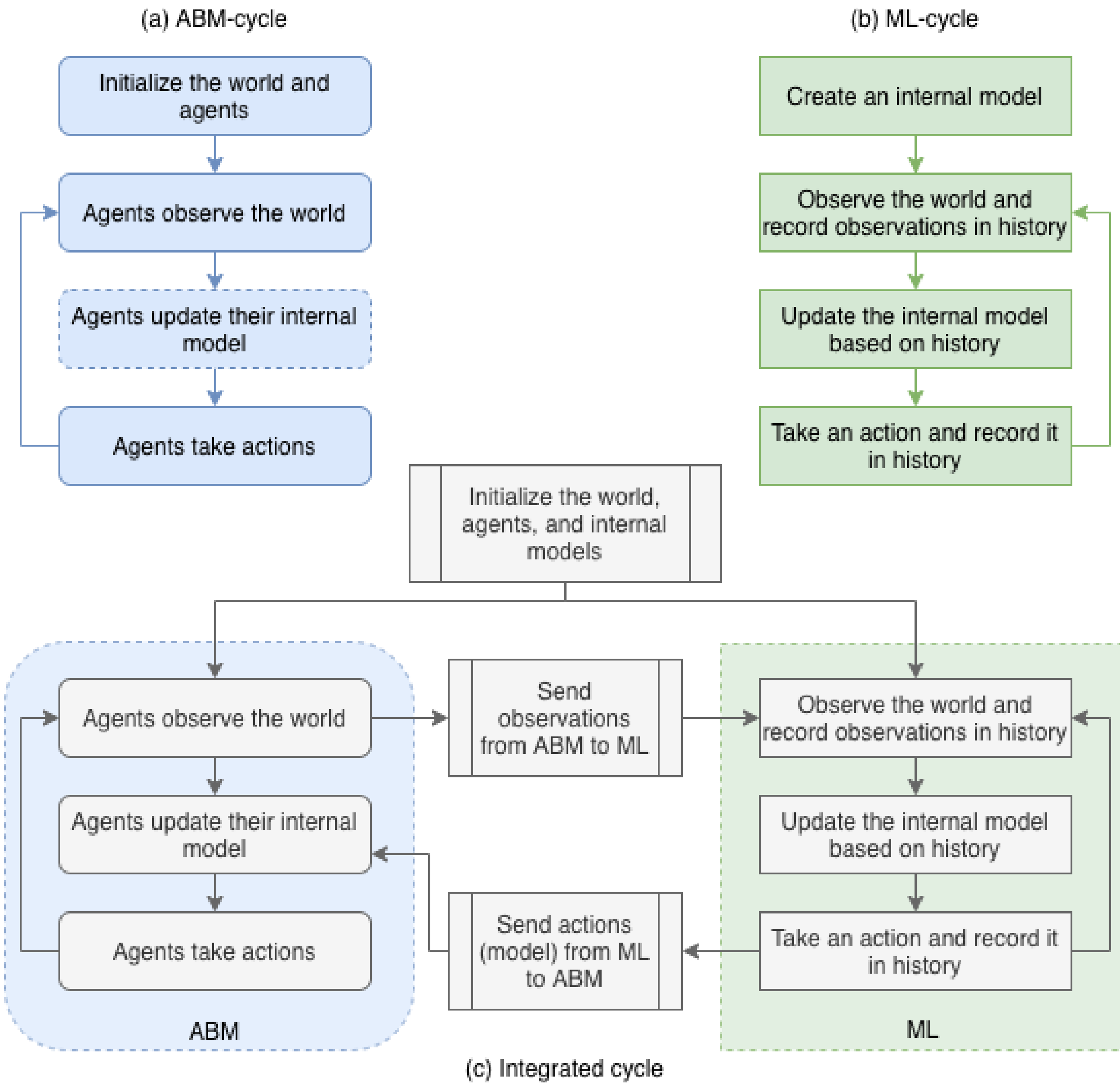

Figure 14: Integration of the ABM and ML algorithmic structures

methods are based on a collection of mathematical functions, trying to emulate nervous systems in the human brain to create learning through experience. ANN techniques are good at classifying large amounts of data fairly quickly, but in the end, they do not yield white box results[26] [170, 171]. Evolutionary algorithms (i.e., reinforcement learning), on the other hand, derive from observations of biological experimentation. In reinforcement learning, agents make a series of decisions to achieve a goal in an uncertain and complex environment (i.e., a game-like situation). Thus, the agents employ a "trial and error" algorithm to come up with a solution to the problem. In the process, agents receive either rewards or penalties for the actions they perform. The goal is to maximize the total reward [172]. It is necessary to mention that simpler algorithms, such as decision trees, are also a good option in the creation of the agent's internal models. Decision trees do create very white box results but are not very good at classifying continuous data [165, 163].

Bootstrapping ABM agents' behavior: Endogenous modeling also allows us to initially define the internal models of the agents based on historical data and ML algorithms. The key difference with the previous technique is that an ML algorithm is set to be the internal engine of the agents during the initialization phase. Further, such a model is fitted with future observations (i.e., data) but the internal model does not change as the simulation progresses [173, 101].

In general, these initialization-based models are created from four main parts, that is a conceptual model, a data source(s), an agent generation system, and a simulation engine (see Figure 15(a)). The conceptual model includes a purpose statement that describes the goal of the model, the agent types, the agents' attributes, and the environment type and variables. The data source system generates or contains the data to be used to generate the agents. The data-driven agent generation system, the core of the approach, takes the data and the conceptual model and creates data-driven agents based on machine learning techniques. Finally, the simulation engine runs previously specified scenarios using the generated agents. To generate such agents it is necessary to establish a data flow that captures the internal

[26] White box models tend to have observable and understandable behaviors, features, and relationships between influencing variables (i.e., features) and the output predictions (e.g., linear regressions and decision trees). On the other hand, in "black box" models, after the algorithms execute for a while, it is difficult to determine how they are making their decisions.

representation between the different components (see Figure 15(b)). This data pipeline contains three main processes, specifically data preparation, attribute model training and fitting, and agent behavior creation.

The specific process to create each type of agent, based on the historical data and machine learning techniques, is depicted in Figure 15(c). The first step is to filter the agent data at the individual level and then separate it into attribute data and behavioral data. From this point on, the process continues along different paths. The attribute data is used in initializing attributes; whereas, the behavioral data is used in creating behavioral rules. Individual-level behavioral data provides signals that represent human actions (e.g., purchase). Behavioral data is organized and transformed in a way that each action and related parameters are captured as a single record (process 3.4). These records are then used in training a machine learning model (process 3.5). In this way, behavioral patterns are captured through a trained machine learning model. This model is then encapsulated as a function and turned into agent programming language statements (process 3.6). In the last step (process 3.7), an actual agent program is created where the model skeleton identified at the conceptual model is used as the blueprint of the agent.

2.5.2.2 Machine learning exogenous modeling in ABM Exogenous applications focus on using machine learning techniques to analyze the resulting data from ABMS [164]. The main intend of exogenous ML modeling is to reveal interesting patterns in the data, predict the outcome of unseen situations, and better model the behavior of overall systems. In this light, machine learning techniques can be the keystone to reveal knowledge expressed by the initial assumptions (at micro-level) and the structure of the society of agents that emerged from the simulation. Machine learning techniques can also be used to build a model supported by statistical evidence that could validate or refuse some initial hypotheses on the system. This can be an important task in agent-based simulations since it provides safe techniques to analyze the results of this kind of simulation paradigm.

Agent-Based Modeling Simulations for machine learning purposes: The main goal is to provide a sufficient amount of ABM-based data with good quality for various ML applications. This can ensure the usability of ML techniques in different domain applications.

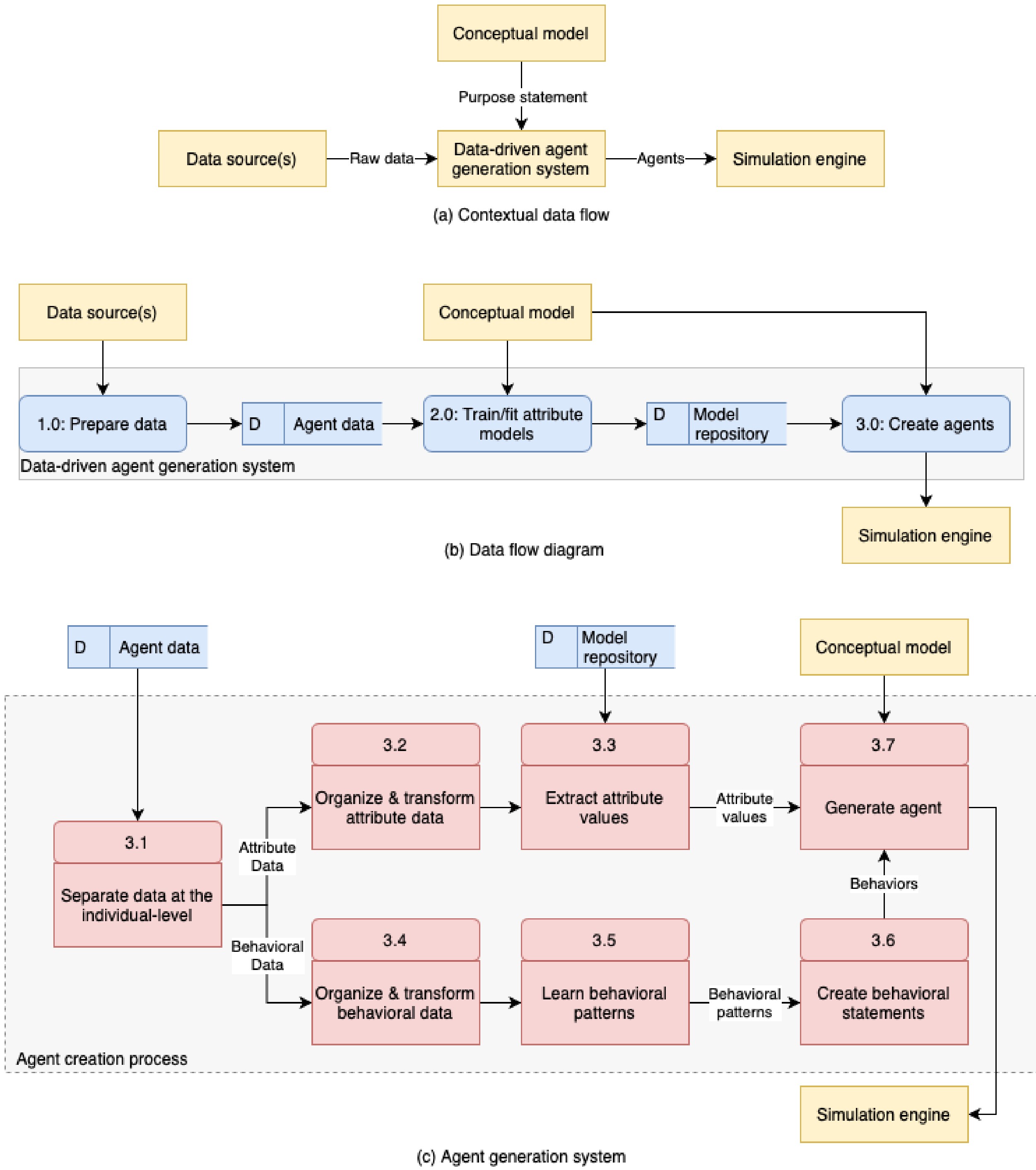

Figure 15: Machine learning-based agent bootstrapping process

In particular, the results of ABMS can be used as quasi-real data when there is a lack (or limited access) of real data for a domain-specific data analysis task [164].

Figure 16 shows the implementation of a system where the synthetic data generated through ABMS could be used for knowledge discovery by using machine learning techniques [164]. For this purpose, the process can be summarized in the following five steps:

- **Problem specification:** Contains the original problem specification contents plus the specification of an ABM system for this application problem.
- **Data preparation:** Generates simulation results for the next stages. These data should be quasi-real (the abstraction is closely related to the "real-world"), suitable-sized (enough information to generate machine learning models), qualified (noisy data should be filtered), and significant.
- **Machine learning:** The core stage for knowledge discovery. The purpose of this stage is to identify the most valuable information in the generated data. For this purpose, we utilize data analysis and knowledge discovery techniques to produce particular enumerations of patterns over the data.
- **Interpretation and evaluation:** The validity of each pattern discovered is interpreted and measured. From this process, the overall quality of the mining performance can be evaluated.
- **Future application:** The set of valuable knowledge mined, interpreted, and measured is then available to be applied for domain-oriented decision-marking.

Agent-Based Model validation through machine learning: The other exogenous application corresponds to the utilization of machine learning to validate the micro-level assumptions of an ABM. One of the most debated issues in the agent-based simulation community is the absence of a widely-spread, robust, and safe technique to validate the simulation results. However, exogenous modeling can provide valid techniques to analyze the results of this kind of simulation paradigm [164].

For instance, as shown in [101], it is possible to validate, at least in a statistical manner, the results obtained from an Agent-Based Modeling Simulation[27].

[27] It is worth noticing that in this example machine learning is also utilized to create the initial internal

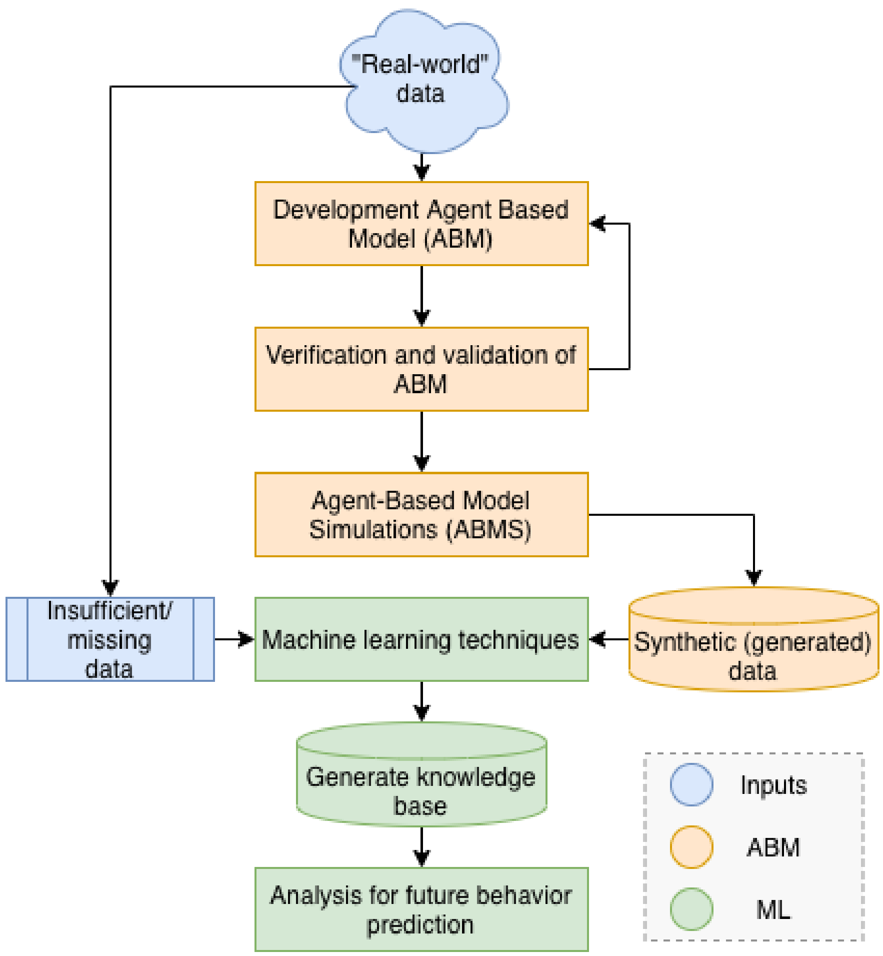

Figure 16: Applying ABMS for data generation of machine learning techniques

We start with a "real-world" data-set, D, (see Expression 2.2) of individual agent behavior over time. Where i indexes agents; t is the simulation time from time zero to time T; x_{it} represents the state of agent i at time t; and y_{it} represents the decisions of agent x_i (e.g., 1 for "adopted" and 0 for "did not adopt" at time t). In this light, it is possible to validate the model by following the subsequent process.

$$D = \{(x_{it}, y_{it})\}_{i,t=0,\ldots T} \tag{2.2}$$

1. Split the data, D, into calibration data, D_c, and validation data, D_v, along the time dimension at time threshold T_c as follows:

$$D_c = \{(x_{it}, y_{it})\}_{i,t \leq T_c} \tag{2.3}$$

$$D_v = \{(x_{it}, y_{it})\}_{i,t > T_c} \tag{2.4}$$

2. Learn a machine model of agent behavior h on D_c. In other words, create the internal model of the agents based on the available data, D_c (see Section 2.5.2.1).
3. Instantiate agents in the ABM using h (learned in the previous step).
4. Initialize the ABM to state x_{j,T_c} for all ABM agents j in the model.
5. Validate the ABM by running it from x_{jT_c} using D_v. It is also possible to have an ABM that is using machine learning and data to adapt the model (see Section 2.5.2.1). In this case, the ABM simulation can be executed from the initial state, and start the validation upon reaching time $T_c + 1$
6. Given that in nature most ABM models are stochastic, the ABM can be validated by comparing its performance to a baseline[28], b, in terms of "log-likelihood of observed action sequence" in the validation data.

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model of the agents.

[28] As it is implied in the discussion, a baseline is needed. For instance, a NULL model, where the probability of action is just the fraction of other actions.

7. Suppose $Dv = \{(x_{it}, yit)\}$ is the sequence of decisions by individuals in the validation data, where x_it evolves in part as a function of past decisions $\{y_{i,t-k}, ...y_{i,t-1}\}$, k is the elapsed time since the start of the validation phase. Letting all aspects relevant to the current decision be a part of the current state x_{it}, it is possible to compute the likelihood of adoption, $L(D_v; p)$, given a model p as:

$$L(D_v; p) = \prod_{i,t \in D_v} p(x_i t)^{y_{it}} (1 - p(x_i t))^{1-y_{it}} \tag{2.5}$$

8. Quality of a model p relative to a baseline b can then be measured using the likelihood ratio R, as follows:

$$R = \frac{L(D_v; p)}{L((D_v; p))} \tag{2.6}$$

9. If $R > 1$, the model p outperforms the baseline b.

2.6 Machine learning and spectrum management

As heterogeneous services become the norm in the next generation of mobile networks (e.g., the fifth-generation cellular networks (5G), wireless sensor networks, etc.), machine learning approaches have become central to the development of adaptive systems. This is evidenced in the spectrum policy and management literature through the study of adaptive resource management systems. This adaptivity refers to the ability to autonomously and automatically select an optimal set of resources to the requirements of a specific service and customer's demand [174, 175]. For instance, supervised learning techniques (e.g., K-Nearest Neighbors and Support Vector Machine) are utilized to determine optimal handover solutions for heterogeneous networks[29], as well as to learn usage patterns of user equipment under different Spatio-temporal conditions.

Another prominent feature of next-generation networks is the fact that networks are expected to operate with an increasingly large number of nodes (e.g., mobile phones). In this light, machine learning techniques become key to provide nodes with the ability to make

[29] Usually formed by diverse cells (e.g., micro-cells, macro-cells, etc.).

decisions based on local observations [176]. For instance, in [177], the authors demonstrate how multi-agent reinforcement learning can be utilized so that "each node in the network can self-optimize its transmission power, sub-channel allocation, and other network-related tasks".

In practical settings, data stemming from the operations of a large number of nodes and services provide information on usage patterns, requirements, and potential usage conflicts. Machine learning approaches become a useful tool for gaining insights from the data that would be otherwise dismissed [177]. Entities who "own" the data, such as network providers or regulatory bodies, can then leverage ML to make data-based resource (e.g., spectrum units) management decisions and network adjustments. This localized and adaptive decision-making process is of particular importance in settings where information on global network operations is not available [176].

3.0 Motivation

In the literature, we have found significant contributions to reach an efficient allocation, assignment, and usage of spectrum resources from a sharing perspective. To the best of our knowledge, the existing literature does not present an approach that captures local spectrum sharing agreements while combining different resource access strategies, governance frameworks and the addition of machine learning algorithms.

In the literature, we find examples of models created to analyze different aspects of a spectrum-sharing framework. Many of the available models are concerned with a particular problem (e.g., defining the size of the restricted areas around the PU) and do not consider other external factors influencing sharing decisions (e.g., the governance framework). We believe that taking into account different aspects in the definition and modeling of spectrum sharing is of critical importance. Therefore, developing a model that incorporates factors such as the resource access strategy and governance framework can lead us to a better understanding of spectrum sharing opportunities and settings. In particular, such a model can be a fundamental asset to analyze spectrum usage conflicts.

There are theoretical examples of the applications of machine learning in the context of wireless resource management. These applications provide insights into the potential for applying ML techniques to the work we propose in this dissertation. Nevertheless, to the best of our knowledge, existing work focuses, individually, on the different components that we aim to tackle. Our goal is to provide a more comprehensive study of adaptive spectrum management systems. Our focus on adaptivity does not only refer to the optimization of resource assignment but also encompasses crucial tasks that ensure the sound operation of an entire wireless system. This includes interference mitigation strategies and adaptivity of agents to their local environment. Exploring better decision-making models (i.e., improved agents' internal models) can help us capture "real-world" scenarios that are not adequately incorporated otherwise.

Finally, although spectrum sharing has been extensively discussed in the scientific, academic, and industry communities, "real world" implementations of such systems are still scarce. Data regarding the operations of wireless systems in the "real-world" cannot be easily (if at all) accessed. Consequently, there is little information to guide policy decisions to create better and more efficient sharing agreements. The enhanced modeling scheme we present combined with local definitions of spectrum sharing has the potential of producing quasi-real, valid, and suitable-sized synthetic datasets. The development of such data pools has myriad benefits, including the potential to create models that predict conflict situations in spectrum usage and other spectrum sharing analysis tools.

4.0 Research framework

The main focus of this dissertation is to examine and analyze spectrum sharing usage conflicts. The primary objective of this project is to capture local resource usage patterns to provide more realistic estimates of the number of conflict situations. In the literature, authors usually study spectrum sharing from either the perspective of the exchanged resources, the access strategy, or the definition of rules. Each of these approaches corresponds to larger areas of study. However, we believe that a comprehensive analysis that combines these elements (i.e., resource access strategy and governance framework) can provide a more realistic perspective when studying and analyzing spectrum usage conflicts. In this manner, the broader questions that guide this research work are:

- Can we include "alternative" governance mechanisms in spectrum sharing agreements?
- Can Radio Environmental Maps (REMs) be improved to analyze dynamic local spectrum sharing scenarios?
- Can we capture the interplay of factors leading to successful localized sharing agreements using Agent-Based Modeling?
- Can we examine and analyze spectrum usage conflicts using local models of spectrum sharing agreements?
- Can we use synthetic and generated through ABMS data to develop conflict prediction models to improve agents' behavior?

4.1 Research questions

The questions included in this section correspond to a broad area of the research we propose. In the following sections, we highlight the subset of questions that best adapt to the research we cover in this dissertation and hypotheses.

Q1. Can "alternative" governance mechanisms be included in spectrum-sharing agreements?

Q1.1. Can polycentric governance be used in different spectrum sharing schemes?

Q1.2. Can self-governance be an alternative for governing spectrum sharing scenarios?

Q1.3. What are the necessary conditions for "alternative" governance mechanisms to be successful in spectrum sharing situations?

Q2. Can the usefulness of Radio Environmental Maps (REMs) be improved?

Q2.1. Can we expand the functionalities of REMs to be used in other resource access strategies and governance frameworks?

Q2.2. Can we transform static REMs into dynamic modeling platforms using Agent-Based Modeling?

Q2.3. What is the impact of noisy REMs on the number of spectrum sharing usage conflicts?

Q2.4. What are the main factors that influence the quality of REMs?

Q3. What are the main components of a model adapted to capture localized spectrum sharing scenarios?

Q3.1. Can the implemented model identify emerging conflict situations in the sharing scenarios?

Q3.2. Can the inclusion of spectrum usage dynamics (e.g., spectrum access strategies) create more dynamic models?

Q3.3. What is the role of the resource access strategy in the number of the exchanged resource units in the model?

Q3.4. Do "alternative" governance mechanisms provide the users with additional incentives to engage in spectrum sharing agreements?

Q4. What are the benefits of adding a dynamic agent behavior in the ABM?

Q4.1. Can we model the adaptability of the agents through machine learning?

Q5. What kind of data produce accurate adaptive agents to mitigate conflict situations?

Q5.1. Can the agents develop their own (not predefined) dynamic strategies?

Q6. Can the generated adaptive ABM models be used to create prediction models?

Q6.1. Can we use machine learning algorithms based on ABM-based synthetic data to predict the emergence of conflict situations?

Q6.2. What type of models results in the lowest number of conflict situations?

Q6.3. What is the impact of the resource access strategy on the performance of the predictive models?

Q6.4. What is the impact of the governance framework on the performance of the predictive models?

Q6.5. What is the impact of noisy maps on the performance of the predictive models?

Q6.6. What ML techniques produce the highest performance (e.g., accuracy) scores?

4.2 Research settings

This dissertation comprises four main research stages, as summarized in Table 5. We design these individual phases to obtain a deep analysis of local spectrum sharing usage and the corresponding conflict situations.

In Stage 1, we focus on testing the viability of "alternative"[1] governance mechanisms in spectrum sharing scenarios. In particular, we analyze the utilization of two governance mechanisms: Centralized and self-governance. We choose these governance systems as both ends of the governance "spectrum". The main goal of this stage is to compare these "extremes" in terms of their enforcement ability and the corresponding stability of the system[2]. To test the viability of alternative governance systems, we build a two-tier spectrum sharing ABM (*Model 1.0*) that captures the interactions between a single PU and multiple SUs.

In Stage 2, we enhance the functionalities provided by REMs by "transforming" them into dynamic Agent-Based Models (*Model 1.1).* Thus, the main goal is to design, develop, and test an REM simulator that generates IC or spectrum maps for their utilization within ABM models. This process allows us to expand the usability of REMs beyond the CRNs and provide agents (in ABM) with dynamic information regarding their local spectrum environment.

[1] The term "alternative" governance refers to governance mechanisms that are not the traditional command-and-control approach. These systems are largely explored, studied, and analyzed in the CPR-management literature (See Section 2.4).

[2] In particular, the stability of self-governance and the ability of the agents to create and maintain sustainable (ex-ante) agreements.

Stage	Settings	Outcome
1	Test the viability of "alternative" governance mechanisms	Two-tier Spectrum Sharing model
	Build a base ABM model (*Model 1.0*)	
2	Simulate REMs for spectrum sharing scenarios	REM-based Agent Based Model
	Incorporate static REMs into dynamic models (*Model 1.1*)	
3	Include multi-tier spectrum sharing characteristics	Governance-based Agent Based Model
	Include additional governance mechanisms (*Model 2.0*)	
4	Improve agents' decision making capabilities (*Model 3.0*)	ML-based Agent Based Model
	Develop conflict detection models (local and global)	

Table 5: Research settings

In Stage 3, we improve the governance-based model developed in the previous stages. This upgraded model, *Model 2.0*, is designed to capture local spectrum sharing characteristics. Thus, we include a multi-tier resource access strategy and an additional governing mechanism in polycentric governance. The addition of a multi-tier design allows us to provide agents with more flexible definitions to access the available resources. The introduction of polycentric governance enhances the learning, cooperation, and adaptiveness of the agents in a sharing agreement. This improved model allows us to capture the interplay of factors leading to usage conflicts in a better way.

Finally, in Stage 4, we enhance *Model 2.0* by improving the agents' internal engines. We leverage the benefits of endogenous ML modeling for ABM to strengthen the agents' decision-making capabilities in *Model 3.0*. The main goal is to construct ML classifiers to detect the possible emergence of conflict situations. For the construction of the models, we utilize two different approaches, specifically a local and a global approach. In the ML local approach, the agent is fully responsible for gathering information, storing the data, and constructing and evaluating the ML models. In the global method, the agent only collects the execution data and transfer it to an external entity (e.g., band coordinator). Then, the latter is responsible for building and evaluating the different ML techniques.

4.3 Hypotheses

In Table 6, we introduce the hypotheses we have formulated to evaluate select research questions. In what follows, we elaborate on the proposed hypotheses.

H1. **REMs with a higher number of IC errors lead to a higher number of conflict situations compared to REMs with fewer IC errors.** This hypothesis is directly related to the environment of our ABM-based models. In other words, this hypothesis is related to the simulated Radio Environment Maps (REMs) and their Interference Cartography (IC) map. The goal of this hypothesis is to measure the impact of noisy REMs in the number of conflict situations. For this purpose, we use the Root Mean Square Error (RMSE) (see Expression 4.1) as our evaluation metric.

$$RMSE_{REM} = \sqrt{\sum_{i=1}^{N} \frac{(Z_{real\_values} - Z_{interpolated})^2}{N}} \tag{4.1}$$

H2. **"Alternative" governance mechanisms reduce conflict situations in most scenarios compared to centralized governance.** To test both distributed governance systems (i.e., polycentric and self-governance), we further divide our second hypothesis into two hypotheses, as follows:

- H2.1. **Self-governance frameworks reduce the number of conflict situations in most scenarios when compared to centralized governance.**
- H2.2. **Polycentric governance frameworks reduce the number of conflict situations in most scenarios when compared to centralized governance.**

As mentioned in Section 2.1.2, the CPR literature opens the door for "alternative" governance and enforcement mechanisms[3]. In this work, we have selected two alternative methods: Ostrom's Polycentric Governance [52, 61] and Leeson's self-governance [55, 56]. For these hypotheses, we compare the average number of conflict situations in self-governance and polycentric governance vs. command-and-control (i.e., centralized

[3] The CPR literature situates enforcement as part of the governance structure and incorporates it into the definition of rules [61].

governance). We expect the models to perform differently depending on the nature of the governance framework in place.

H3. **Resource efficiency achieved by the new entrants is higher in most scenarios when "alternative" governance systems are utilized compared to centralized governance.** The mitigation of conflict situations is considered the main priority in spectrum sharing systems[4]. However, for these systems to be successful, the new entrants of the band should also receive enough incentives to participate. In other words, there should be enough opportunities for secondary users to utilize the available resources. In this hypothesis, we seek to find the most suitable governance mechanism in terms of the efficiency of resource allocation and utilization by the new entrants (see Expression 4.2).

$$ResourceEfficiency = \frac{ResourcesUsed}{ResourcesAvailable} \tag{4.2}$$

In the same way as H1, H3 is further divided into two hypotheses to test both distributed governance systems.

H3.1. **Resource efficiency achieved by the new entrants is higher in most scenarios when self-governance mechanisms are utilized compared to centralized governance.**

H3.2. **Resource efficiency achieved by the new entrants is higher in most scenarios when polycentric governance mechanisms are utilized compared to centralized governance.**

H4. **In centralized governance systems, Agent-Based Models improved using endogenous machine learning generate fewer usage conflict situations compared to models without machine learning.** A primary component in this dissertation is the inclusion of endogenous machine learning into ABM. In H4, we test the impact of improving the agent's internal decision-making behaviors using different machine learning algorithms. We ground the model built in Stages 2 and 3 (i.e., *Model 2.0*) on the classic rule-based mechanism of ABM. On the other hand, the improved ABM (i.e., *Model*

[4] In particular, conflict situations that impact the normal operations of the agents in higher tiers.

3.0), developed in Stage 4, incorporates dynamic agents' internal models. This hypothesis aims to quantify the impact on the number of events when comparing the original model against the ML-based model when the system implements centralized governance approaches.

H5. **"Alternative" governance frameworks result in ML-based conflict event prediction models with higher accuracy in most scenarios when compared to centralized governance frameworks.** This hypothesis is also divided into two "sub"-hypotheses to test both distributed governance systems in our models.

   H5.1. **Self-governance approaches result in ML-based conflict event prediction models with higher accuracy in most scenarios when compared to centralized governance frameworks.**

   H5.2. **Polycentric governance systems result in ML-based conflict event prediction models with higher accuracy in most scenarios when compared to centralized governance frameworks.**

The two main components of this work are the inclusion of governance frameworks at the core of the sharing agreements and the improvement of the agents' decision-making engine. To improve the agents' decision-making capabilities, we rely on different machine learning techniques. We expect the ML algorithms to vary and perform differently depending on the nature of the governance framework. For instance, in centralized governance, an entity with noisy global knowledge may use the ML-based prediction models differently than an entity with direct and local information as in polycentric governance or self-governance. We aim to find out if alternative governance frameworks have an impact on the accuracy of the interference prediction models compared to centralized mechanisms. For this purpose, we use the accuracy of the constructed prediction models as our evaluation criterion. In the case of regression-based models, we use RMSE as our evaluation criterion (see Expression 4.3). On the other hand, for classification-based models, we use the model accuracy as our evaluation criterion (see Expression 4.4)[5].

$$RMSE_{model} = \sqrt{\sum_{i=1}^{N} \frac{(Z_{real\_values} - Z_{predicted})^2}{N}} \quad (4.3)$$

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \quad (4.4)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4.5)$$

H6. **Coordination in “alternative” governance systems leads to fewer conflict events in most scenarios when compared to situations where endogenous machine learning is utilized.** In this hypothesis, we compare the number of conflict situations between our governance-based ABM and our ML-based ABM. “Alternative” governance mechanisms are based on “simple” coordination activities between the interacting agents of the systems. In self-governance, this coordination is directly related to the principle of continuous dealing. In polycentric governance, this coordination occurs between the agents in the different jurisdictions. In our ML-based model, we have “improved” agents, who use different machine learning techniques to enhance their decision-making capabilities. However, this improvement comes at a “price”, where the agents need to gather and store historical data about themselves and the environment around them. They are also required to build and evaluate decision-making models. These activities require the modeling of more complex agents with additional computational requirements. The goal of this hypothesis is to test, in distributed governance settings, whether the scenarios with “improved agents” lead to fewer conflict situations when compared to models where simple coordination is implemented (i.e., models without ML).

H7. **Models using a local machine learning approach lead to fewer conflict situations when compared to models using a global machine learning approach.** In Stage 4, we design two mechanisms to add ML models into ABM. A local approach, where the agent is solely responsible for the whole process (i.e., gather, store, and use

[5] The models’ accuracy can also be calculated as a function of the values of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN), as shown in Equation 4.5.

the data) and a global approach, where the agent is only responsible for collecting the data and an external entity is responsible for the remaining of the process (i.e., store the data and build ML models). In this hypothesis, the goal is to test what approach produces fewer conflict situations.

The questions, research settings, and hypotheses that we study in this dissertation are summarized in Table 7.

Number	Hypothesis
H1	REMs with a higher number of IC errors lead to a higher number of conflict situations compared to REMs with fewer IC errors
H2.1	Self-governance frameworks reduce the number of conflict situations in most scenarios when compared to centralized governance
H2.2	Polycentric governance frameworks reduce the number of conflict situations in most scenarios when compared to centralized governance
H3.1	Resource efficiency achieved by the new entrants is higher in most scenarios when self-governance mechanisms are utilized compared to centralized governance
H3.2	Resource efficiency achieved by the new entrants is higher in most scenarios when polycentric governance mechanisms are utilized compared to centralized governance
H4	In centralized governance systems, Agent-Based Models improved using endogenous machine learning generate fewer usage conflict situations compared to models without machine learning
H5.1	Self-governance approaches result in ML-based conflict event prediction models with higher accuracy in most scenarios when compared to centralized governance frameworks
H5.2	Polycentric governance approaches result in ML-based conflict event prediction models with higher accuracy in most scenarios when compared to centralized governance frameworks
H6	Coordination in "alternative" governance systems leads to fewer conflict events in most scenarios when compared to situations where endogenous machine learning is utilized
H7	Models using a local machine learning approach lead to fewer conflict situations when compared to models using a global machine learning approach

Table 6: Proposed hypotheses

Stage	Research Questions	Hypotheses
1	Q1.1, Q1.2, Q1.3, Q3.1 & Q3.4	H2.1 & H2.2
2	Q2.1, Q2.2, Q2.3 & Q6.5	H1
3	Q1.1, Q1.2, Q3.1, Q3.2, Q3.3, Q3.4 & Q6.4	H2.1, H2.2., H3.1, H3.2, H4, & H6
4	Q4.1, Q5.1, Q6.1, Q6.2, Q6.3, Q6.4, & Q6.5	H4, H5.1, H5.2, H6, & H7

Table 7: Correspondence among research stages, hypotheses, and research questions

5.0 Usage conflicts in localized spectrum sharing scenarios

The most common approach to regulate, govern, and enforce telecommunications-related issues has been command-and-control [178, 179]. This process includes the allocation and assignment of spectrum rights. However, as the CPR literature extensively discusses, centralized approaches are inefficient when capturing local interactions among the stakeholders. For instance, many centralized systems fail to recognize the ability of stakeholders to organize themselves. One of the problems is that centralized systems have global (usually noisy) knowledge about the local activities, which leads to the application of global solutions. In this light, the main focus of this dissertation is to study systems that can capture local usage patterns and their corresponding usage conflict situations. In the following sections, we analyze the research stages we implement to apply local solutions to local problems.

5.1 Stage 1: Including alternative (localized) governance mechanisms in spectrum sharing agreements (two-tier model)

The first step in this work is to test the viability of non-traditional (i.e., "alternative") governance mechanisms in spectrum sharing schemes. We leverage the fact that the use of spectrum bands for transmissions purposes is consistent with the definition of a CPR (see Section 2). This definition allows us to utilize many concepts, definitions, frameworks, and strategies implemented in the CPR-management literature.

In contrast with the case of CPRs, which situates enforcement as part of the governance structure and incorporates it into the definition of rules, the most common governance mechanism for regulating the exploitation of spectrum bands in the United States has been centralized specification and enforcement of property rights. Usually, a government agency such as the FCC and/or NTIA requires or prohibits specific actions or technologies. Rule-breakers are subject to fines, sanctions, and/or imprisonment, depending on the seriousness of the infraction. This system has been the *de facto* approach for spectrum allocation and enforcement in the U.S. since the Radio Act of 1927 [48].

Initially, the spectrum was allocated through bureaucratic priorities in a command-and-control fashion. Inspired by the property rights approach of Coase, the FCC instituted markets to allocate spectrum [180, 40]. The primary mechanism for spectrum assignment and allocation used by the FCC (and most regulators internationally) has been spectrum licensing. Licenses provide incumbents with exclusive property rights to use the corresponding frequency bands if they remain consistent with the underlying license conditions [181].

In recent years, telecommunications regulators in the U.S. have been working towards shifting from an exclusive licensing scheme to more technically and economically efficient methods for the use and allocation of spectrum bands. One of the most recent approaches has been spectrum sharing between Federal and commercial entities [21]. This allocation approach aims to change the current exclusive licensing methods to allow for more flexible resource allocation that addresses many of the challenges stemming from centralized, property-rights approaches.

Based on the concepts of alternative governance mechanisms (presented in the CPR literature) and the "newer" spectrum allocating and assigning systems proposed by the FCC (and other regulators), in this stage, we explore the two "extremes" of governance, namely centralized (i.e., command and control) and distributed (i.e., self-governance) systems. Self-governance may be a more appropriate institutional arrangement to allocate spectrum. This situation is particularly true in cases where more than one user is concurrently accessing the bands, as in spectrum sharing scenarios.

The comparative institutional analysis developed in Stage 1 considers both ends of the governance structures and enforcement systems, which are the formal institutions in command-and-control and the self-policing frameworks. In the case of the latter, government controllers or community structures (e.g., third-party agencies) are not required (at least as principal actors). This government-less or "anarchy" environment constitutes a distributed enforcement approach, which is defined by a lack of formal government intervention, where norms, rules, and enforcement mechanisms are solely the product of repeated interactions among the intervening agents in a given environment [182, 55].

In this stage, we design a CPR-based governance model for self-governing and selfmonitoring in Federal–commercial spectrum sharing scenarios. For our analysis, we have selected a well-defined and widely-known sharing framework: the 1695MHz and 1710MHz frequency range (i.e., the 1695-1710MHz band). This environment is characterized by its simplicity and well-defined rules, which allows us to illustrate how self-governance would look like in a spectrum-sharing scenario.

We use Agent-Based Modeling (ABM) to analyze the suitability of the proposed self-governance mechanism in greater detail and compare it to a more traditional governance approach (i.e., command-and-control).

5.1.1 Two-tier spectrum sharing framework

In stage 1, we focus on the scheme defined for the 1695-1710MHz band as our base spectrum sharing model. In this Federal-commercial sharing framework, the participants have been defined by the FCC and NTIA in a "license-like" manner. The incumbents or Primary Users (PUs) are the meteorological satellites of the National Oceanic and Atmospheric Administration (NOAA). The Secondary Users (SUs) or new entrants are mobile phones (i.e., LTE Mobile Stations (MS)) [32, 33]. Note that, even though the number of PUs is predefined, the number of SUs may vary according to the locations of the incumbents, and transmission opportunities which depend on traffic and congestion in the radio spectrum.

One key aspect in spectrum sharing scenarios is that incumbents or PUs should be protected against "harmful interference," which can be defined as external wireless transmissions that impact the normal operations of a given station. This interference is usually the product of the operations of other users in the band (e.g., new entrants) [67]. For the 1695-1710MHz band, the FCC and NTIA proposed two static protection zones to mitigate possible conflict events: 1) an Exclusion Zone (EZ), which is a restricted area where no new entrants are allowed to operate, and 2) a Coordination Zone (CZ), which extends beyond the EZ boundaries, and allows for new entrants' operations under predefined circumstances [31]. The size (i.e., boundary) of these protected areas is based on several technical factors, including transmission power, time variations, receiver susceptibility to interference, propagation effects of radio waves, among others [5]. Note that, even though the boundaries of these "protection zones" have been revised on multiple occasions by the FCC and NTIA, they are still static [7], hence representing a centralized governance approach. This centralized approach has the potential of reducing the value and incentives for new entrants, and it disregards important factors that impact local sharing conditions.

Based on the definitions of exclusion and coordination zones, several authors [5, 6, 7] have designed methods to specify the characteristics of this Federal–commercial sharing environment. In particular, authors have sought to develop methods for creating and sizing both restricted zones. Existing approaches propose a more flexible scheme than the one suggested by the FCC/NTIA, as their main objective is to reduce the size of both zones to increase the value and incentives for SUs. In this work, we use the notation introduced by Bhattarai et al. [5] to define the "Multi-Tiered Incumbent Protection Zones (MIPZ)." This framework allows the PU to adjust the size of the coordination and exclusion zones "on the fly." As a result, three zones are defined around the PUs' transmitters (see Figure 17):

- **No Access Zone (NAZ):** Spatial area near the Primary User, where transmission privileges are limited to licensed incumbents.
- **Limited Access Zone (LAZ):** Spatial area surrounding the NAZ. In this region, a limited number of new entrants are allowed to transmit simultaneously. The limit in the number of simultaneous transmissions is determined by the PU.
- **Unlimited Access Zone (UAZ):** The region that lies outside the outer boundary of the LAZ. Unlimited transmission privileges are granted to the SUs in this area.

5.1.2 Self-governing systems

A common, "alternative" governance system that has emerged from the study of CPRs is self-governance [49]. In such systems, all appropriators of CPRs repeatedly show their capacity to organize themselves, create rules, monitor others and themselves, and successfully enforce the agreed-upon norms. Hence, these self-governed organizations can create self-organized and self-controlled institutions without the need to entirely rely on central authorities (e.g., governmental entities). As explained by Ostrom [51], the self-governance

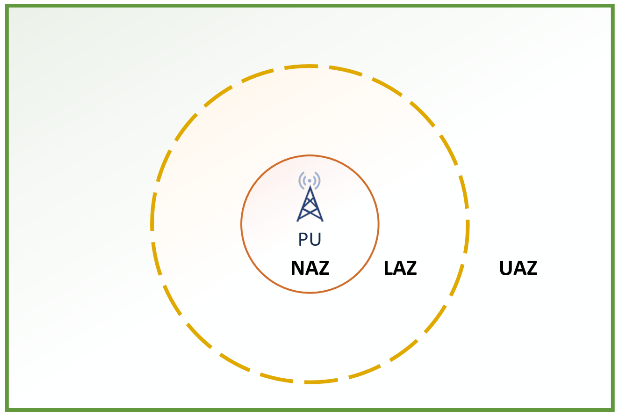

Figure 17: Stage 1 - 1695-1710MHz band environment definitions

institutions that have emerged have been sustained over long periods without the participation (at least as principal actors) of any external agency. Thus, self-governance has become a viable mechanism to govern complex CPRs.

Note that self-governance does not refer to the complete absence of law; instead, it refers to the lack of a formal government or state dictating and enforcing the law. Agents who find themselves in government-less situations (or choose to eschew government) develop their own, privately-created law [56].

A common characteristic of centralized approaches is the need for an "authority" figure (e.g., law enforcers). This authority is deemed a necessary mechanism to guarantee that agents will "behave" and not break the agreements (ex-ante) in future interactions (ex-post). Consequently, the natural question in private-governing arrangements is: how is the law enforced? The short answer to this question comes from the "discipline of continuous dealing". The idea behind this principle is simple, "if you do not behave today, I will take repressive actions" [56, 183, 184]. These actions include ceasing interactions with you tomorrow, telling others not to interact with you, reducing your future privileges, among others. If an agent values future interactions with a given user and their social network (e.g., neighbors), the interested party will not break the ex-ante agreements. In this type of system, continuous interactions usually lead to a stable state. In other words, a point in the dealing process where the agents agree to a given set of system parameters.

Note that, contrary to the centralized approach, self-enforcement is not a "one-size-fits-all" solution. Different self-enforcement contexts come with different problems of property protection and conflict resolution. Therefore, one particular model of a private-governing institution will not necessarily be successful in a different context. More importantly, these emerging institutions are fitted to maximize the well-being of the members of a specific community by continuously adapting their rules, norms, and practices [182].

Self-governance can help us overcome many of the challenges stemming from decisions made by centralized government entities. A more flexible or dynamic scheme could reduce the size of the restricted areas, which would increase the value of the spectrum and provide incentives for new entrants. Besides, all decisions would be made at a local level, taking into account local interests. Such an approach would help reduce possible negative externalities and would address the actual needs of local communities.

5.2 Stage 2: Radio Environment Maps to construct local and dynamic environments

In the first stage of this work, we introduce a governance mechanism (self-governance) that better captures the local behaviors in spectrum sharing schemes [185]. This introduction is done in a setting where stakeholders (e.g., SUs) are still using a static set of rules (e.g., exclusion and coordination zone) globally defined. In Stage 2, we add a new layer to the spectrum sharing agreements that we have been analyzing so far. This layer aims to overcome problems with global definitions by providing stakeholders with access to information about their local "spectrum environment".

Dongier et al. [186] argue that one of the principles for sustainability and effectiveness of community-driven developments in CPR settings is to facilitate access to information. To this end, we need mechanisms that guarantee the flow of information among all members of a community. For instance, stakeholders in local arrangements need information about market opportunities, what resources are available, and how to use these resources productively and efficiently. The lack of local data is often deemed one of the most significant limitations for community-based organizations to create and maintain successful decentralized governance mechanisms [187].

In the spectrum context, Radio Environment Maps (REMs) provide the means for all agents in a sharing scheme to access multi-domain information of entities in the network and the history of data of the (local) environment. In this light, REMs help support cognitive functionality for radios (e.g., new entrants) with different levels of "intelligence" while being transparent to the radio access technology to be deployed [77]. The principal difference between REMs and geolocation databases is that REMs can generate spectrum maps by processing the data collected from multiple sources (e.g., MCDs, regulatory bodies, mobile users, among others). Hence, REMs can adapt to dynamic operating environments, whereas database-enabled approaches store quasi-static information [188].

5.2.1 Radio Environment Maps and Agent Based Modeling

The exogenous variables in the IAD framework (see Section 2.4.3.1) include environmental conditions. These exogenous variables influence participant's behavior (e.g., PUs and SUs) in the action situation, including the physical environment, that sets the context within which an action arena is situated [189] (see Figure 9). The ABM philosophy also considers the definition of an environment as part of its core elements [145]. Usually, environments in ABM are spaces (static or dynamic) in which agents exist (see Section 2.5) [161]. These overlapping definitions between REMs and ABM allow us to connect both components to provide agents with more dynamic environmental conditions.

In the previous stage of this dissertation, the environment was given by exclusion (NAZ) and coordination (LAZ) areas. It is worth noting that although the size of these areas could be dynamically adjusted in the case of self-governance, the information received by the SU refers to global dimensions instead of local conditions. In Stage 2, we improve the environment of a given spectrum sharing scenario within our Agent-Based Model. Our goal is to present agents with a more dynamic environment to supply them with additional (local) information about the spectrum situation. Hence, the environment of the ABM developed

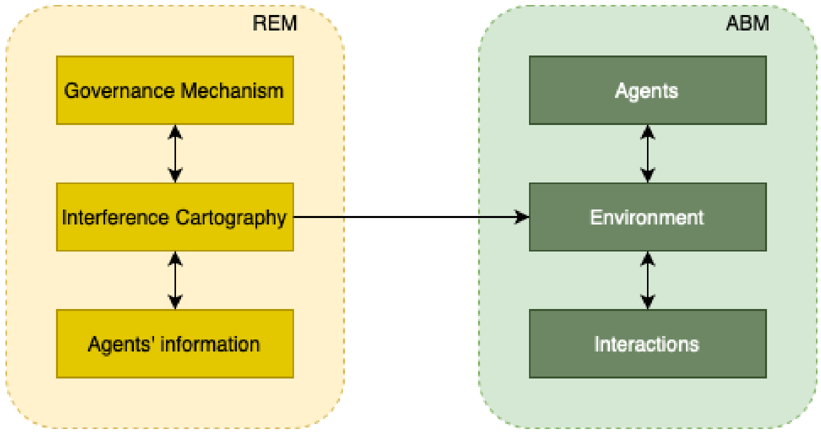

Figure 18: Stage 2 - REM and ABM integration

in Stage 2 is given by the Interference Cartography of a Radio Environment Map (see Figure 18). This system allows lower-tier users (e.g., secondary users) to have up-to-date and local information about multiple components of the environment. For instance, an SU could infer when the PU is transmitting (i.e., active) and its relative position to such transmitter.

5.2.2 Building Radio Environment Maps (REMs)

The starting point of this stage is closely related to the study of Radio Environment Maps (REMs). In particular, the analysis of the development of Interference Cartography (IC) (i.e., spectrum) maps. As previously mentioned, the availability of up-to-date and extensive measurements of wireless signals (e.g., Received Signal Strength (RSS)) is limited. Consequently, to create a valid representation of the spectrum environment, we simulate a set of measurements that can be later interpolated to obtain a complete view of the spectrum situation in a given location (i.e., region of interest). This two-step operation allows us to closely emulate the process for obtaining the IC of a given REM. The result of this simulation is “translated” as the environment of the governance-based ABM.

5.3 Stage 3: A local and multi-tier spectrum sharing scenario under different governance systems

In the first two stages, we define the implementation of "alternative" governance mechanisms in spectrum sharing agreements that rely on REMs to develop local and dynamic model environments. In this stage, we continue improving our governance-based model towards a localized spectrum sharing agreement. For this purpose, we begin by enhancing the agents' access strategies by creating a multi-tier sharing arrangement, and then we include an additional governance mechanism in polycentric governance.

As Hayek argues, "[i]f we can agree that the economic problem of society is mainly one of rapid adaptation to changes in the particular circumstances of time and place, it would seem to follow that the ultimate decisions must be left to the people who are familiar with these circumstances, who know directly of the relevant changes, and of the resources immediately available to meet them." [190]. Thus, to solve collective action problems from a global perspective, it is necessary to communicate all the localized knowledge to a central board, which, after integrating all knowledge, issues its orders (i.e., makes decisions). Due to the inefficiency of this approach, it is best to solve these problems by some form of decentralization. These systems would ensure that the knowledge of the particular circumstances of time and place will be promptly used [191]. In this light, polycentric and self-governance (i.e., distributed or decentralized governance systems) seem more suitable to gather the required local information and application of local solutions than centralized systems.

Note that for this model we focus exclusively on *Type I* events[1]. We do not mean to imply that *Type I* events are the most important or most serious. It may be the case that *Type II* events have more severe consequences, particularly in a cooperative setting as is the case of spectrum sharing. Examples of this could include mobile phone jamming, GPS spoofing, and other events that disrupt the operations of socially fundamental wireless systems. *Type II* events also include actors such as "radio pirates" who broadcast license-free in licensed broadcast bands. It is also true that different types of interference may

[1] Generally, this is also the focus within the CPR literature.

have varying consequences for distinct users or use cases. For example, emissions from LED lighting (*Type III* interference) have been shown to interfere with scientific uses of radio spectrum. The main point we wish to make is that *Type I* events are most likely amenable to automated communications-related radioelectric spectrum uses and governance that employs spectrum sharing strategies and technologies.

5.3.1 Multi-tier spectrum arrangement

Traditionally, spectrum sharing schemes define only two types of agents or participants (as in the case of Stage 1): A single primary user and multiple secondary users. However, in multi-tier systems, more than two types of agents can be present. The sharing agreement places these agents in various tiers or levels within a hierarchical scheme.

To design an ABM that recreates a multi-tier spectrum sharing scheme, we also use a well-known example of a proposed spectrum sharing system, namely the Citizens Broadband Radio Service (CBRS). The CBRS is a three-tier spectrum sharing model created for the 3.5GHz band[2] designed to accommodate Federal and commercial use of the band [36]. The model defines three types of users (see Figure 19): Incumbent Access (IA) users represent the highest tier (Tier 1); hence, they receive the highest conflict (e.g., interference) protection from other CBRS users and devices (CBRD). These PUs include federal shipborne and ground-based radar operations and fixed satellite service (FSS) earth stations in the 3550–3700 MHz band[3] [28]. The band definitions further divide the non-incumbent users into two tiers: the Priority Access License (PAL) and the General Authorized Access (GAA) users. The newly introduced Spectrum Access System (SAS) assigns resources to these "low-level" participants [37]. In this multi-tier model, operations from the PAL users (Tier 2) receive protection from GAA (Tier 3) operations, while the lowest-tiered users (i.e., GAA) do not receive any interference protection [38].

The CBRS definitions also include two additional entities that are very important for

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[2] This system is located between 3550MHz and 3700MHz.

[3] For a finite period, the band also includes grandfathered terrestrial wireless operations in the 3650–3700 MHz band.

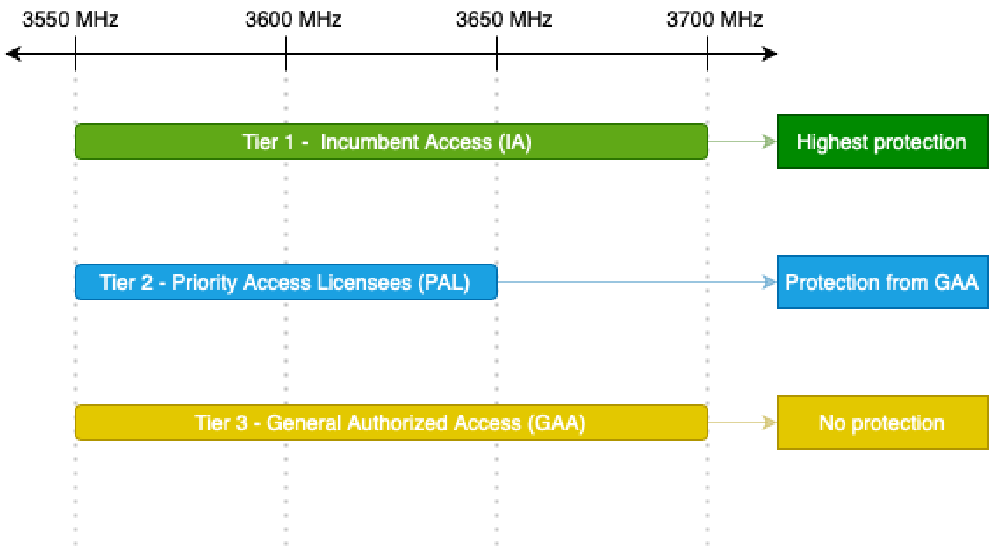

Figure 19: Stage 3 - Tiers (levels) of the proposed Citizens Broadband Radio Service (CBRS)

the characterization of local spectrum usage patterns, namely the Spectrum Access System (SAS) and an Environmental Sensing Capability (ESC) component (see Figure 20).

The Spectrum Access Systems (SASs) facilitate resource-sharing among the three tiers in the 3.5 GHz band. The SAS authorizes PALs and GAA operations with information from an approved Environmental Sensing Capability (ESC) sensor network. This new entity allows us to explore different combinations of frameworks. For instance, it is possible to create a polycentric governance mechanism based on the definitions of the SAS and its local characteristics (see Section 5.3.2).

The Environmental Sensing Capability (ESC) component enables the SAS to sense the spectrum. The SAS uses a combination of databases and ESC measurements to assign channels to CBRS devices (CBSDs). This structure is very similar to the fundamental composition of REMs, in that both are based on measurements (i.e., interference cartography) with information about the band, users, services, among others. Thus, we can see how the definitions of the CBRS sharing approach align with the previously discussed ideas for the construction of an Agent-Based Model combining the concepts of CBRS, REM, and alternative governance systems.

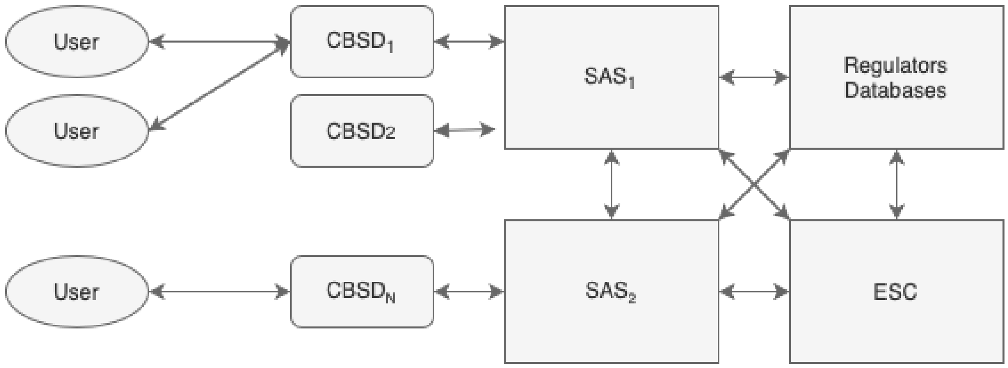

Figure 20: Stage 3 - FCC's illustrative end-to-end CBRS architecture

5.3.2 Polycentric governance of spectrum

Polycentric governance involves multiple centers of decision-making. Each of these centers operates with a degree of autonomy and has control over specific jurisdictions [49]. These decision-making units are often nested at multiple levels (e.g., local, state, and national). This configuration means that governance arrangements may be capable of striking a balance between centralized (e.g., command-and-control) and fully decentralized (e.g., self-governing) governance systems [192, 193].

In the CBRS regulation, we find the concept of automated frequency coordinators, known as Spectrum Access Systems (SASs). The goal of these coordinators is to facilitate sharing among the different tiers of authorized users in the 3.5GHz band. In our model, we expand the inclusion of SASs in CBRS to create a polycentric governance structure of *coordinators* (see Figure 21). The lower tier in this structure is composed of local *coordinators*. A polycentric system assigns these local agents a jurisdiction area within the sharing environment known as local coordination zones. For this purpose, each local *coordinator* defines a set of strategies to handle conflict situations.

To minimize the number of conflict situations, the local *coordinator* agent implements a series of actions under its strategy. These actions are very similar to the actions taken by other agents in the centralized and self-governance approaches. The primary difference is that these actions are applied only to the agents located within the local coordination zone.

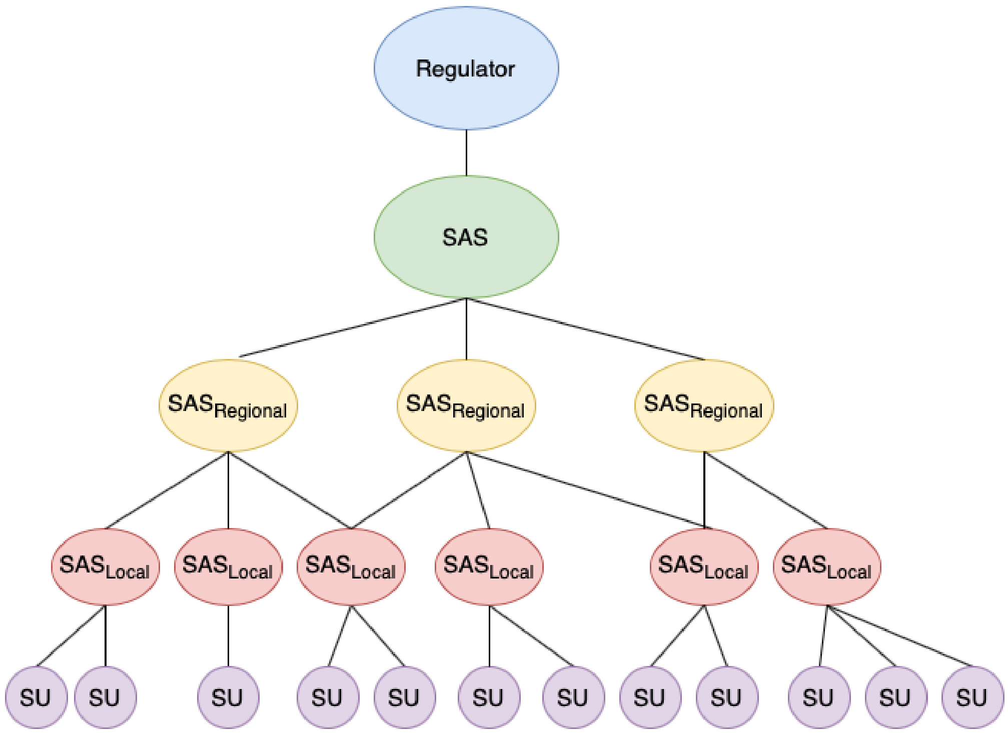

Figure 21: Stage 3 - Polycentric governance organization for a multi-tier spectrum sharing scheme

Number	Design principle
1	Clearly defined boundaries
2	Congruence between appropriation, provision rules, and local conditions
3	Collective-choice arrangements
4	Monitoring
5	Graduated sanctions
6	Conflict-resolution mechanisms
7	Minimal recognition of rights to organize
8	Nested enterprises

Table 8: Stage 3 - Ostrom's critical attributes of long surviving CPR systems

The main ideas behind polycentrism come from successful management and governance examples of CPRs [49]. As part of the polycentric framework, Ostrom identified a list of attributes for the ruling of long "surviving CPRs", as summarized in Table 8. Typically, the study and analysis of CPR systems are related to natural resources (e.g., fisheries, forests, irrigation systems, land allocations, air pollution, among others). Unlike these systems, the exploitation of spectrum for wireless transmissions purposes is a constructed resource that does not exist apart from radio technologies [194]. Consequently, as argued by Weiss et al. [195], it is necessary to construct a technological foundation for a polycentric governance mechanism within spectrum sharing scenarios.

5.3.2.1 Technological foundation for polycentric governance To construct a technological foundation for a decentralized governance system for spectrum (i.e., a polycentric arrangement), we use the list of attributes for sustainable CPRs developed by Ostrom [195].

- **Boundaries:** Two types of boundaries are usually defined, namely community and resource boundaries. Since most CPR examples are directly related to physical resources

Right	Full owner	Appropriator	Authorized transmitter	Authorized receiver
Access	X	X	X	X
Withdraw	X	X	X	
Management	X	X		
Exclusion	X	X		
Alienation	X			

Table 9: Stage 3 - Distribution of rights by user type applied to spectrum systems

(e.g., fish, water, trees, among others), resource boundaries are often physical delimitations of what is included and what is excluded. In the case of spectrum sharing, the electromagnetic space of the transmission system defines this delimitation. In other words, technical characteristics such as transmission power, frequency, time, antenna type, etc. define the physical boundaries of the resource. On the other hand, user boundaries are more difficult to define. In the community boundaries, the rights structure and governance mechanism come into play. To define the rights structure we can use the definitions presented in [196] and adapt them to the application of radio spectrum (see Table 9) [152]. In this classification, *access* and *withdrawal* rights refer to the usage rights, and all other rights are defined as collective action rights. In our polycentric arrangement, collective action rights are implemented directly in the governance organization. Further, these collective action rights govern the usage rights (i.e., *access* and *withdraw*) and are implemented in the lower level of the organization (i.e., the SAS_{local}).

- **Appropriateness to local conditions:** This attribute includes the rules[4] and the benefits obtained by users. In our polycentric arrangement, the circumstances of the sharing agreement define the rules, and the benefits are directly related to the rewards (e.g., transmitting data) for using the available resources.

[4] Such rules restrict time, place, technology, and/or quantity of resource units directly related to the local conditions.

- **Collective choice arrangements:** This attribute determines the number of say participants have in the community system. In other words, the extent to which participants are endowed with and able to execute their collective choice rights. For the spectrum sharing scheme implemented in this stage, the collective choice is embodied in the lowest tier of the organization (Local SASs) and the organization or system of *coordinators*.
- **Graduated sanctions:** When conflict situations occur within the context of the CPR management mechanisms, sustainable systems allow for actions (e.g., sanctions) that are scaled to the seriousness and context of the offense. In our case, sanctions are envisioned as modifications to the transmission parameters of the agents to avoid future conflict situations. These actions are scaled in terms of the restrictions imposed on future transmissions. For instance, switching channels impose fewer restrictions on transmission opportunities than limiting transmission power.
- **Conflict resolution mechanism:** This is a crucial component of sustainable CPRs. Agents need rapid access to low-cost arenas to resolve conflicts among benefactors or between benefactors and officials. The federal enforcement system (i.e., centralized approach) currently in place through the FCC's enforcement bureau does not meet this criterion[5]. Consequently, a local system must include a mechanism for automated or semi-automated coordination among users of the agreement. In our model, with the inclusion of local *coordinators*, participants can access a conflict resolution system that is closer to them and has local knowledge about the conflict situations.
- **Minimal recognition of rights:** This attribute refers to formal or informal recognition by central authorities of the local authorities. The CBRS regulation being used in our model already includes a SAS recognized by central authorities (i.e., the FCC) [1].
- **Nested enterprises:** The final component for sustainable CPR management is related to the organization of enterprises within the spectrum arrangements. In most CPR examples, the use, provision, monitoring, enforcement, conflict resolution, and governance activities are organized in multiple layers of nested enterprises. This organization has a similar structure to the one we implement in our model. It is necessary to point out that

[5] It is neither local nor low cost.

not all conflicts and disputes are resolved locally, so, at some point, it might be necessary to appeal to an independent and higher-level authority (e.g., the regulator).

5.4 Stage 4: Smarter agents in spectrum sharing scenarios

The outcome of stages 2 and 3 is a dynamic governance-based ABM (*Model 2.0*). We design this model using a rule-based approach. In other words, agents follow a predefined and static set of rules. We base these decisions on the current conditions of the agents (e.g., the RSS at a given position). However, these decisions do not consider previous experiences or the utilization of more complex decision-making mechanisms. In the final stage of this dissertation, we aim to improve the internal decision-making model of such agents.

To improve the decision-making capabilities of the participants in the sharing agreement, we rely on machine learning (ML) techniques. In particular, we leverage the benefits of endogenous ML for Agent-Based Modeling. The goal is for ML techniques (models) to provide individual agents with an intelligent behavior that analyzes data of past executions and allows them to learn from such experiences to maximize some outcomes.

In the same way as Stage 3, in this stage, we focus on *Type I* conflict events; thus, we assume that all the parties involved in the sharing agreement are cooperative. In our model, the main objective of the agents is to guarantee the proper operation of the system. Hence, all agents are continuously trying to avoid conflict situations in the band. In previous stages, the agents follow a predefined set of strategies to prevent conflict situations (e.g., switch channels). In this final stage, agents implement an endogenous machine learning model to avoid conflict situations. Figure 22 summarizes the general process we implement in Stage 4. In the first part of this process, agents collect and store data about their current environment, including conflict situations that result from the agent's operation (e.g., interference to higher tier users). Once enough data is collected, the agents analyze data from past executions through the construction and fitting of machine learning models (e.g., classification models). Finally, the agents can use these ML algorithms to minimize the probability of generating conflict events.

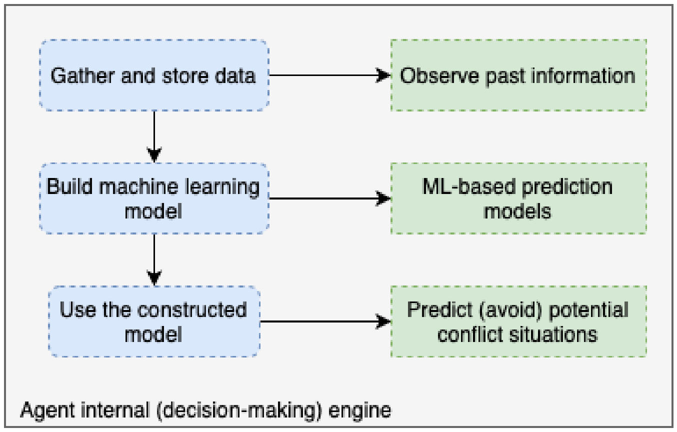

Figure 22: Stage 4 - General (local) machine learning process

5.4.1 Local vs. global endogenous machine learning

One of the main goals of this dissertation is to capture local behaviors to provide local solutions. We also design Stage 4 to help us solve this problem. Hence, we implement two distinct approaches to include endogenous machine learning in our model: a local and a global approach.

In the local approach, each agent is solely responsible for the whole process of improving its decision-making capabilities. This process includes collecting data, storing past executions, constructing ML models, evaluating their performance, and using the final models to try and avoid conflict situations. This process means that every agent trying to gain intelligent behaviors will be using an ML technique exclusively tailored to its (localized) executions and experiences (see Figure 22).

In the global approach both, interacting agents (e.g., SUs) and an external entity (e.g., a polycentric *coordinator*), collaborate to supplement decision-making capabilities to the system (see Figure 23). Thus, the interacting agent is solely responsible for gathering the data of its current experience and sending it to an external entity. Every interacting agent in the system is responsible for these gathering and transmitting processes. The external agent receives multiple pieces of data in each time interaction of the system. Once enough

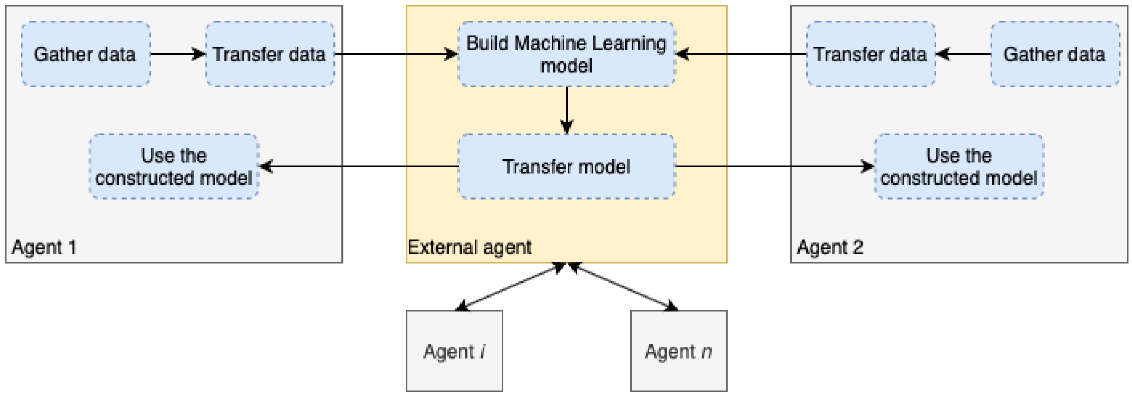

Figure 23: Stage 4 - General (global) machine learning process

data is received, the external agent builds and evaluates a machine learning model. This model is transferred back to the agents in the jurisdiction of the external agent. Finally, the interacting agents start using the (fitted) model to make decisions and avoid conflict situations.

6.0 Model implementation and experiments

In Chapter 5, we provide a broad overview of the conceptual foundations and the workings of the stages we analyze in this dissertation. In this chapter, we delve into the particulars of the modeling process of each stage by elaborating on the parameters utilized, working assumptions, and scope. The modeling considerations presented in this chapter lead us to the results presented in Chapter 7.

6.1 Stage 1: Including alternative (localized) governance mechanisms in spectrum sharing agreements (two-tier model)

The goal of Stage 1 is to test the viability of alternative governance mechanisms in spectrum sharing scenarios. In particular, the application of self-governance and how it compares to other governance mechanisms such as command-and-control. To test the application of self-governing, we create an Agent-Based Model for the 1695-1710MHz band (*Model 1.0*).

6.1.1 The 1695-1710MHz Agent-Based Model (two-tier model)

In the literature of Common Pool Resources (CPRs), many authors have successfully explored CPR management and governance problems through the implementation of ABMs [139, 138, 140, 197]. In this work, our model simulates the interaction of two main types of agents: 1) a single primary user or incumbent (e.g., meteorological satellite), and 2) several secondary users or new entrants (i.e., LTE handsets). We place all the agents on a simulation environment that captures the transmission zones (i.e., NAZ, LAZ, and UAZ) defined for the sharing scheme in the 1695-1710MHz band. The model considers that conflict situations may arise, and these represent circumstances where actions by one or more new entrants (or SUs) impact the normal operations of the incumbent. These conflict situations arise in the restricted areas of the sharing scheme (i.e., LAZ and NAZ).

To “translate” the definitions of the 1695-1710MHz spectrum sharing framework into an Agent-Based model that allows us to simulate the different behavioral situations in the sharing agreement, we define the following: Agents, environment, rules, norms, and strategies. In the following sections, we provide additional details about each of these components.

6.1.1.1 Agents The spectrum sharing framework of the 1695-1710MHz band comprises three types of equipment utilized by the PUs and SUs: meteorological stations, mobile handsets, and base stations. These entities are represented as independent agents in our model (see Figure 24). First, the NOAA Meteorological Satellite (MetSat Station) is a single, static agent located in the middle of the protection zones. Second, the LTE Mobile Stations (LTE Handsets) are multiple agents that move around the zones while communicating to their corresponding eNodeBs. Each of the SU participants is assigned a risk profile[1]. The assigned risk profile dictates the behavior of the new entrant when moving and transmitting in the environment. The system contemplates three different risk profiles: *Risk-prone*, *risk-neutral*, and *risk-averse*. Finally, Base Stations (eNodeBs) are four static agents that serve as coordination and communication points between the PU and SUs.

6.1.1.2 Environment We ground the ABM environment of *Model 1.0* on the definitions presented in Section 5.1.1. In this way, the “world”[2] where we place the different agents is divided into three zones: No Access Zone (NAZ), Limited Access Zone (LAZ), and Unlimited Access Zone (UAZ) (see Figure 24).

6.1.1.3 Rules, norms, and strategies (interactions) Once the primary functionalities of the agents are assigned, we define the rules, norms, and individual strategies that the agents follow throughout the simulation. As defined by North [131], institutions are “[t]he set of rules actually used by a set of individuals to organize repetitive activities that

[1] From the economics literature, a risk profile “identifies the acceptable level of risk an individual or corporation is prepared to accept. A corporation (or institution) risk profile attempts to determine how a willingness to take a risk (or aversion of risk) will affect an overall decision-making strategy” [198].

[2] Defined as the logical or physical plane where the agents are located and interact with each other [199].

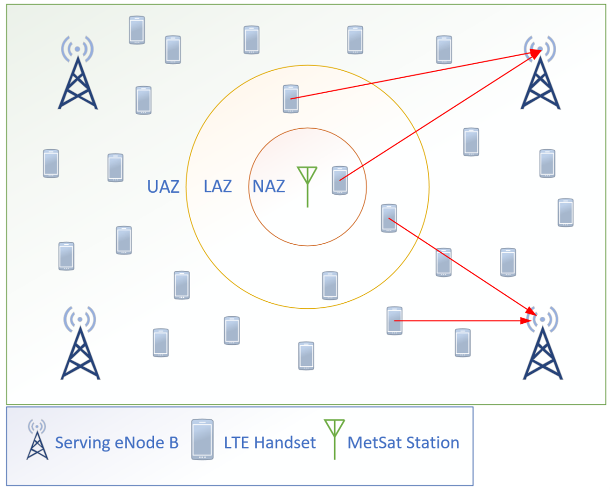

Figure 24: Stage 1 - 1695-1710MHz Spectrum sharing model - Agents, environment, and interactions setup

produce outcomes affecting those individuals and potentially affecting others." Based on this definition, we can see that the 1695-1710MHz sharing framework can be categorized as an institution: the actions of the incumbents have an impact on the new entrants and vice versa. This new definition is key to leveraging the benefits of the ADICO Grammar of Institutions. We leverage the simplicity of the ADICO model to define the rules for the primary and secondary users in our system.

Definitions for the primary user: In this stage, we explore both "extremes" of governing a spectrum-sharing framework. Hence, our agents possess two sets of definitions, one for the centralized approach and one for the distributed perspective in self-governing. Table 10 presents the rules that we define for the Meteorological Satellites (i.e., the incumbent of the band). The actions with the white background apply in all enforcement situations (government-centric and self-enforcement), while the operations with the blue background apply only in decentralized enforcement scenarios (i.e., self-enforcement).

Strategy definitions in the centralized approach: In the centralized governance scenario, the MetSat has little control over the sharing parameters; particularly, the size of the protection areas LAZ and NAZ. A central entity (i.e., the "government") defines most sharing criteria that the PU cannot update. Consequently, MetSat's only strategy in this scenario is to communicate the sharing parameters to the network coordination points (i.e., eNodeBs).

To detect unauthorized transmissions by the SUs, a detection system is assumed to be deployed. In our scheme, this system is given by the detection rate, d. This rate simulates the effectiveness of detection imposed by the government enforcer. The detection rate is a constant given to the system during the initialization phase and it is fixed throughout the entire simulation process to emulate the governance structure in place.

Strategy definitions in the distributed approach: In the self-enforcement scenario, the PU has greater control over the sharing parameters. The main task of the PU is to update the boundaries (i.e., size) of its surrounding exclusion and protection zones. We base this update process on the behavior of the SU agents and the continuous dealing process. The MetSat can reduce the size of the LAZ and NAZ areas if it receives a "good" or "trust" signal from the SUs (e.g., no interference has occurred). It can also increase the size of both zones to achieve superior protection against conflict situations. The variation in the size of these zones has a direct impact on the ability to detect enforceable events (i.e, the detection rate decreases when the monitoring area increases). For our model, we select a linear relationship to capture this problem[3], which is described in expression 6.1.

$$d = \frac{M \times E}{S} \tag{6.1}$$

Expression 6.1 captures the relation between increasing the size of the protection zones, S, and the ability of the system to detect interference situations, d. This detection rate of interference events is also the product of M, which represents the minimum size of the zone to avoid interference, and E, which is the detection effectiveness of the equipment being used (i.e., a probabilistic variable of whether an interfering agent is "caught"). The latter is included in the model to capture the access to information by the centralized authority. Since a single global entity is in place, it might receive incorrect or noisy information about the sharing conditions of the band[4].

[3] We select a linear relationship for the detection rate due to its simplicity and explicability. However, other expressions can be used to design and evaluate the relation between the size of the protected areas and the detection rate, d.

[4]

	MetSat definitions				
Agent	MetSat	MetSat	MetSat	MetSat	MetSat
Deontic	Obligated	Obligated	Obligated	Permitted	Permitted
aIm	Communicate LAZ size	Communicate NAZ Size	Communicate LAZ Threshold	Increase LAZ & NAZ size	Decrease LAZ & NAZ size
Condition	All the time	All the time	All the time	Interference happen	No interference
Or Else	None	None	None	None	None

Table 10: Stage 1 - Rules, norms, and strategies for the primary user

The size of the restricted areas is dynamically adjusted in the system as the simulation progresses. However, the PU still has to "decide" the initial boundary of the restricted areas, and the number of policing equipment units that simulate the "effectiveness", E, of such system. In self-enforcement, this is considered as an "initial gesture of trust" to start a dealing process [46]. Whether an interference event is detected or not by the system in place, the PU is responsible for updating the size of the restricted zones. This is given by the strategy for the PU to modify the boundaries defined according to expression 6.2.

$$S = \begin{cases} Increase, & Conflicts \geq 1 \text{ and } S < 1 \\ Decrease, & Conflicts = 0 \text{ and } S > 0 \end{cases} \tag{6.2}$$

Definitions for the Secondary User: In Table 11, we observe the rules defined for the secondary users or mobile stations. One important thing to note is that the rules defined do not vary with the governance system in place. The reason behind this assumption is that the SU always follows the same regulation, that is, only transmit when authorized.

We ground this notion on Hayek's analysis of the use of knowledge (i.e., information). Decentralized systems tend to be more efficient since we do not need to "...put at the disposal of a single central authority all the knowledge which ought to be used but which is initially dispersed among many different individuals..." [190].

	Handset definitions				
Attributes	Handset	Handset	Handset	Handset	Handset
Deontic	Obligated	Forbidden	Permitted	Permitted	Permitted
aIm	Associate with eNodeB	Transmit in NAZ	Transmit in LAZ	Transmit in UAZ	Move around
Condition	All the time	All the time	TXs <Threshold	All the time	All the time
Or Else	None	Sanction	Sanction	None	None

Table 11: Stage 1 - Rules, norms, and strategies for the secondary users

The new entrants in the band start by obtaining information on the size of restriction zones from the LTE eNodeBs. At the same time, SUs are moving around the environment while transmitting using the available spectrum space. To model the behavioral strategies of SUs, we rely on the tax evasion literature, particularly on the works by Bloomquist [200], Mittone and Patelli [201], and Davids et al. [202]. This well-known modeling strategy allows us to capture user perception of enforcement when complying with the assigned rules. In this manner, although all SU agents have a set of rules to follow (see Table 11), they might break them from time to time based on their enforcement perception and associated risk profiles. For instance, a *risk-prone* participant might choose to transmit in the NAZ or the LAZ (when the system reaches the maximum threshold), even though this would cause a spectrum usage conflict.

To account for this perception-based decision-making process, we ground our model on the standard macroeconomics theory of Allinghman and Sandmo [203]. This economics theorem states that a given user will break the rules whenever the perceived caught rate, p, and penalty rate (i.e., sanction), f (where $f \geq 0$), take on values that make expression 6.3 true.

$$p < \frac{1}{1+f} \tag{6.3}$$

The problem with Equation 6.3 is that it does not capture other factors that affect the decision-making process of a given agent. Bloomquist [200] argues that rule-breakers with high compliance opportunity costs (i.e., high discount rates) are more likely to break the rules than other agents. Nonetheless, this is not the only factor that influences the decisions of a given agent. For instance, the system should also consider the time lag between breaking the rule and the sanction or the perceived detection ability of the system. Consequently, we can use the alternative decision-making expression shown in equation 6.4.

$$p < \frac{1}{1 + cr} \tag{6.4}$$

$$cr = \frac{f \times d}{(1 + r_i)^t} \tag{6.5}$$

With our new parameters, a given user will break the rules if, and only if, expression 6.4 is true. The cr factor is the product of the interaction of the most important factors affecting the decisions of a given agent, and it is defined by Equation 6.5. In expression 6.5, t, is the average number of time periods between the infraction and the detection; d, is the detection rate of the enforcer, where $0 \leq d \leq 1$; and r_i is the discount rate for the agent i [200]. Based on expressions 6.4 and 6.5, an SU agent will break the rules whenever the perceived caught rate, p, and the agent perception, cr, take on values that make expression 6.6 true.

$$T_x = \begin{cases} No, & \text{if } p \geq \dfrac{1}{1 + cr} \\ Yes, & \text{Otherwise} \end{cases} \tag{6.6}$$

The factors described in expressions 6.4, 6.5, and 6.6 can take on multiple levels. Further, different combinations of these factors can result in distinct decision-making processes for the agents, as depicted in Figure 25. For example, if the detection is immediate, the decision to transmit depends only on the detection rate, d. If only one time period passes between the infraction and the sanction, an agent's transmission decision is based only on its discount rate, r_i. We also observe that the discount rate, detection time, and detection rate impact the different features of the decision-making process, hence providing different outcomes. These results show that Bloomquist's expression captures all the factors involved in the decisions

ABM Variable	Name	Levels
PerceptionFunction	Agent Perception: p	Actual, Perceived, Actual+Random, Perceived+Random
DetectionRateNAZ	Detection Rate in NAZ: d	From 0 to 100%
DetectionRateLAZ	Detection Rate in LAZ: d	From 0 to 100%
AverageDiscountRate	Discount Rate: r_i	From 0 to 100%
AdjudicationTime	Time to be sanctioned: t	From 0 to 10 time periods
PenaltyRate	Penalty: f	From 0 to 10 Units

Table 12: Stage 1 - Variables, levels, and parameters included in the two-tier (governance-based) spectrum sharing ABM (*Model 2.0)*

of an independent agent in a very concrete manner. In our agent-based model, we capture all the mentioned above parameters (see Table 12).

Different Perceptions We ground our model on the agents' perception regarding the probability of being caught and the status of the neighbors (i.e., a "social network"). Thus, the individual perception of each agent can take four types of functions:

1. <u>Actual:</u> The agents know the exact detection rate, d. All agents have the same perception with no distinctions.
2. <u>Actual + Random:</u> The agents know the exact detection rate, d. Nevertheless, they have different perceptions based on their risk profiles.
3. <u>Perceived:</u> The agents do not know the exact detection rate, d. We assign a random perceived rate to each agent. The risk profiles dictate these rates. Note that these agents' perception is updated according to their own experiences and those of their neighbors. Hence, when a certain agent or one of its closest "friends" is sanctioned (i.e., "caught"), it changes its perception and corresponding future behavior according to the previously explained expressions.
4. <u>Perceived + Random:</u> The agents do not know the exact detection rate, d. We assign a random perceived rate to each agent. These rates vary according to the agents' risk

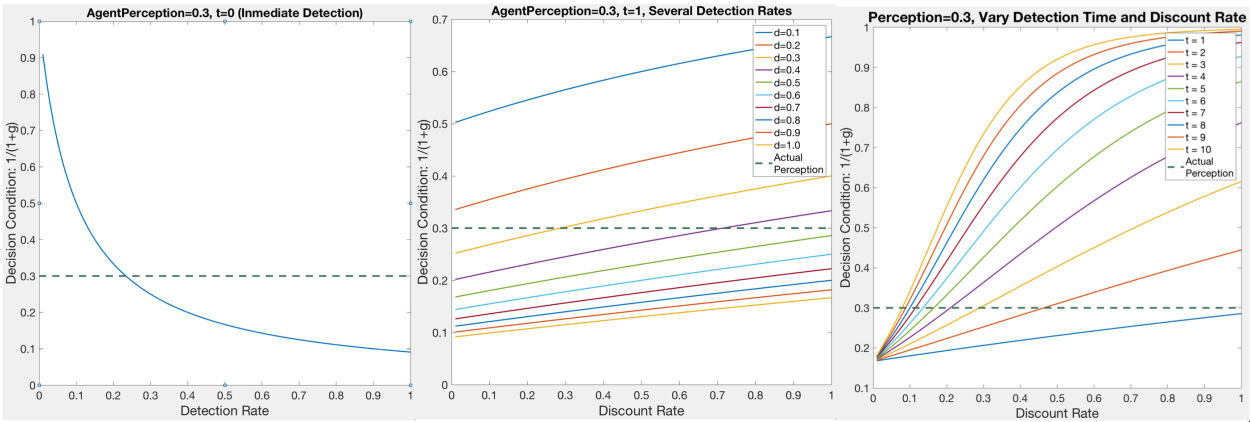

Figure 25: Stage 1 - Effects of the different parameters in the decision-making process of a given SU agent

profiles. This perception is dynamically updated based on the experiences of an agent and its neighbors.

The agent social network refers to the "status" of the neighbors of a given agent. In other words, neighbor's sanctions have an impact on an agent's perception regarding future interactions. Consequently, the social network of an agent modifies its behavior and strategies. We include this characteristic to capture the effect of "social pressure" in the agents' decision-making process. This model characteristic allows us to simulate what happens when communication and information exchange between agents is added to the system [49].

6.1.2 Self-governance in spectrum sharing scenarios

The fundamental premise of the distributed governance model (i.e., self-governance) is that the size or boundaries of the restricted zones are not static. Instead, zone boundaries result from the continuous interactions and communication efforts among the PU and SUs. The principal intent of this negotiation process is for the agents, and only the agents, to agree on optimal boundaries for the restricted zones (LAZ and NAZ) that protect the incumbent and provide enough incentives for the new entrants. These negotiations capture a crucial aspect of self-governance, the "discipline of continuous dealing". To avoid future conflict situations, the PU increases the size of the restricted areas to obtain additional interference protection against unauthorized SUs' transmissions. Nonetheless, an increase in the size of the restricted areas reduces the available spectrum space for new entrants. In absence of conflict (i.e., when SUs are complying with the transmission requirements), the PU reduces the size of its protection zones, hence increasing participation incentives and resource value for the SUs.

The ideal scenario in this continuous dealing framework is to find the "optimal" boundaries for the different sharing zones, which would lead to a setting where the system is in a "stable" state. In the context of this stage, stability means that there are no future drastic changes in the size of the restricted zones. In other words, a stable system would represent a well self-governed band where agents agree on a restricted zone size that guarantees that conflict situations would not impact the normal operations of the PU while providing incentives for SUs. Thus, the main goal of the experiments presented in this stage is to observe the viability of having a self-governing scheme in spectrum sharing scenarios and the conditions leading to it.

6.1.3 Experiment setup

To capture all the possible combinations of the factors and variables implemented in the ABM model constructed in Stage 1, we utilize Full Factorial Experimental Design: all combinations of levels, assuming k factors, every i_{th} factor with n levels and r repetitions for each level being tested (see expression 6.7). To capture the variance in the model, we choose a total of 10 replications for each experiment. It is necessary to point out that in the results highlighted in Section 7, all figures capture the average behavior of the different factors, levels, and repetitions.

$$TNE = r[\prod_{i=1}^{k}(n_i)] \tag{6.7}$$

In a self-enforcement governance mechanism, the different factors of the system are coordinated between the agents representing the primary and secondary users. However, as

Independent variables	
Factors	**Levels**
Initial Size LAZ (%)	20 40 60 80
Initial Size NAZ (%)	20 40 60 80
Detection Effectiveness (%)	25 50 75 100

Table 13: Stage 1 - Experiment setup - Self-governance model parameters, factors, and levels

an initial setup of the system, the model requires the input of two key factors: Initial Zone Size (LAZ and NAZ) and Detection Effectiveness (see Table 13). To simulate the different interactions, we also need to define some essential characteristics about the agents and the environment, which are detailed in Table 14.

From the variables and levels in the experiment design of Stage 1, we define three system scenarios, namely *Best Case Scenario (BCS)*, *Worst Case Scenario (WCS)*, and *Middle Case Scenario (MCS)*. The *BCS* implies that the governance parameters are at their highest level possible. In other words, the adjudication time is 0 (no delay between infraction and sanction), the penalty rate is the maximum possible, and the discount rate for the users is 0. On the other hand, the *Worst Case Scenario* is the complete opposite, where the adjudication time is 10 (maximum), each agent has a high discount rate, and the penalty is at its lowest possible. Lastly, the *MCS* captures an intermediate point between the two previously described system situations[5].

[5] The details of the implementation of *Model 1.0* are included in Appendix F.

Independent variables	
Factors	**Levels**
"Risk-Averse" Handsets	100
"Risk-Neutral" Handsets	100
"Risk-Prone" Handsets	100
Average Discount Rate	10, 20, and 50
Adjudication Time	0, 1, 5, and 10
Penalty Rate	0, 10
Social Network	ON and OFF
Perception Function	Actual, Perceived, and Perceived+Random
LAZ Threshold	1, 5, and 10

Table 14: Stage 1 - Experiment setup - General environment model parameters, factors, and levels

6.2 Stage 2: Radio Environment Maps to construct local and dynamic ABM environments

In Stage 2, the main objective is to provide local knowledge about the spectrum situation to agents in the spectrum sharing agreement. For this purpose, we use Interference Cartography (IC) or the spectrum map component of REMs. As shown in Section 5.2, by leveraging the definition of exogenous variables in the IAD framework and the structure of ABMS, we can connect the IC spectrum map with the environment of our ABM model. It is worth mentioning that the creation of REMs implies the widespread availability of spectrum measurement across multiple bands and periods. Nonetheless, the availability of up-to-date and extensive measurement campaigns of wireless signals (e.g., RSS or SNR) is limited. Thus, to create a valid IC map, we first simulate measurements in a given spectrum band (i.e., time, frequency, and space).

6.2.1 Simulated measurements

The first step to building an Interference Cartography (IC) map is to generate enough measurements that can later be interpolated. In this light, we have defined three possible map scenarios, specifically 1) an urban scenario with a map dimension of $1km^2$, 2) a suburban case with a $3km^2$ map area, and 3) a rural scenario with a map area of $5km^2$. The map region is divided into small meshes or cells with a $25m \times 25m$ area (see Figure 26). A set of simulated receivers or Measurement Capable Devices (MDCs) is deployed on the IC map (i.e., region of interest). These sensors can represent network detectors, spectrum sensing entities, user equipment (UE), among others.

The REM literature considers two sensor deployment schemes: one-mesh-one-sensor and random sensor deployment [77, 78]. In the one-mesh-one-sensor scheme, a sensor is deployed in each mesh randomly. Thus, the maximum number of sensors to be deployed is equal to the total number of cells[6]. The value of the cell is the measurement obtained by the sensor in such a cell. Thus, after gathering measurements from all sensors in a map region, the REM

[6] In other words, a single cell cannot have more than one sensor.

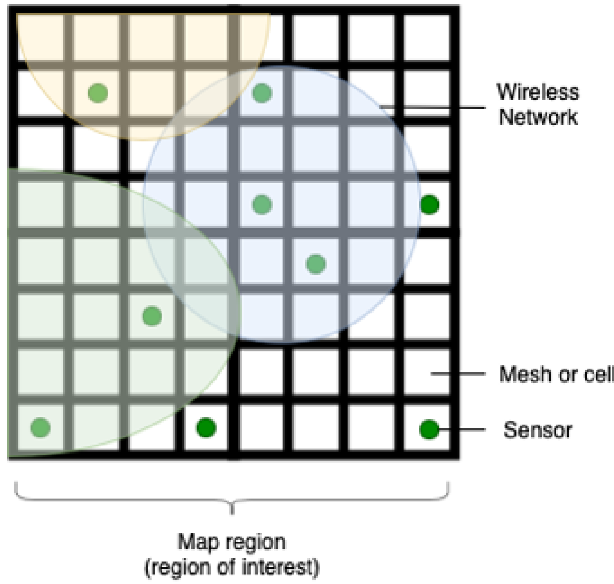

Figure 26: Stage 2 - Map distribution and sensor deployment for the REM construction (simulation)

can be constructed. In random sensor deployment, the sensors are randomly deployed in the map without regard for mesh boundaries. In this case, the average radio signal measurement of the sensors in a mesh is considered the value for such a cell. In this work, we utilize the one-mesh-one-sensor scheme to maximize the results obtained from the measuring devices[7].

In each spectrum environment map, a varying number of incumbents or Primary Users' transmitters (PuTx) can be simulated. To capture as many REM components as possible, each PuTx can be simulated independently and with different features. Hence, each PuTx is represented as a combination of name, location (latitude & longitude), antenna height, frequency, and transmission power (see Figure 27).

In our REM simulator, a variable number of receivers acting as MCDs are deployed (simulated) on top of the IC map. These receivers are modeled according to a location (latitude & longitude), antenna height, and receiver sensitivity (see Figure 27). Finally, the

[7] It is worth noticing that due to the modularity of our REM simulator, we can also include the random sensor deployment as an external function of the model.

simulated receivers can detect two types of measurements. 1) the Received Signal Strength (RSS) from each transmitter or 2) the total Signal-to-Noise plus Interference (SNIR) ratio[8].

The final component in our REM simulator generates the data for the following stages. It combines the information received from the map generation (i.e., type and dimensions of the map), the calculated measurements from the set of receivers (i.e., MCDs), and the real (simulated) measurements from the transmitters (see Figure 27). The latter represents the "real-values" of the received signal for each cell in the map. The first outcome of our REM-simulator is a vector representation that contains the location (longitude & latitude) and received signal at the measurement points (i.e., *measured_values*). The second outcome is a matrix that contains the location (longitude & latitude) of all the cells in the map and their corresponding received signals (i.e., *real_values*)[9].

6.2.2 Interpolation

Typically, a limited number of measurements are taken (simulated) to construct the IC map. In other words, not all the cells in the mesh map have access to a direct measurement from a sensor. Consequently, the remaining signal-related values for the cells without a measurement need to be estimated. Two methods are usually utilized to interpolate/extrapolate the remaining measurements to generate the IC map for an REM, specifically indirect and direct methods (see Section 2.3.1).

Direct methods interpolate the remaining missing values of a spectrum map through various spatial statistics techniques. In the literature, there are many methods for spatial interpolation that have been applied to the development of REMs (see Section 4). In our REM-simulator, we implement the following spatial interpolation techniques: linear, nearest neighbor, or natural neighbor interpolation.

[8] In the case of a single transmitter, the Signal-to-Noise (SNR) ratio is calculated instead.

[9] These values allow us to evaluate the interpolation performance of the map by comparing the interpolated value with the "real" (simulated) measurement.

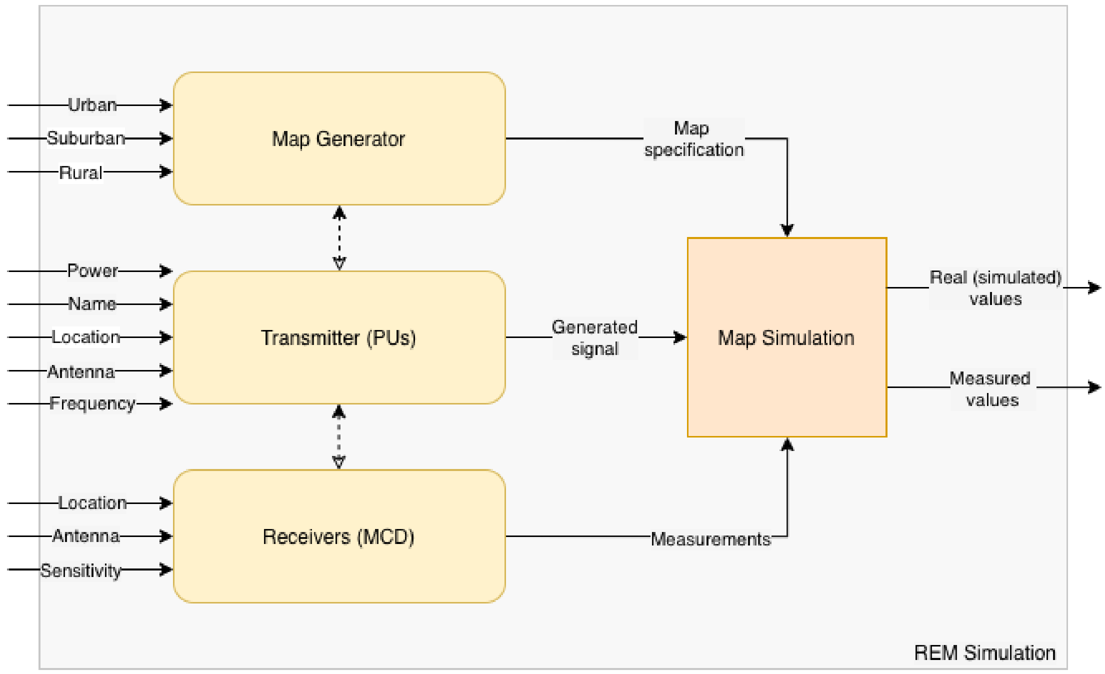

Figure 27: Stage 2 - REM simulation process

6.2.2.1 Linear interpolation Linear interpolation is a method of curve fitting using linear polynomials to obtain new data points based on a set of known measurements. If two set of measurements are respectively located at x_1, y_1 and x_2, y_2, the "linear interpolant" is then the straight line connecting these measurement points. If a point located in position x_i is to be interpolated, its corresponding y_i value is located along the linear interpolant and its value is given from the corresponding slope equations, as follows:

$$\frac{y_i - y_1}{x_i - x_1} = \frac{y_2 - y_1}{x_2 - x_1} \tag{6.8}$$

Solving expression 6.8 for y_i, which is the unknown value corresponding to x_i, we have:

$$y_i = y_1 + (x_i - x_1)\frac{y_2 - y_1}{x_2 - x_1} = \frac{y_1(x_2 - x_i) + y_2(x_i - x_1)}{x_2 - x_1} \tag{6.9}$$

Equation 6.9 can also be considered as a weighted average. The weights are inversely related to the distance from the endpoints of the straight line (i.e., the linear interpolant) to the unknown point, x_i. In other words, the closer the point the more influence it has in the resulting value, y_i. Given that the weights $\frac{x_i - x_1}{x_2 - x_1}$ and $\frac{x_2 - x_i}{x_2 - x_1}$ are normalized distances between the unknown point, x_i, and each of the endpoints, x_1, y_1 and x_2, y_2, and the sum is equal to 1, we have:

$$y = y_1\left(1 - \frac{x_i - x_1}{x_2 - x_1}\right) + y_2\left(1 - \frac{x_2 - x_i}{x_2 - x_1}\right) = y_1\left(1 - \frac{x_i - x_1}{x_2 - x_1}\right) + y_2\left(\frac{x_i - x_1}{x_2 - x_1}\right) \quad (6.10)$$

6.2.2.2 Nearest neighbor interpolation Nearest neighbor interpolation is widely used in various fields such as image processing and reconstruction. This method is the simplest technique to find unknown pixels (i.e., values). To understand nearest neighbor interpolation, let us consider the following example:

- Consider a quadratic matrix of known values (i.e., measurements), A.

$$A = \begin{bmatrix} 10 & 4 & 22 \\ 2 & 18 & 7 \\ 9 & 14 & 25 \end{bmatrix} \quad (6.11)$$

- Define the new size for the matrix of the interpolated values. In other words, the number of matrix entries to be estimated (i.e., the size of the region of interest). In our example, we can consider a quadratic matrix, I, with a 6×6 dimension.
- Find the ratio of matrix A compared to matrix I, as follows:

$$Ratio_{Row} = \frac{3}{6} \quad Radio_{Column} = \frac{3}{6} \quad (6.12)$$

- Normalize the row-wise pixel (i.e., measurement) positions and column-wise positions based on the new size.

$$Row_{positions} = \frac{\begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 \end{bmatrix}}{Ratio_{Row}} = \begin{bmatrix} 0.5 & 1 & 1.5 & 2 & 2.5 & 3 \end{bmatrix} \quad (6.13)$$

- Round the values to the nearest integer greater or equal to the value. In other words, find the nearest neighbor matrix.

$$Column_{position} = \begin{bmatrix} 1 & 1 & 2 & 2 & 3 & 3 \end{bmatrix} \quad Row_{position} = \begin{bmatrix} 1 \\ 1 \\ 2 \\ 2 \\ 3 \\ 3 \end{bmatrix} \tag{6.14}$$

- Using matrix A and the $Row_{position}$ vector, it is possible to perform row-wise interpolation on the columns of matrix I. Let us consider the first column of matrix A:

$$A(:,1) = \begin{bmatrix} 10 \\ 2 \\ 9 \end{bmatrix} \rightarrow A_{pos} = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} \quad Interpolating \quad I_{pos} = \begin{bmatrix} 1 \\ 1 \\ 2 \\ 2 \\ 3 \\ 3 \end{bmatrix} \rightarrow I(:,1) = \begin{bmatrix} 10 \\ 10 \\ 2 \\ 2 \\ 9 \\ 9 \end{bmatrix} \tag{6.15}$$

- After interpolation has been completed for all columns in our matrix A, the resulting matrix I is:

$$I = \begin{bmatrix} 10 & 4 & 22 \\ 10 & 4 & 22 \\ 2 & 18 & 7 \\ 2 & 18 & 7 \\ 9 & 14 & 25 \\ 9 & 14 & 25 \end{bmatrix} \tag{6.16}$$

- After the row-wise interpolation is finalized, the column-wise interpolation starts. Similarly to row-wise, to interpolate the values on the new matrix I the original matrix A and the vector $Column_{position}$ are combined. For instance, take the first row from the row-wise interpolation matrix, $A(1,:) = [10 \quad 4 \quad 22]$. Using the column position vector the values are interpolated as follows:

$$\begin{aligned} A(1,:) &= \begin{bmatrix} 10 & 4 & 22 \end{bmatrix} \rightarrow A_{pos} = \begin{bmatrix} 1 & 2 & 3 \end{bmatrix} \quad \textit{Interpolating}: \\ I_{pos} &= \begin{bmatrix} 1 & 1 & 2 & 2 & 3 & 3 \end{bmatrix} \rightarrow I(1,:) = \begin{bmatrix} 10 & 10 & 4 & 4 & 22 & 22 \end{bmatrix} \end{aligned} \tag{6.17}$$

- After the column-wise and row-wise interpolations are completed, the new interpolated matrix, I, is fully interpolated as follows:

$$I = \begin{bmatrix} 10 & 10 & 4 & 4 & 22 & 22 \\ 10 & 10 & 4 & 4 & 22 & 22 \\ 2 & 2 & 18 & 18 & 7 & 7 \\ 2 & 2 & 18 & 18 & 7 & 7 \\ 9 & 9 & 14 & 14 & 25 & 25 \\ 9 & 9 & 14 & 14 & 25 & 25 \end{bmatrix} \tag{6.18}$$

6.2.2.3 Natural neighbor interpolation This is the final spatial statistics-based technique in our REM simulator. This technique has advantages over simpler methods of interpolation (e.g., nearest neighbor) since it provides a smoother approximation to the underlying "true" function describing the known values. This method is based on a "Voronoi Tessellation"[10] of a discrete set of known spatial points (i.e., measurements).

The basic equation of natural neighbor interpolation is given by expression 6.19, where $G(x)$ is the estimate at point x, w_i are the weights, $f(x_i)$ are the known data at x_i, and n is the total number of available measurements (i.e., known values).

$$G(x) = \sum_{i=1}^{n} w_i f(x_i) \tag{6.19}$$

After inserting the new point x within the existing Voronoi tessellation, a new Voronoi cell is created. The weights, w_i, represent the intersection of the new cell with each of the surrounding cells. These weights are calculated by finding how much of each of the

[10] A partition of a plane into regions close to each of a given set of objects called seeds, sites, or generators. For each seed, there is a corresponding region consisting of all points of the plane closer to that seed than to any other. These regions are called Voronoi cells.

surrounding areas is "stolen" when inserting x into the tessellation. To calculate w_i two methods are usually implemented: the "Sibson" and "Laplace" weights.

In 6.20, we find the calculations for w_i using the Sibson weights technique. $A(x)$ is the volume of the new Voronoi cell centered in x, and $A(x_i)$ is the volume of the intersection between the new cell and the old cell centered in x_i

$$w_i(x) = \frac{A(x_i)}{A(x)} \tag{6.20}$$

Another approach to calculate w_i is using the Laplace weights technique as shown in Equation 6.21. $l(x_i)$ is the measure of the interface between the cells linked to x and x_i, and $d(x_i)$ is the distance between x and x_i.

$$w_i(x) = \frac{\frac{l(x_i)}{d(x_i)}}{\sum_{k=1}^{n} \frac{l(x_k)}{d(x_k)}} \tag{6.21}$$

6.2.2.4 Received Signal Strength Difference (RSSD) The REM simulator also includes an indirect method for the interpolation of the missing values. For this purpose, we rely on the RSSD transmitter-location-based approach. The principal assumption behind this technique is that the transmitter's location (e.g., PU) is not known, but an estimate of its transmission power is available for the MCDs. Therefore, it is possible to estimate the transmitter's location and calculate the missing measurements using propagation models.

In section 6.2.3, we expand on the process utilized to estimate the location of the transmitter. Note that we can use this location in other stages of this work. For instance, we can utilize it in cases where the location of the PU is unknown but necessary, such as to locate restricted zones for passive users such as the Fixed Satellite Service (FSS) in CBRS.

Once the location of the transmitters is estimated, we use different propagation models (e.g., Longley-rice, Free space path loss (FSPL), among others) to interpolate the missing values[11]. In our simulated REM, we implement a Free Space Path Loss (FSPL) propagation model, as described in Equation 6.22. We assume long-term fading that arises when the coherence time of the channel is large relative to the delay constraint of the channel. In this

[11] The baseline parameters of the propagation models we use are available in Appendix A.

model, the amplitude and phase change imposed by the frequency band can be considered roughly constant over the period of use. We assume slow fading since it is usually caused by events such as shadowing, where a considerable obstruction (e.g., hills or buildings) obscures the main signal between the transmitter and the receiver.

$$P_i^{rx}[dB] = P^{tx}[dB] - P_{Lo} - 10log_{10}d^{\alpha}_{x_i,y_i} + S_i \tag{6.22}$$

The ideal RSS at the ith MCD is denoted by P_i^{rx}, where P_{Lo} and α are the path loss correction and path loss exponents, respectively. P^{tx} is the transmission power of the primary user, d_{x_i,y_i} is the distance between the transmitter and the ith secondary user or MCD, and S_i is a Gaussian random variable with mean zero and variance σ_s^2 for expressing the effects of log-normal shadowing.

RSS values at each MCD could have severe disturbances caused by the shadowing effect. Hence, the simulated REM indirect interpolation includes an option to simulate "raw" RSS signals and evaluate the sample mean to reduce the shadowing effect as follows:

$$\overline{P_i^{rx}}[dB] = \sum_{j=1}^{N_m} \frac{P_{i,j}^{rx}[dB]}{N_m} \tag{6.23}$$

Where $P_{i,j}^{rx}$ is the jth measured RSS value at the ith MCD and N_m is the total number of samples for unit measurement.

6.2.3 Experiment setup

As previously explained, the construction of the IC or spectrum map implies two main steps, namely the simulation of wireless signals and the interpolation of values in cells without sensor measurements. Thus, we divide the evaluation of Stage 2 into two phases: 1) map representation, and 2) interpolation performance.

The main goal when testing the map representation is to observe the ability of the REM Simulator to generate measurements at different receiver (e.g., sensors) locations and for different types of maps (see Table 15). Similarly to Stage 1, to capture all the possible combinations of the factors, k, and levels, n, we utilize a Full Factorial Experimental Design with $r = 10$ repetitions for each level.

Experiment setup for the map representation	
Factors	**Levels**
Type of map	[Urban, suburban, & rural]
Number of MCDs	0:4:40
Repetitions	100

Table 15: Stage 2 - Experiment design for the map representation component of the REM Simulator

After testing the measurement simulation across different locations in a region of interest, the next step in the IC map construction is to interpolate the missing cell values. A fundamental aspect of this interpolation process is to evaluate the error between the real (measured) and interpolated values. We use the Root Mean Square Error (RMSE) between the simulated (measurements) and the resulting map as our main evaluation criterion (see Expression 6.24[12]). To evaluate the performance of the interpolation models, we run the experiments shown in Table 16. Each experiment is the result of the combination of each factor, k and level n in a Full Factorial Design.

$$RMSE_{Interpolation} = \sqrt{\left(\frac{\sum_{i=1}^{N}(x_i - \widehat{x_i})}{N}\right)} \tag{6.24}$$

6.3 Stage 3: A local and multi-tier spectrum sharing scenario under different governance systems

The goal of Stage 3 is to incorporate the remaining components that allow us to capture local usage patterns. In particular, additional localized governance mechanisms and resource

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In this equation, i is the variable being tested, N is the number of non-missing data points, x_i is the actual observation (simulated measurement) and $\widehat{x_i}$ is the estimated value (i.e., interpolated value).

Experiment setup for the interpolation performance	
Factors	**Levels**
Type of map	[Urban, suburban, & rural]
Number of MCDs	0:4:40
Interpolation method	[Linear, nearest neighbor, natural neighbor, & RSSD]
Repetitions	100

Table 16: Stage 2 - Experiment design for the interpolation component of the REM Simulator

access strategies. We find it valuable to place this sharing model within broader frameworks that permit us to take a more comprehensive view of the entire system. Leveraging the fact that the exploitation of spectrum bands for wireless transmissions fits the definition of a CPR, we can situate, study, model, and test the design of Stage 3 within the IAD and EG frameworks. Presenting our ABM in this manner, allows us to place the problem within a broader context, which also points to possible future directions and applications of this research[13].

6.3.1 Identifying the variables in spectrum sharing agreements

The IAD framework allows us to identify the main variables present in the institutional arrangement of spectrum sharing. Since this framework considers the interplay of multiple agents and entities in the system, it is of particular interest for Stage 3. In Figure 28, we summarize the general components of the sharing agreement we analyze from an IAD perspective. As we can observe, the actions of each of the agents impact the system performance, but at the same time, feedback is provided from current outcomes, which may influence subsequent operations.

[13] In Appendix G, we find the details regarding the modeling implementation of *Model 2.0* using Python and the *Mesa* framework.

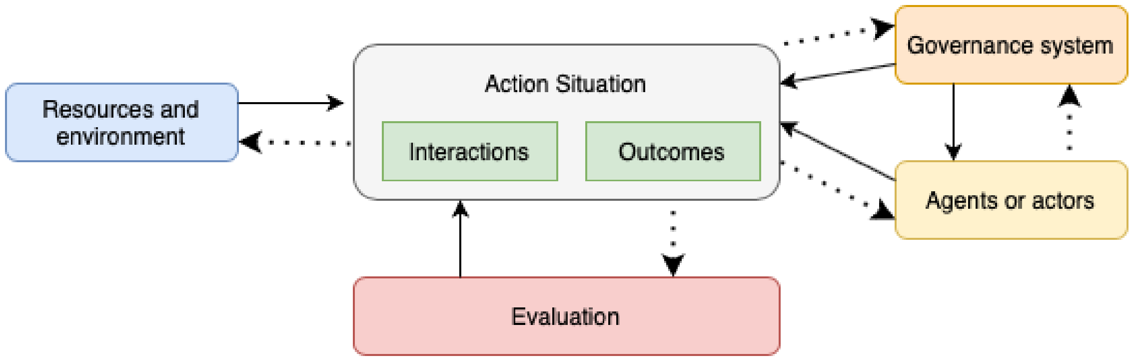

Figure 28: Stage 3 - Spectrum sharing IAD Framework

6.3.1.1 Actors (agents) In Stage 3, we use the definitions of the CBRS band as a base for our spectrum sharing model. There are three tiers (levels) of users in the band. These tiers determine the main types of agents (participants) in our model.

- **Incumbent Access (IA):** The incumbent users are the current license holders of the spectrum sharing agreement. They receive the highest protection levels against conflict situations from any other agent in the system. In the CBRS definitions, these agents are divided into two categories. First, Federal participants, located in the 3550-3700MHz band, are active users relying on the band for transmission and reception of wireless signals. Second, Fixed Satellite Service (FSS) users located in the 3600-3650MHz band, which are passive users relying on the band for downlink transmissions (space-to-earth)[14].
- **Priority Access Licensees (PAL):** This second type of agent receives protection against conflict situations from lower-tier users (i.e., GAA). Thus, PALs should protect and accept interference from higher tiers (e.g., IA users). These users can also be classified as primary users in our sharing agreement since they are licensed users[15]. Each PAL receives a fixed (10MHz) channel within the 3550-3650MHz band.

14 Temporally, the band also considers grandfathered wireless broadband licensees as part of the IA users. However, since this inclusion is only for a finite period, they are not considered in our model.

15 PALs are licensed county-by-county with a 10-year (renewable) license, where up to seven PALS may be licensed in any given county [204].

- **General Authorized Access (GAA):** The final agents in our model are licensed-by-rule participants to permit open, flexible access to the 3.5GHz band. In other words, GAA users are opportunistic secondary users or new entrants in the sharing agreement. Therefore, they should not generate any conflict event with the higher-tier users (i.e., IA and PAL), and they should accept interference from them[16]. GAAs are free to use any portion of the band between 3550-3700MHz.

The model simulates the interaction of the previously described sharing agents in the CBRS scheme. The Primary Users (PUs) include both the Incumbent Access (IA) and the Priority Access License (PAL). On the other hand, the General Authorized Access (GAA) actors are the Secondary Users (SUs) in the the band. Depending on the governance system in place, a governance *coordinator* is added as an complementary actor in the sharing scheme. This agent plays a role in the centralized and polycentric approaches. In Section 6.3.1.4, we detail the main functionalities of this actor. The model also considers one additional, non-interacting, agent of the type *sensor*. This agent measures the wireless signals (e.g., Received Signal Strength (RSS)) of the different PUs in the band. These values are then stored in the REM and can be accessed by the Secondary Users to identify the presence of a Priority user to facilitate shared spectrum access. The introduction of this sensor-like agent and an REM database simulates the CBRS concept of the Environmental Sensing Capability (ESC) mechanism.

6.3.1.2 Resources and environment The conditions of the CBRS band definitions also dictate the available resources. The only frequency band where all the previously analyzed agents are allowed to concurrently operate is the 3550-3650MHz band (see Figure 29[17]). However, as defined by the FCC, this portion of the band does not include the FSS earth stations that operate in the 3600-3650MHz band. Therefore, we define the resources in the sharing agreement as two independent channels or frequency bands (*c1* and *c2*). These channels are located in the 3600MHz and 3640MHz frequency bands with a bandwidth of

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GAA uses also have no expectation of conflict protection from other users in the same tier. However, an analysis of this type of conflict situation lies outside the scope of this dissertation.

17

Original figure taken from `https://www.fcc.gov/35-ghz-band-overview`.

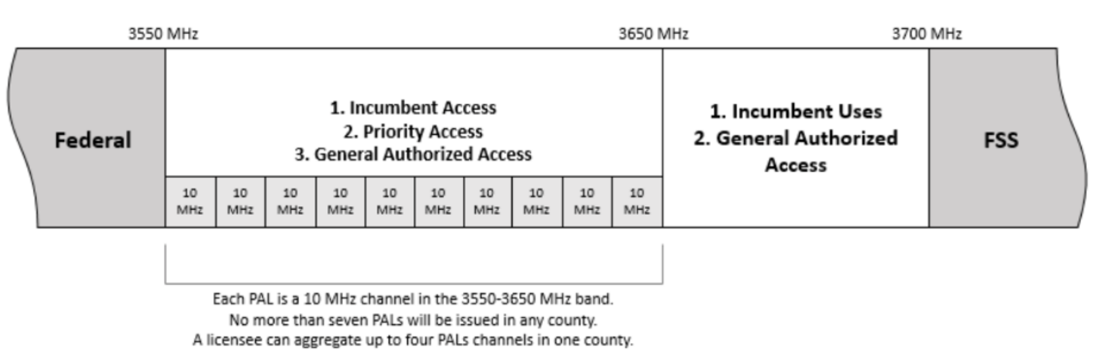

Figure 29: Stage 3 - FCC's CBRS band structure

10MHz each. These channels simulate an environment where all agents (i.e., Federal, FSS, PAL, and GAA) are authorized to access the shared spectrum. In addition, these channels are aligned with the first and last (10MHz) assignable channels for PAL users.

As explained in Section 5.2, the environment for the spectrum sharing scenario corresponds to the Interference Cartography (IC) map of the band. In this way, either an urban, semi-urban, or rural map is created (simulated) for the model. This map is further divided into meshes or cells that contain local information about the spectrum situation in their particular location (e.g., RSS). The different agents are deployed within these cells. When a user needs to know its local spectrum conditions (e.g., RSS), it queries the IC map of the REM and obtains the spectrum information from the particular cell where the agent is located.

6.3.1.3 Action Situation The Action Situation is the core component of the IAD Framework. As described by Ostrom, the action situation is the "social space where individuals interact, exchange goods and services, solve problems, dominate one another, or fight (among the many things that individuals do in action situations)" [135]. In this section, we study the connection between the components of the action situation and the different parts of our spectrum sharing model. For this purpose, we use the set of variables that best describe the action situation, as follows:

- The set of actors: Who and how many participants withdraw resource units from this resource system?
- Positions: The specific positions filled by the participants (actors).
- The set of allowable actions (and their linkage to outcomes)
- The potential outcomes: Linked to a specific action, what chain of events links actions to outcomes?
- The level of control each participant has over choice

Using these variables, we define the action situation of our particular institution, namely a local multi-tier spectrum sharing scenario.

Actors: The set of actors interacting in our system are Incumbent Access (IA) (Federal and FSS), Priority Access License (PALs), General Authorized Access (GAA) users, and governance coordinators.

Positions The positions of the different agents or actors are derived from the set of rights that are assigned to them. In other words, the set of rights associated with each tier in the sharing agreement.

Set of allowable actions: The set of allowable actions is also directly derived from the band definitions. In this light, primary users are allowed to operate (i.e., transmit) at any time, frequency, and space. On the other hand, the secondary users' agreement states that they should operate only when no conflict is caused to higher-tier users. For instance, when the PU is not transmitting, or the SU's transmitted signals do not impact the normal operations of higher-tier actors. To define the set of allowable actions for the different actors (agents), we rely on the ADICO framework (see Section 2.4.3.3). To set these actions (strategies), we use the Attribute (A), aIm (I), and Condition (C) components as summarized in Table 17.

An important component as part of the allowable actions is the definition of load in the system. To capture this component, we include an *SU load* variable to simulate situations with high (SU) congestion and their impact on the sharing agreement. Thus, agents emulating SUs are assigned a *transmission probability*. The agents use this variable to decide whether they have data to transmit[18]. This *transmission probability* is drawn from a normal

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Allowable actions		
A	**I**	**C**
PU	Transmit	When needed (no restriction)
SU	Transmit	If PU not active
SU	Transmit	No conflict events to higher tiers
SU	Change transmission parameters	If required (by coordinator)
Coordinator	Check conflicts	All the time
Coordinator	Implement actions	If conflict
Coordinator	Change transmission parameters	If required
Sensor	Measure (local) spectrum value	All the time
Sensor	Update REM's IC map	All the time

Table 17: Stage 3 - Actors' allowable actions in the action situation

distribution with an average given by the variable *SU load*. Therefore, the *SU load* variable dictates the level of congestion in the system given by the activity extent of the different secondary users.

Potential outcomes: The outputs of the institution are the result of the interactions among the actors in the network. Due to the nature of the sharing scheme, the model generates conflict situations (e.g., interference) impacting the normal operations of the system. These conflict events are one of the potential outcomes of the spectrum-sharing institution. In our model, we consider two types of conflict events: *Type A*, and *Type B*.

Type A: These events occur when an SU is located within the protection area or zone of an active (i.e., transmitting) PU, which is given by the Interference Threshold (IT) value in the model. In this light, the new entrants of the band query the IC map of the REM to identify the presence of an active primary user before transmitting any data. This process is similar to Carrier Sensing Multiple Access (CSMA), where active nodes "sense or listen" to the shared medium before transmitting [205]. If no signal (given by the RSS value in the location of the SU) is detected, the SU is authorized to utilize the available resources. On the other hand, if a PU's signal is detected, the SU is required to wait until the medium is idle to complete its transmission (Equation 6.25).

$$SU_{transmission} = \begin{cases} Authorized, & \text{if } RSS \leq Interference\ Threshold \\ Non-Authorized, & \text{Otherwise} \end{cases} \tag{6.25}$$

A *Type A* conflict event occurs when the RSS value measured and stored by the REM is not 100% accurate. The accuracy problems of the REM come from two sources. First, we have interpolation problems. The REM is divided into smaller cells that obtain its wireless signals values from the network of sensors deployed in the environment. Nevertheless, not all cells have access to a sensor in its location. Hence, the REM values for these cells come from an interpolation process (e.g., nearest neighbor algorithm). This interpolation process leads to inaccurate signal readings in the different cells of the IC map. To capture

The agent simulates a random number in each interaction (between 0 and 1). Then, it compares the generated number with its *transmission probability*. If *transmission probability* $>$ *random number*, it is assumed that the agent has data to transmit.

this phenomenon, a *sensor density* variable is included in *Model 3.0*. This variable dictates the proportion of the REM covered by MCDs or sensors. In other words, *sensor density* establishes the proportion of cells in the IC map that have direct access to a sensor.

Even if an REM cell has direct access to a sensor, wireless transmission phenomena (e.g., slow fading) may impact the accuracy of a measurement. In our simulated REM, we utilize the Free Space Path Loss (FSPL) propagation model to measure (simulate) the wireless values for each sensor[19]. Our ABM also captures this situation, where we include a *fading deviation* variable. This *fading deviation*, S_i, is the mean of a Rayleigh distribution value added to each of the sensor measurements. We include this variable as a means to introduce errors in the measurement process that captures a variety of wireless factors.

To summarize, a *Type A* conflict event occurs when the incorrect value or RSS is passed from the REM to the SU. Thus, the SU may assume that it is either outside the protected area of the PU (given by the interference threshold (IT)) or that the PU is not currently active (see Figure 30 and Equation 6.27).

$$P_i^{rx}[dB] = P^{tx}[dB] - P_{Lo} - 10log_{10}d^{\alpha}_{x_i,y_i} + S_i \tag{6.26}$$

$$Conflict\ Event\ Type\ A = \begin{cases} Yes, & \text{if } RSS \leq IT \text{ and } Actual\ signal \geq IT \\ No, & \text{Otherwise} \end{cases} \tag{6.27}$$

Type B: These events are not a direct product of the inaccuracies of the Interference Cartography map of the REM. Instead, these conflict situations are caused by the overlapping of the signals of the Primary and Secondary users. In this scenario, the SU is outside the protection zone of the primary user, i.e., it is outside the defined Interference Threshold (IT) value. Consequently, the SU is authorized to transmit ($RSS \leq IT$). Due to the transmission characteristics of the agent and the wireless environment, a part of the SU's signal may overlap with the PU's protection zone. Note that, in our model, conflict events

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As described in Equation 6.26, the ideal RSS at the *ith* MCD or sensor is denoted by P_i^{rx}, where P_{Lo} and α are the path loss correction and path loss exponents, respectively. P^{tx} is the transmission power of the primary user, d_{x_i,y_i} is the 2D distance between the transmitter and the *ith* secondary user or MCD, and S_i is a Gaussian random variable with mean zero and variance σ_s^2.

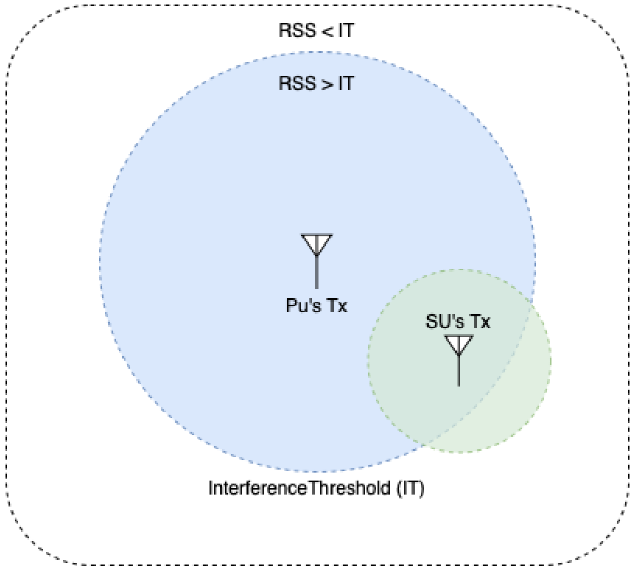

Figure 30: Stage 3 - *Type A* conflict event

are produced only on the reception end of the communication (e.g., reception devices of the primary user); thus, the simple overlap of signals is not considered a usage conflict event. If a receiver device (e.g., a mobile user)[20] is located within the overlapping areas, a usage conflict event occurs (See Equation 6.28 and Figure 31). This event is referred to as conflict situation *Type B* in our model.

$$Conflict\ Event\ Type\ B = \begin{cases} Yes, & \text{if } RSS_{SU} \geq IT \text{ and } RSS_{PU} \geq IT \\ No, & \text{Otherwise} \end{cases} \tag{6.28}$$

Level of control: The level of control of each participant of the band is directly related to the governance system in place.

20 In our model, a part of the sensor network deployed in the sharing environment are receivers (e.g., mobile users) of the primary user.

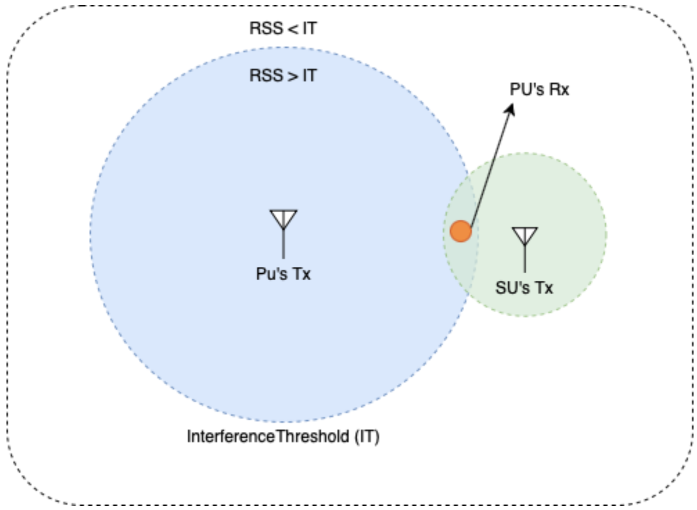

Figure 31: Stage 3 - *Type B* conflict event

6.3.1.4 Governance system Since conflict events arise in the system, the system implements different governance mechanisms to minimize the number of conflict situations. The main goal of each governance system is to guarantee the sound operation of the system. In our model, three different types of governance systems are implemented: centralized, polycentric, and self-governance.

Centralized governance: Simulates a command-and-control-like approach. A single entity (e.g., a regulatory institution) is in charge of defining the different parameters of the sharing agreement (e.g., interference threshold, SUs' transmission parameters, etc.). In our model, we implement a single (*coordinator*) agent in charge of receiving information of potential conflict events and taking action towards reducing such events. The central *coordinator* implements two separate strategies to reduce the number of usage conflict events, one for events of *Type A* and another for events of *Type B*.

To deal with IC map errors (i.e., *Type A* conflicts), the central *coordinator* modifies the size of the PU's protection zone by adjusting the Interference Threshold (IT) value of the model[21]. In the centralized approach, this change applies to the whole area (i.e., region of

[21] It increases the size of the protection zone by increasing the interference threshold (IT).

interest) under the control of the central entity (See Figure 32).

To reduce the number of *Type B* events, the central *coordinator* asks all secondary users in the agreement to modify their transmission characteristics. In particular, it mandates the reduction of the maximum allowed transmission power of the secondary users (see Figure 32). The goal is to reduce the signal overlapping and avoid conflict situations between the receivers of the PUs and the lower-tier users.

Note that if there are no conflict events, the central authority (*coordinator*) is allowed to increase the incentives for new SUs to operate. For instance, it reduces the size of the protection area of higher-tier users by reducing the value of the IT. This results in additional transmission opportunities for new entrants (see Expression 6.29). The decrease in the size of the protected areas is not in the same magnitude as the increase (if there are conflict events). The decrease in the IT is several magnitudes smaller than the corresponding increase. This particular characteristic of the system is modeled after the Transport Control Protocol (TCP) congestion avoidance mechanism [206]. In particular, the system mimics the "Congestion Avoidance Phase", where the sliding window of TCP has a linear growth, and the "Fast recovery phase", where the sliding window has a significant reduction. In our model, the size of the sliding windows is related to the size of the restricted areas through the Interference Threshold (IT) parameter. Thus, if there are no conflict events, we have a linear decrease in the size of the restricted area, but if some conflict situation is detected, the size of the restricted area experiences a significant decrease (see Figure 33).

$$Central\ Coordinator_{behavior} = \begin{cases} Change\ parameters, & \text{if } Total\ Conflicts > 0 \\ Decrease\ IT, & \text{Otherwise} \end{cases} \tag{6.29}$$

Self-governance: We ground the second governance approach on the concepts of continuous dealing or continuous interactions presented by Robert Axelrod and Peter Leeson (see Section 6.1). All the actions, strategies, and outcomes are solely the product of the agents interacting in the sharing scheme. There is no centralized entity (at least as a principal actor) in this institution. In this approach, the PU and SU continuously modify their behaviors to

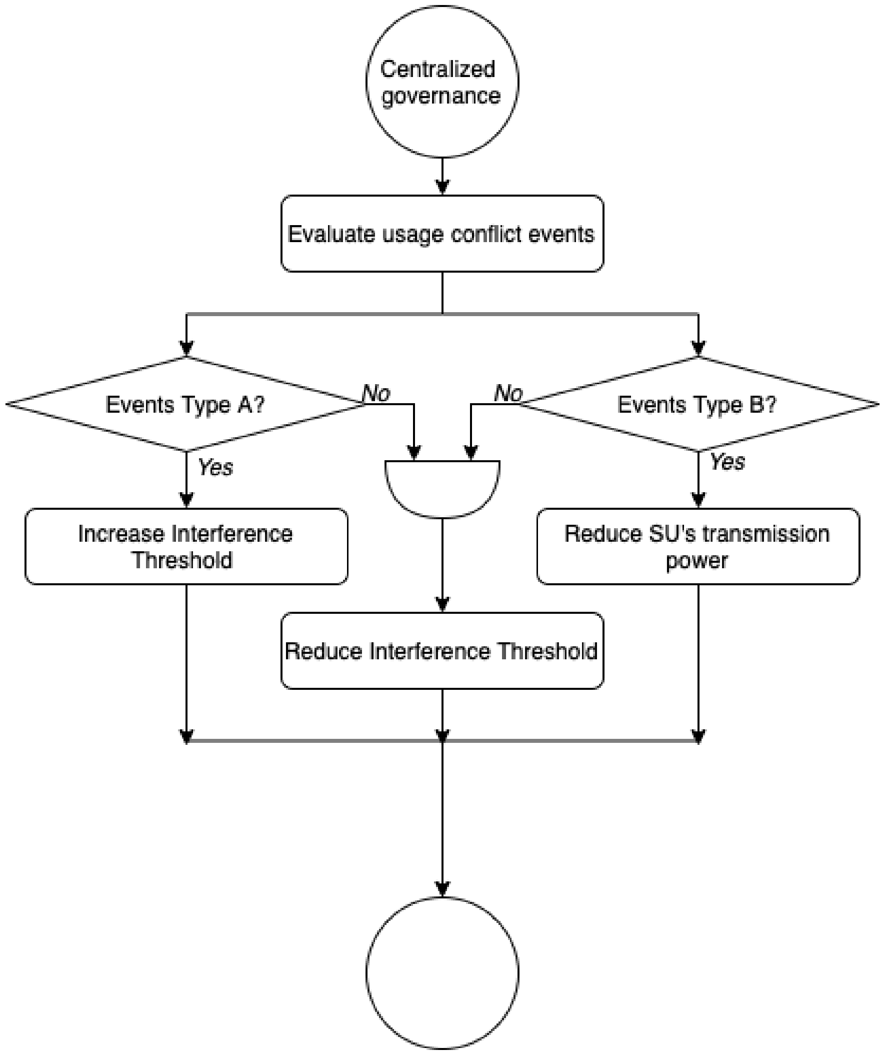

Figure 32: Stage 3 - Flow diagram of the conflict mitigation strategies implemented in centralized governance

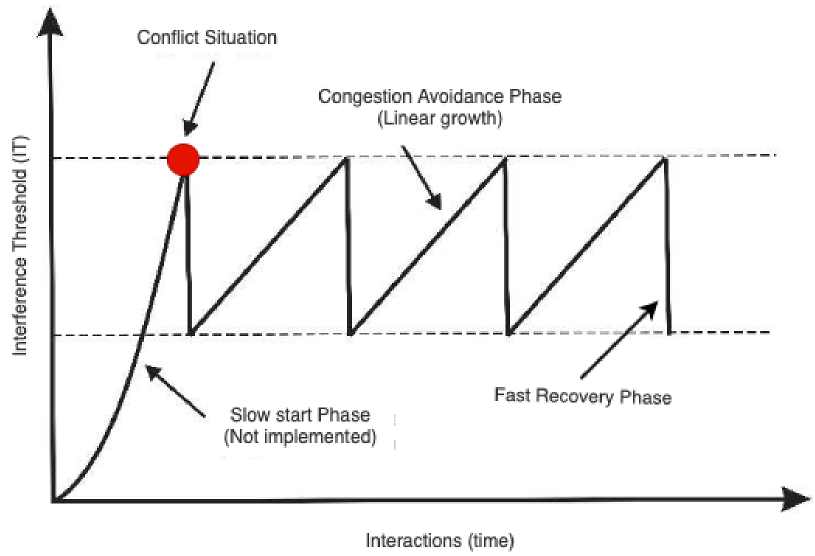

Figure 33: Stage 3 - TCP Congestion Avoidance Protocol (adapted to the Interference Threshold (IT) variable)

maintain a dealing relationship (see Figure 34). Thus, they are always cooperating to reduce the number of conflict situations.

The primary user is in charge of defining its protection criteria, such as the size of its protection zones through the IT variable. In most continuous dealing relationships, the agents receive two types of dealing signals: a "trust" or a "conflict" signal. In the case of our sharing agreement, the PU gets a trust signal when no usage conflicts have occurred. On the other hand, the PU receives a conflict signal when some form of conflict situation (e.g., *Type A* event) is present in the agreement. The primary user reacts according to these signals. In the case of a trust or "good" gesture, the PU also sends a trust signal to the SUs by reducing the size of its protection area (i.e., by decreasing the interference threshold). On the other hand, if conflict situations have arisen during the sharing process, the PU is allowed to increase its protection area by increasing the interference threshold (see Equation 6.30). This change in the restricted zones follows the same increase/decrease dynamic as in centralized governance[22].

$$PU_{behavior} = \begin{cases} Increase\ IT, & \text{if } Total\ Conflicts > 0 \\ Decrease\ IT, & \text{Otherwise} \end{cases} \tag{6.30}$$

The secondary users also react to the emergence of usage conflict events. They share the same goal with the PU of minimizing the number of conflict situations. In self-governance, this is equivalent to sending "trust signals" to the incumbents and priority users. The goal is to maintain the dealing relationship to keep using the shared resources that are available. To this end, the SU adjusts its transmission parameters based on the presence of conflict events. In the case of a *Type A* conflict situation, the SU has two alternatives: it can switch channels (e.g., from *c1* to *c2*) with a lower probability, or it can increase its *margin of error* (see Equation 6.31). The variable *margin of error* is introduced in the model to compensate for the errors present in the Interference Cartography (IC) map. The objective is to increase this value to a point where it limits the amount of non-authorized transmissions (see Figure 34). When a conflict event of *Type B* is detected, the SU also has two alternatives to adjust its parameters. It can switch channels, or it can decrease its transmission power to a minimum (See Equation 6.32, and Figure 34).

$$SU_{behavior_{TypeA}} = \begin{cases} Switch\ channels, & \text{if } Total\ Conflicts_{TypeA} > 0 \\ None, & \text{Otherwise} \end{cases}$$
$$SU_{behavior_{TypeA}} = \begin{cases} Increase\ error\ margin, & \text{if } Total\ Conflicts_{TypeA} > 0 \\ None, & \text{Otherwise} \end{cases} \tag{6.31}$$

22

It follows the adapted TCP Congestion Avoidance Protocol.

$$SU_{behavior_{TypeB}} = \begin{cases} Switch\ channels, & \text{if } Total\ Conflicts_{TypeB} > 0 \\ None, & \text{Otherwise} \end{cases}$$

$$SU_{behavior_{TypeB}} = \begin{cases} Decrease\ Tx\ power, & \text{if } Total\ Conflicts_{TypeB} > 0 \\ None, & \text{Otherwise} \end{cases} \tag{6.32}$$

Polycentric governance: This governance method serves as our localized spectrum sharing scenario. The polycentric configuration strikes a balance between centralized and fully decentralized governance systems (see Section 5.3.2). Polycentric governance involves multiple centers of decision-making. Each of these centers operates with a degree of autonomy and is in control of a specific jurisdiction. In the case of our model, we divide the region of interest (e.g., rural map) into smaller independent coordination areas. In each of these zones, a local *coordinator* is in charge of all the governance-related actives. The $Local_{SAS}$ has complete knowledge of the sharing agreement, including conflict situations, and has the authority to take mitigation actions within its jurisdiction (see Figure 35). It is important to note that these are not isolated institutions. As previously mentioned, these are nested institutions designed to collaborate while maintaining their jurisdiction autonomy (see Figure 21).

All local *coordinators* share the objective of minimizing the number of conflict situations in their local coordination areas. Each *coordinator* implements a series of strategies to deal with the presence of conflict events. To comply with the principle of graduated sanctions (see Section 5.3.2), these strategies increase in complexity and limitations for the agents. Thus, the first strategy is to relocate SUs from one channel to the other (e.g., from *c2* to *c1*). This first strategy does not limit the transmission capabilities of the new entrants of the band. The initial strategy is the same for both types of conflict situations (*Type A* and *Type B*). If the outcome of the first strategy does not lead to a positive result (i.e., there is no reduction in the number of conflict events), the local *coordinator* implements a different strategy to mitigate the number of conflict situations. In the case of *Type A* events, the second strategy

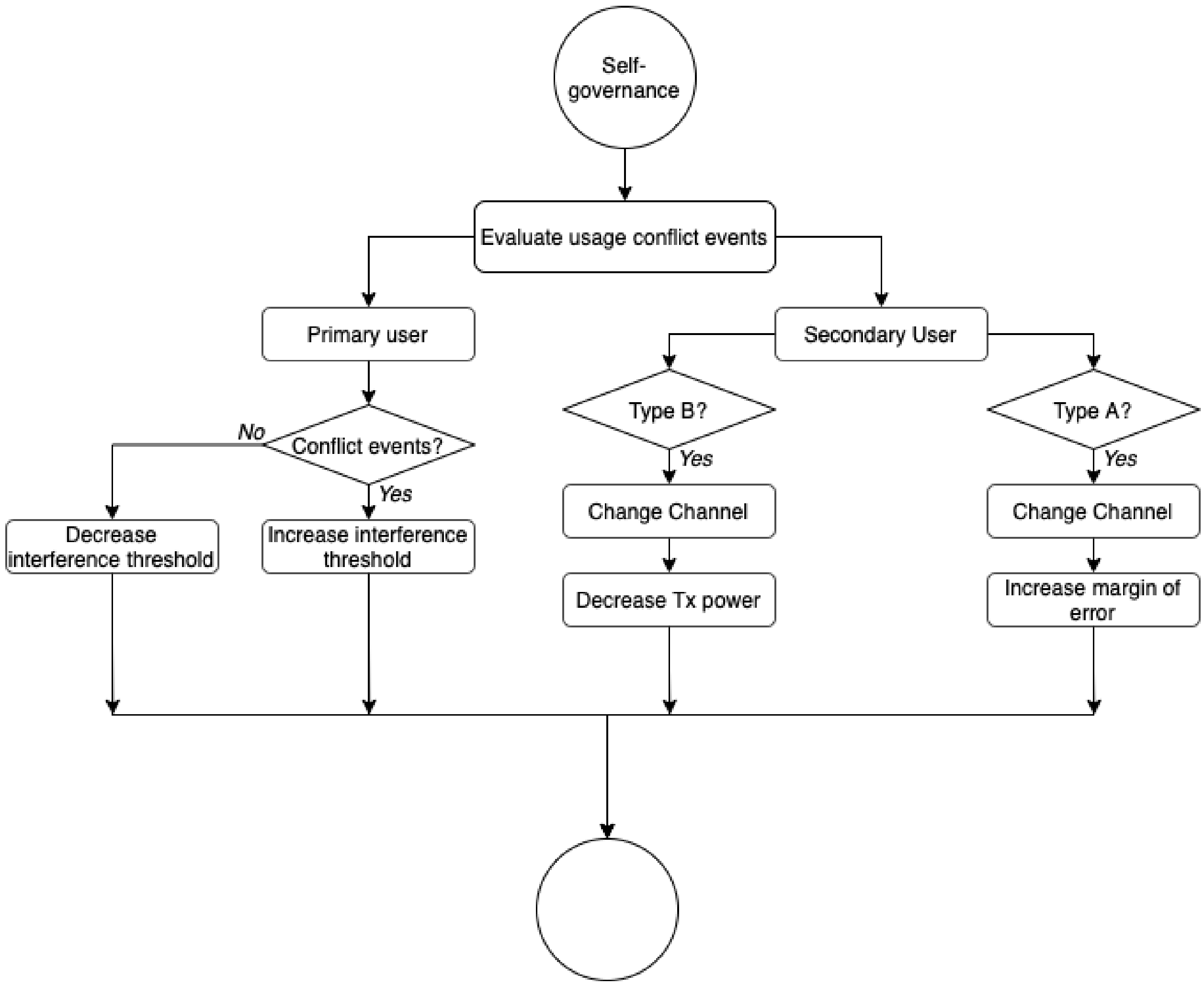

Figure 34: Stage 3 - Flow diagram of the conflict mitigation strategies implemented in self-governance

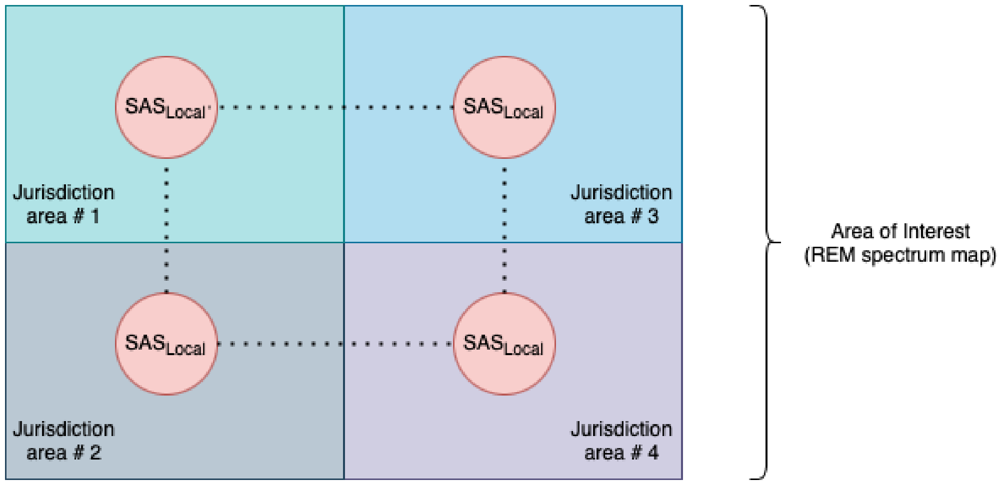

Figure 35: Stage 3 - Polycentric governance jurisdiction distribution

is to increase the *margin of error* of the agents involved in conflict situations. Finally, the last strategy is to increase the interference threshold in the local coordination area. For *Type B* conflict events, the local *coordinator*, after switching users from one channel to another, asks the SUs involved in conflict situations to reduce their transmission power as a second attempt to reduce the number of conflict events. If these strategies are not successful, the local coordinator increases the interference threshold in its area (See Figure 36). Similar to the other governance mechanism, the local *coordinator* is also allowed to increase the incentives for new entrants if there are no conflict situations in the local coordination area (i.e., jurisdiction area). In such cases, the local *coordinator* may reduce the protection criteria (e.g., interference threshold) for higher-tier users (see Expression 6.33)[23].

$$Local\ Coordinator_{behavior} = \begin{cases} Change\ jurisdiction\ parameters, & \text{if } Total\ Conflicts > 0 \\ Decrease\ jurisdiction\ IT, & \text{Otherwise} \end{cases} \tag{6.33}$$

23 The local *coordinator* also follows the adapted TCP Congestion Avoidance Protocol for these activities.

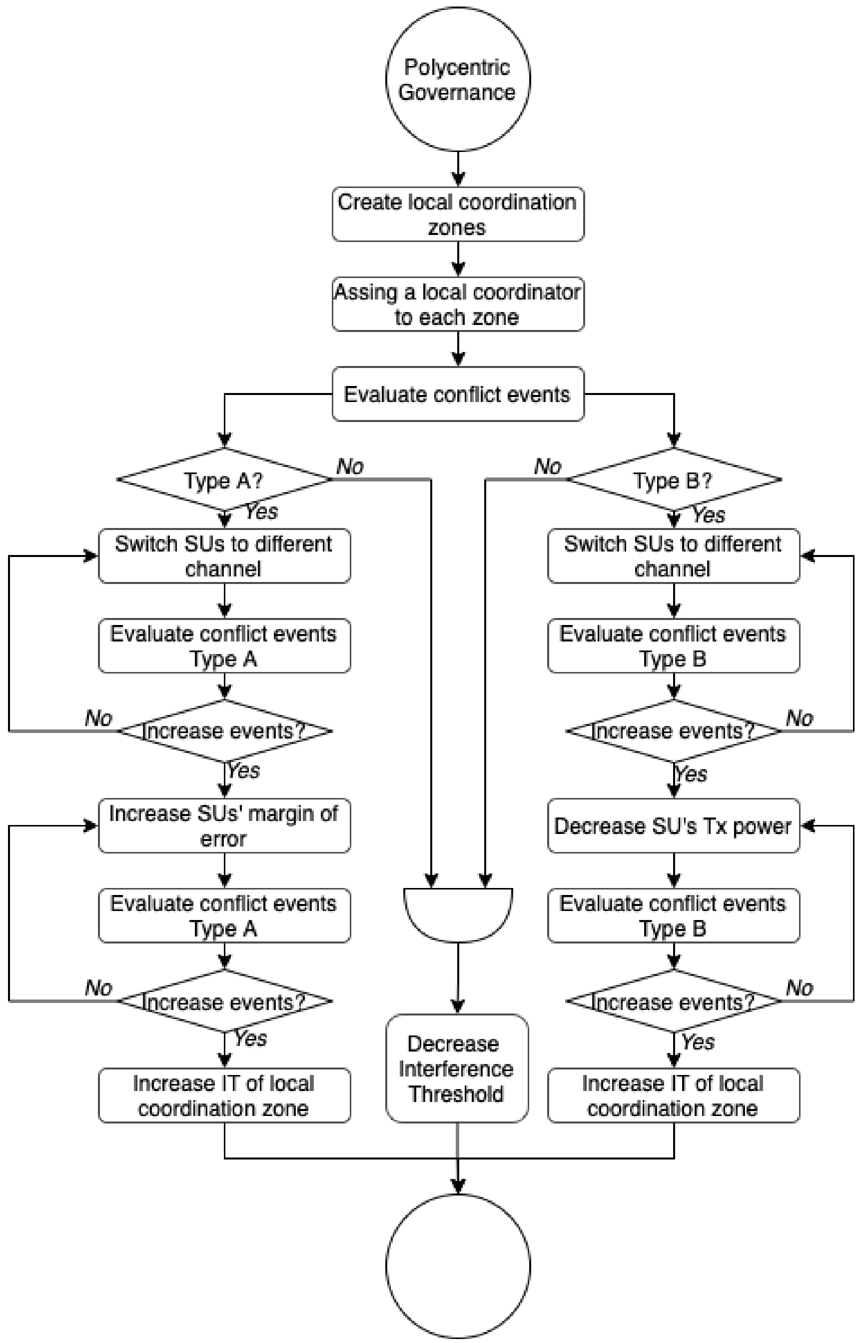

Figure 36: Stage 3 - Flow diagram of the conflict mitigation strategies implemented in polycentric governance

6.3.1.5 Interactions The agents' interactions are an integral part of the action situation in the IAD framework. In this space, the general behavior of the different participants (i.e., agents) is defined using all the components presented in the action situation (see Section 6.3.1.3) and the governance system (see Section 6.3.1.4) in place. The following questions and flow diagram presented in Figure 37 serve as a base to define the interactions in the system.

- Who are the participants (i.e., agents) in the system?
- What are the positions or roles that actors (i.e., agents) play in this situation?
- What actions can participants take?
- How are actions linked to outcomes?
- What is the level of control that each participant has over each action?

In Appendix C, we include flow diagrams of the agents' interactions in the different governance systems to be implemented in the sharing agreement.

6.3.1.6 Rules-in-use A set of rules is necessary to explain actions, interactions, and outcomes. The rules defined in the institutional analysis have a direct impact on the action situation (see Figure 38). In our model, we focus on the operating rules, the source of these rules, who observes them, and who does not observe them. These rules can be further classified into seven categories as shown in Table 18. In this work, we define the position, authority, aggregation, and information rules for each of the implemented governance systems[24]. In Appendix D, we include the defined rules for each implemented governance system.

6.3.2 Policy "games" in spectrum sharing agreements

So far, we have defined the main components for our multi-tier spectrum sharing model. As explained in Section 2.4.3.2, governance systems are usually the result of multiple policy "games" operating simultaneously within a geographically defined policy "arena" [207]. The

[24] We use the ADICO Grammar of Institutions (see Section 2.4.3.3) to define these rules.

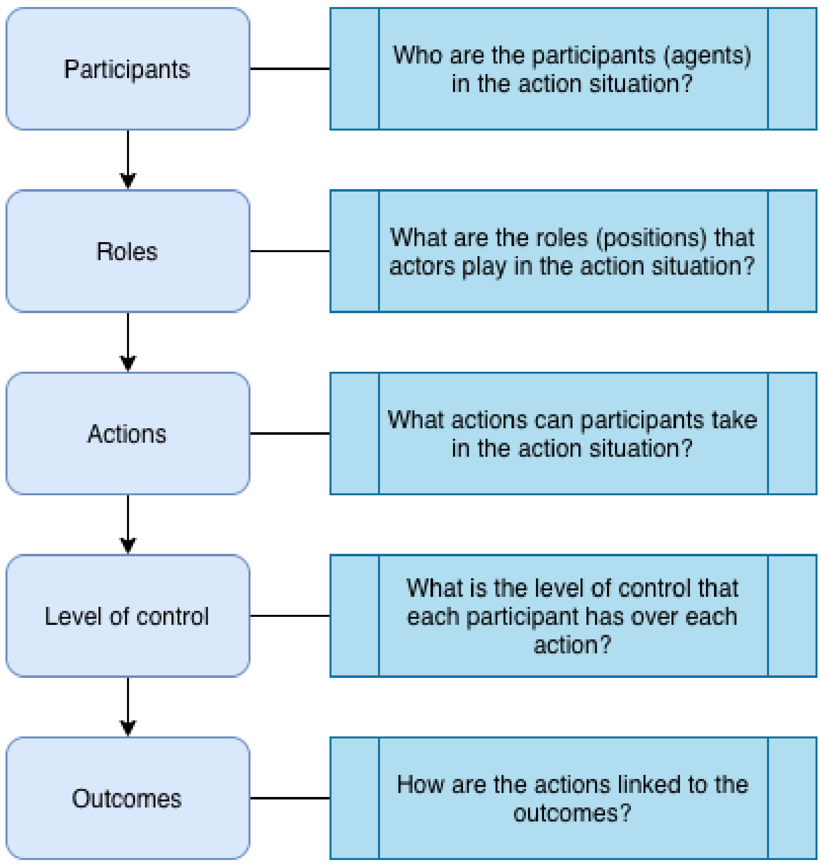

Figure 37: Stage 3 - Flow diagram of the agents' interactions in the IAD's *action situation*

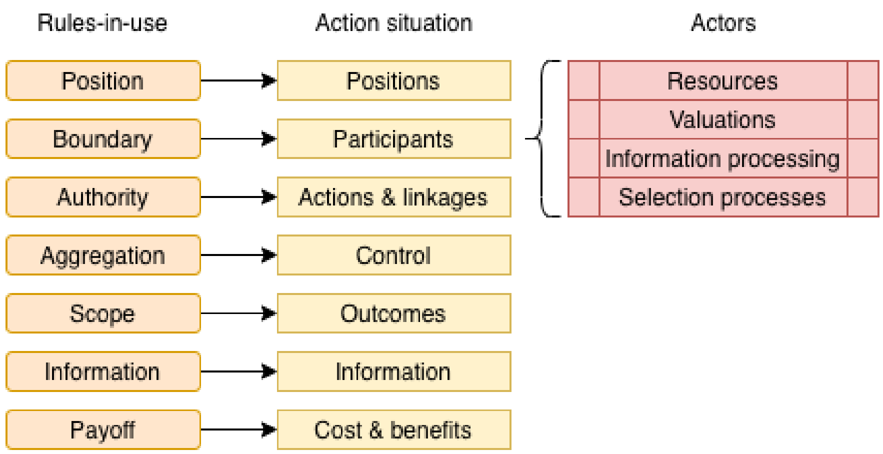

Figure 38: Stage 3 - Relationship between *rules-in-use* and *action situation* in the IAD framework

Rules	Description
Position	Specify the set of positions or roles that agents assume in each action situation, and the number and type of participants who hold each position (e.g., PU, SU, and SAS)
Boundary	Can be thought of as exit and entry rules. They specify which agents enter or leave positions and how they do so (e.g., an SU can change tiers under certain circumstances)
Authority	Specify the actions agents in given positions may take (e.g., provide communication channels between PUs and SUs)
Aggregation	Determine how decisions are made in an action situation (e.g., how to occupy available resources)
Scope	Specify the jurisdiction of outcomes that can be affected (e.g., local vs. global)
Information	Affect the amount and type of information available to participants in the action arena (e.g., access to environment information)
Payoff	Determine how the costs and benefits are meted-out in the action arena (e.g., who bears the cost of usage violations)

Table 18: Stage 3 - Types of *rules-in-use* in the IAD framework

Ecology of Games (EG) framework allows us to capture such interactions (games). The EG framework uses the same definitions of the IAD framework but stresses that multiple actors are involved with governing the authority of more than one institution. In other words, the EG framework adds a layer of analysis by combining overlapping jurisdictions. This framework relies on six interrelated concepts for the construction of policy interactions [136]:

- Policy games: Constellation of policy actors, institutions, and issues
- Policy issues: Collective action problems that may be interconnected through biophysical, economic, and/or social processes
- Policy outcomes: Results of the individuals' decisions regarding the use of resources involved in a policy issue
- Policy institutions: Rules, norms, and strategies that structure how actors make collective decisions
- Policy actor: Individuals (or groups of individuals) that have some interest or stake in the outcomes of decisions made in policy intuitions and the resulting operational rules
- Policy systems: Geographically defined territories that encompass multiple policy issues, multiple institutions, and multiple actors.

Each of the governance mechanisms implemented in our ABM can be represented as a policy "game". For this purpose, we define each of the required components in the EG framework (see Table 19).

First, the actors of the policy game correspond to the participants of the sharing agreement, previously defined using the IAD framework. Thus, the policy actors include the primary users (Federal, FSS, and PAL), secondary users (GAA), and, for some governance systems, an external coordination agent (central or local *coordinator*).

The next component is the policy issues of the policy game. In the spectrum sharing model, we consider two collective action problems: access to the shared resources, which refers to the ability of all the actors to use the resources for their "benefit" (i.e., transmission activities). A connected collective action problem to the use of resources is the emergence of usage conflict situations (e.g., "harmful" interference). The connection between these issues is rooted in multiple processes, including physical (wireless transmissions), economic (impact

Policy games for governance systems	
Component	**Elements**
Issues	Spectrum access
	Conflict situations
Outcome	ADICO-defined set of rules and strategies
Actors	PU (Federal, FSS, & PAL)
	SU (GAA)
	External (Band coordinators)
System	Radio Environment Map

Table 19: Stage 3 - Definition of the main components of policy games in the EG framework

to the normal operations of the system), and social (trust problems among stakeholders).

The definitions of the band and the governance system dictate the rules, norms, and strategies that are part of the policy institution. In the same light, the policy outcomes are directly related to the defined rules and the actions of the participants in the game.

Finally, the policy system in our sharing agreement is the geographical area defined by the Radio Environment Map (REM). In other words, the policy system is composed of the environment of our model, which is defined by the Interference Cartography (IC) map.

Once all the components are defined and rooted in the EG framework, we can add an extra layer to the exiting IAD definitions. This extra layer allows us to explore the different interactions in the action situation in a better way. We observe how the agents' actions impact the collective action problem and its corresponding outcomes. In Appendix E, we include the multi-game settings for each governance mechanism in our spectrum sharing model.

Experiment setup	
Variable	**Levels**
Number of primary users	[5, 10]
Number of secondary users	[10, 100]
Sensor density	[0.8, 0.4]
Average *fading deviation*	[0.5, 4]
SU load	[0.2, 0.7]
Governance system	[Centralized, polycentric & self-governance]

Table 20: Stage 3 - Experiment setup model parameters, variables, and levels

6.3.3 Experiment setup

To capture all the possible combinations of the factors in the system, we use a Full Factorial Experimental Design. To test our multi-tier governance-based model, we select five (5) variables directly related to the conditions of the sharing agreement. Thus, the variables tested in Stage 3 are the number of primary users, the number of secondary users, the *sensor density* in the environment, the mean of the Rayleigh distribution for the *fading deviation* variable, and a load of secondary users (*SU load*) as summarized in Table 20. Additionally, we repeat this set of experiments for each of the governance systems in our Model.

From the variables and levels in our experiment setup, we create two distinct scenarios: a *Best Case Scenario (BCS)*, and a *Worst Case Scenario (WCS)*. In *BCS*, we assume a limited number of participants in the sharing environment, i.e., the minimum number of Primary and Secondary users. Additionally, we assume a high density of sensors used to construct the REM and a low fading component in the sensor measurements. We also assume that the secondary users are active, on average, 20% of the time (*SU load*). On the other hand, in the *Worst Case Scenario (WCS)*, we assume a high number of participants in the sharing agreement, with a low *sensor density*, a very high *fading deviation*, and very active secondary users. We utilize these scenarios in different stages of our analysis to compare extreme situations in the sharing scheme.

The number of interactions[25] for each previously described experiment is three-hundred and sixty (360). This number is the result of twelve (12) daily interactions during a month of operations in the system. In our preliminary testing, we observe that this value captures enough agents' interactions while showing a stable state in all experimental scenarios.

6.4 Stage 4: Smarter agents in spectrum sharing scenarios

As discussed in Section 2.5.2, it is possible to successfully integrate Agent-Based Modeling and machine learning to obtain more realistic models, where this integration can be either exogenous or endogenous. In *Model 3.0*, we implement an endogenous ABM-ML integration to improve the agents' internal decision-making capabilities.

6.4.1 Conflict prediction models based on machine learning techniques

Since the secondary users or new entrants of the band are the typical "source" of conflict situations, these are the agents that would benefit the most from enhanced decision-making capabilities. In this light, we apply ML techniques at the agent level by improving the internal engine of the secondary users (e.g., GAA) of the band. The overall goal is to reduce the number of conflict situations caused by the operations of new entrants. In the previous version of the model (*Model 2.0*), these lower-tier users only consider the current spectrum environment to decide the availability of resources ($RSS < IT$). The agents do not take into account their past experiences to make these decisions. By applying ML models, we can provide individual agents with an intelligent behavior that allows them to analyze data from past executions to minimize the number of conflict events.

Figure 39 depicts the general process to include machine learning techniques in *Model 2.0*. As shown, now the interactions in the system are divided into two phases. First, a "data-

[25] The time frame or the number of "ticks" for each simulation.

gathering phase", in which the SUs do not possess an improved decision-making module. Instead, they keep using the definitions and rules generated in the governance-based model (see Expression 6.34). The only difference with *Model 2.0* is that now agents are gathering and storing the data about their current environment. This information includes whether the operations of the SU caused any conflict situation to higher-tier users. The latter is the target value in the machine learning models we build. Thus, the main goal of the initial phase is to collect a combination of features (e.g., spectrum situation) and whether they lead to a conflict situation (see Table 21).

$$SU_{model} = \begin{cases} Governance-based, & \text{if } Time <= Data\ gathering\ period \\ Improved\ model, & \text{Otherwise} \end{cases} \tag{6.34}$$

Once the data-gathering phase finalizes, the next stage begins, namely the "improved model" chapter. The first step is to build an ML model that helps the agents to "predict" potential occurrence of conflict situations. To build (fit) the ML model, an agent utilizes the data obtained in the first stage. Once the system fits the model, the agent utilizes the fitted model to decide whether to use the available resources based on its current environmental conditions. The outcome of this process is a probability, $P|Event$, that a conflict situation occurs. As shown in Expression 6.35, given the fact that we assume cooperative agents, if $P|Event$ is higher than a certain decision threshold (e.g., 50%), the SU decides not to use the available resources and waits until the next interaction to avoid any conflicts.

$$SU_{ML\ decision} = \begin{cases} Use\ resources, & \text{if } P|Event <= Threshold \\ Do\ not\ use, & \text{Otherwise} \end{cases} \tag{6.35}$$

6.4.1.1 Supervised machine learning algorithms Figure 40 shows the connection between the governance-based ABM (i.e., *Model 2.0*) and the ML parts of the system. The connection between these modules begins after the data collection period. In this light, the ABM generates the required data to construct the models, and the ML module provides an outcome for the agents to make a decision. The goal is to build ML models that learn from

Data structure		
Variable	**Values**	**Type**
Conflict	[0,1]	Target
RSS	IC map value	Feature
TxPower	SU (local)	Feature
Channel	SU (local)	Feature
Margin of Error	SU (local)	Feature
Interference Threshold (IT)	System	Feature

Table 21: Stage 4 - Data structure for agent-level (SU) machine learning models

the past experiences of the agent and can "predict" the presence of a conflict situation given the current conditions. Hence, the most appropriate ML technique to construct (fit) the required ML models is ML supervised learning [208].

Supervised learning allows us to classify and process data. In our context, we use the data collected by the different agents, which is data that has been classified[26], to infer a learning algorithm. The combination of the data and the ML algorithm is used as the basis for predicting a classification (conflict or not conflict) of other unlabeled data (new interactions) [209].

In general, the ML literature classifies supervised learning into regression and classification techniques [210]. Regression techniques are typically used in predicting, forecasting, and finding relationships between quantitative data. Classification techniques focus on predicting a qualitative (e.g., the presence or absence of a conflict situation) response by analyzing data and recognizing patterns [211]. In Stage 4, we implement classification supervised learning techniques. The goal is to use these algorithms to identify patterns in past executions (i.e., agent-gathered data) and predict (i.e., classify) the presence of conflict situations in future interactions. Due to the popularity of ML in multiple fields and applications, there are many

[26] This is labeled data. A key element present in the gathered data is whether a conflict occurred or not as a result of the current conditions of the agent.

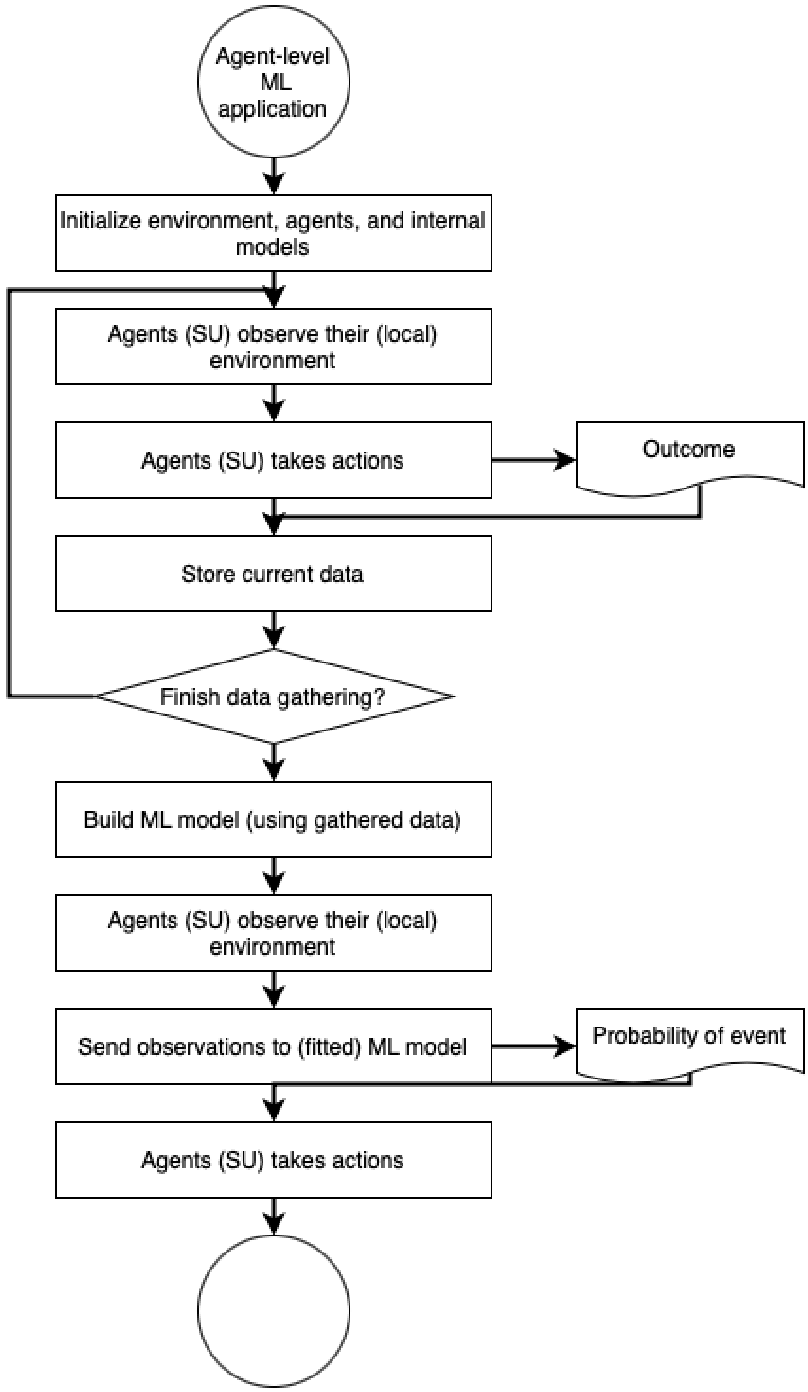

Figure 39: Stage 4 - Flow diagram of the ML-based model for conflict prediction

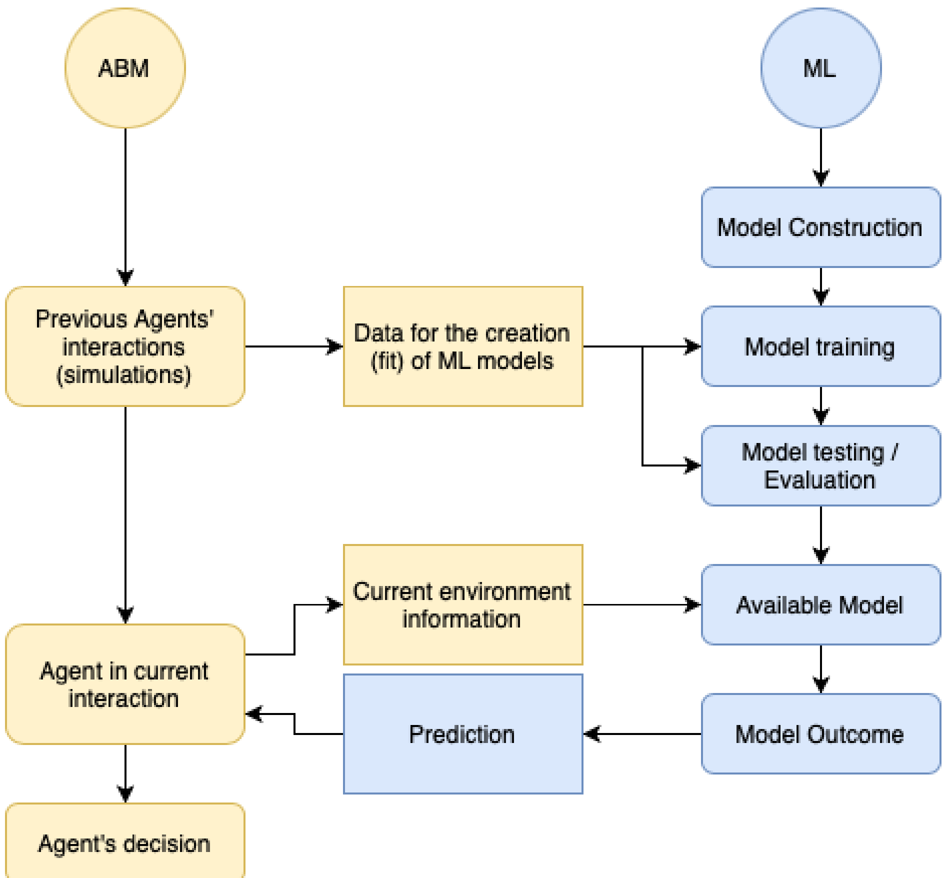

Figure 40: Stage 4 - Agent-Based Modeling and machine learning integration in *Model 3.0*

classification techniques or classifiers available in the literature. In this work, we use Logistic Regression (LR) Classifier, Support Vector Machine (SVM), Nearest Neighbor (NN) Classifier, Random Forests (RF), and Gradient Boosted Decision Trees (xGBoost), which provide different levels of complexity and accuracy[27].

6.4.1.2 Conditions for the addition of machine learning models by the SUs To improve the agents' decision-making capabilities, two different ML approaches are utilized: a local and a global approach.

In the local approach, agents are responsible for the whole improvement process. Thus, agents gather and store the data, construct (fit), evaluate, and use an ML model. Although all agents in the system collect and store data about their local environment, not all agents need to build and utilize an ML model. Due to the local conditions of some agents (e.g., distance to the PU's transmitters), they do not produce a significant number of conflict situations, which results in biased datasets[28]. Consequently, to avoid the "Garbage in-Garbage out"[29] problems, these agents are not required to build ML models. This situation is captured in Expression 6.36, where agents with a disproportionate number of either conflict or non-conflict data instances are not required to build ML models. In this expression, X, where $0 < X < 1$, represents the proportion of data representing conflict instances required to build an ML model.

$$SU_{build\ model} = \begin{cases} Yes, & \text{if } Data_{with\ conflicts} \geq X * (Data_{total}) \\ Do\ not\ use, & \text{Otherwise} \end{cases} \tag{6.36}$$

In addition, even when the agents collect enough and diverse data, the built ML models could have a deficient performance. In this light, it is necessary to validate the different ML algorithms being developed. This validation is the process of deciding whether the results quantifying hypothesized relationships between variables are acceptable descriptors of the

27 The baseline parameters of the ML algorithms we use are available in Appendix A.

28 Datasets with a disproportionate number of non-conflict instances compared to instances with conflicts.

29 A colloquial recognition of poor quality data entry leading to unreliable data output [212].

data. In other words, the goal is to test the models with unseen data to check whether the model is under-fitted, over-fitted, or well generalized [213].

To measure the performance of the ML algorithms, we implement two approaches in *Model 3.0*: 1) A simple test/train split approach. We randomly split the complete data into training and test sets. Then perform the model training (fitting) on the training set and use the test set for validation purposes. In this approach, there is a possibility of high bias if we have limited data. 2) We also implement a K-fold Cross-validation approach. The goal is to construct less biased models and ensure that every observation from the original dataset has the chance of appearing in the training and test sets. For this purpose, we split the entire data randomly into K-folds[30]. Then fit the model using the $K-1$ folds and validate the model using the remaining K_{th} fold. Repeat this process until every $K-fold$ serves as the test set. Finally, we take the average of the recorded scores (in each fold) as the performance metric for the model. Using the result of the validation techniques, agents use Expression 6.37 to decide whether to use the constructed ML models. If the accuracy of the ML model is higher than a given *threshold*, the agent uses the model to predict the emergence of conflict situations in its future interactions.

$$SU_{use\ model} = \begin{cases} Yes, & \text{if } Model_{accuracy} \geq validation\ threshold \\ Do\ not\ use, & \text{Otherwise} \end{cases} \quad (6.37)$$

To evaluate the performance of the ML techniques, we define three evaluation parameters, namely accuracy (see Expression 6.38[31]), precision (see Expression 6.39), and recall (see Expression 6.40).

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} = \frac{TP+TN}{TP+TN+FP+FN} \quad (6.38)$$

$$Precision = \frac{Number\ of\ correct\ positive\ predictions}{Total\ number\ of\ positive\ predictions} = \frac{TP}{TP+FP} \quad (6.39)$$

---

30 In *Model 3.0*, we implement five (5) folds. In other words, $k = 5$.

31 In Expressions 6.38, 6.39, and 6.40, TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives.

Experiment setup	
Variable	**Levels**
Number of primary users	10
Number of secondary users	100
Sensor density	0.4
Fading deviation	4
SU load	0.7
Governance system	[Centralized, polycentric & self-governance]
ML application approach	[Local & global]
ML classification model	[Logistic regression, SVM, Nearest Neighbor, Random Forests & xGBoost]

Table 22: Stage 4 - Experiment setup model parameters, variables, and levels

$$Recall = \frac{Number\ of\ correct\ positive\ predictions}{Total\ number\ of\ correct\ positive\ predictions} = \frac{TP}{TP + FN} \tag{6.40}$$

6.4.2 Experiment setup

In stage 4, we rely on Full Factorial Experimental Design to capture all the possible combinations of the factors. To guarantee that the system captures the variance in the model, we choose a total of 10 replications (i.e., $r = 10$) for each experiment. To better capture the effect of ML in the agents' internal engines, we only consider the *Worst Case Scenario (WCS)* defined for the previous stages. This scenario includes a high number of participants, a low *sensor density*, a high *fading deviation*, and significantly active secondary users (i.e., high *SU load*). In addition, we test each of the classification techniques under the different governance systems in the model (see Table 22).

7.0 Results

In this chapter, we present the results and main findings from the models and experiments described in Section 6.

7.1 Stage 1: Including alternative (localized) governance mechanisms in spectrum sharing scenarios (two-tier model)

In the first stage of this dissertation, we evaluate the possible application of distributed governance systems in spectrum sharing agreements. In particular, we test the applicability of self-governance in the two-tiered model of the 1695-1710MHz band.

7.1.1 Results of the centralized governance approach

The predefined governance system of the band is a centralized scheme (e.g., command-and-control), where a central entity (e.g., the FCC) dictates all the sharing conditions. In the case of our two-tiered model, this refers to the boundaries of the exclusion (NAZ) and coordination (LAZ) zones. In command-and-control, the band conditions are predefined, cannot be changed or negotiated, and are constant throughout the agents' interactions (i.e., simulation period).

One of the fundamental characteristics of the government-centric framework is that an external agent (i.e., the central entity) is responsible for the detection rate of enforceable events. This value is fixed throughout the entire simulation to emulate governmental processes of evaluating and monitoring the environment. As shown in Figure 41, the detection rate follows the expected outcome, specifically as the detection rate increases, there is a reduction in the average number of conflict situations in both zones, LAZ and NAZ. Since the detection rate, d, assigned during the model initialization phase, does not change, agents present the same behavior during the entire simulation. In other words, the system reaches a stable state where agents know or perceive the ability of the enforcer to detect unauthorized transmissions and behave solely according to their risk profiles. Consequently, even with high detection rates (e.g., $d = 75\%$) conflict situations continue to occur in the system (e.g., transmission surpassing interference thresholds).

Another primary component in centralized approaches is the behavior of the SUs under different institutional scenarios (e.g., the time delay between the infraction and the "punishment" or the individual discount rate). As we can observe in Figure 42, we have a relatively low number of events only when the sharing agreement is under its best conditions (i.e., *BCS*). Otherwise, even in the "middle point" of the *MCS*, we have an almost as high number of conflict situations (e.g., interference events) as in our *Worst Case Scenario (WCS)*.

In Figure 43, we find the distribution of the total number of events in the protected areas NAZ and LAZ for centralized governance systems. We observe that the distribution is skewed to the right, where a substantial number of agents' interactions show a considerable average number of conflict events per tick. When analyzing the perception function, we see that when the agents know the *actual* detection rate (red bins), there are more conflict events than when agents have a *perception* of the rate (blue bins). An explanation for this outcome comes from the impact of information access in institutions such as spectrum sharing scenarios. The average number of events per interaction in centralized systems is substantially larger than in self-governance (see Figure 44). Thus, we observe that the average number of conflict events triples in centralized governance compared to self-governance settings. We notice this outcome regardless of the enforcement perception function and the size of the restricted areas.

7.1.2 Results of the distributed (self-enforcement) governance approach

The main objective of self-governance approaches in the two-tiered spectrum sharing model is that the size or boundaries of the restricted zones are not static. Instead, zone boundaries are the result of the continuous interactions and communication efforts among the PU and SUs[1]. The principal intent of this negotiation process is for the agents, and only the agents, to agree on boundaries for the exclusion (NAZ) and coordination (LAZ)

[1]

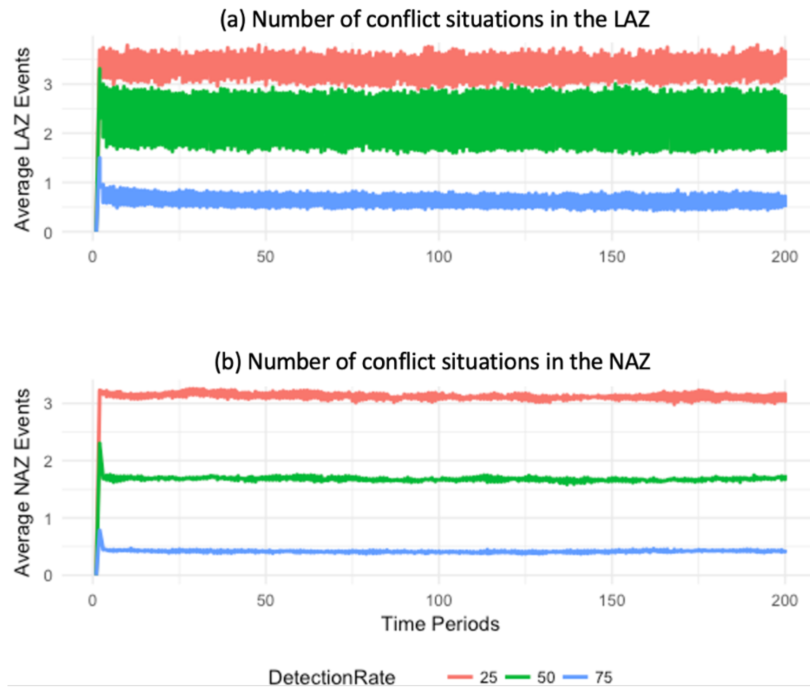

Figure 41: Stage 1 - Government-centric 1695-1710MHz model - Detection rate and number of conflict events in the restricted areas LAZ (upper graph) and NAZ (lower graph)

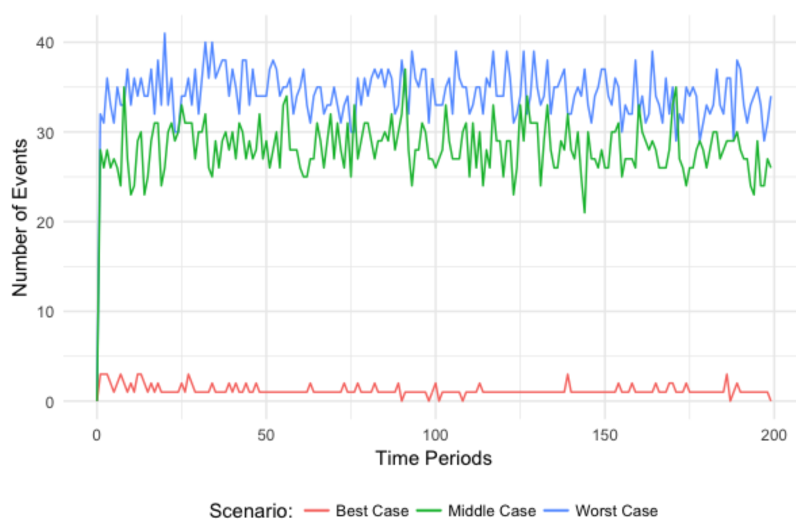

Figure 42: Stage 1 - Government-centric 1695-1710MHz model - Simulation and experimental scenarios

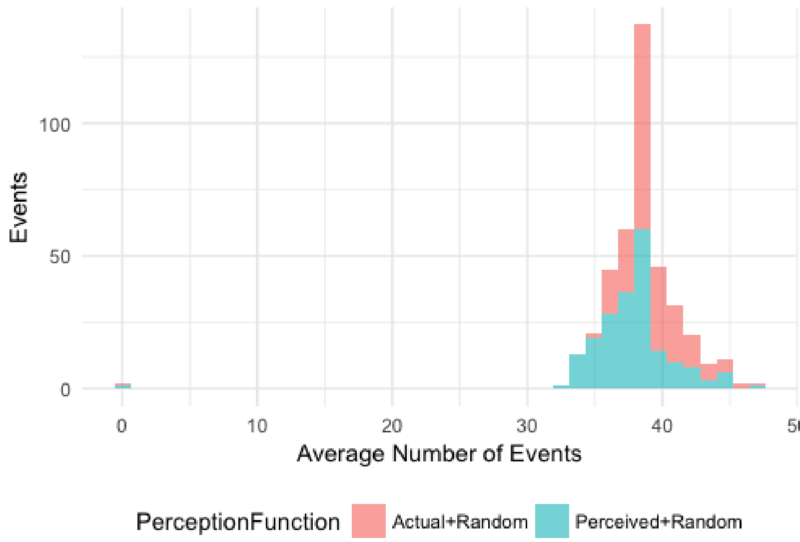

Figure 43: Stage 1 - Government-centric 1695-1710MHz model - Distribution of the total number of conflict situations in the restricted zones LAZ and NAZ

zones. Note that the system creates these areas to "protect" the incumbent and provide incentives for the new entrants in the band. This negotiation captures a crucial aspect of self-governance: the discipline of continuous dealing.

The first step in validating our self-enforcement scenario is to verify that the model is, indeed, capturing the principal components of detection and size conditions. We start by analyzing that a change in the boundaries of the restricted zones results in changes in the transmission conditions for the new entrants in the band. From previous sections, we know that the boundaries of the restricted zones stem only from the interactions between the incumbent and the new entrants. Similarly, the ability to detect a conflict event is based on the size of the area to monitor and the effectiveness of the method used to detect these potential events.

In Figure 44 (upper-left corner graph), we observe the impact of the size of the NAZ on the average number of possible enforceable events. We observe that the mean number

The agreements reached by the agents in the system are not necessarily efficient or "fair" in terms of the resource usage by the new entrants of the band.

of events increases as the size of the NAZ increases. The graph on the lower-left corner shows the relationship between the detection effectiveness in the NAZ and the number of interference events. The resulting detection rate in the zone negatively impacts the average number of interference events as it increases from 0 to 100%. The same phenomena are described in the case of the LAZ, in the upper and lower right graphs of Figure 44. These results concur with the initial design of the model in terms of the global behavior of agents, the detection system in place, and the boundaries of the restricted zones.

A primary feature of our model is that the SUs' behavior is based on their perception of the environment[2]. We capture this through agents' knowledge of the enforcement rate of the system. For instance, a given agent can learn the actual enforcement (i.e., detection) rate or have a perception about it. We observe that this characteristic has a significant impact on the number of events. We observe that knowing the actual detection rate avoids some unauthorized transmissions, which would occur where agents rely only on their rate perception (see the color of the "dots" in Figure 44). Our results show that, in cases where the detection rate is low, full knowledge of this characteristic results in a maximum peak in the number of events in the system. This is consistent with the behavior of users and their perceptions of auditing and enforcement described in the tax literature (see for example [200]).

While negotiations of the different band specifications take place dynamically, two initial parameters are still necessary for our simulation: the boundaries of the restricted areas and the detection effectiveness of the enforcement system (i.e., the number of policing elements). These parameters are crucial due to the significance of initial signaling or initial gestures of trust in self-governing arrangements [56, 55, 182]. In Figure 45, we highlight the influence of the initial size of both areas, NAZ (upper graph) and LAZ (lower graph), on the average number of conflict events. When considering the smallest restricted zone, which represents the highest trust gesture, we find that 25% of the time there is a small number of conflict situations. For larger initial area sizes (e.g., 75% and 100%), we observe a higher average number of enforceable events. This is more evident when the initial boundary is at its

[2] This includes the enforcement perceptions, the detection perception, and the status of their "social network".

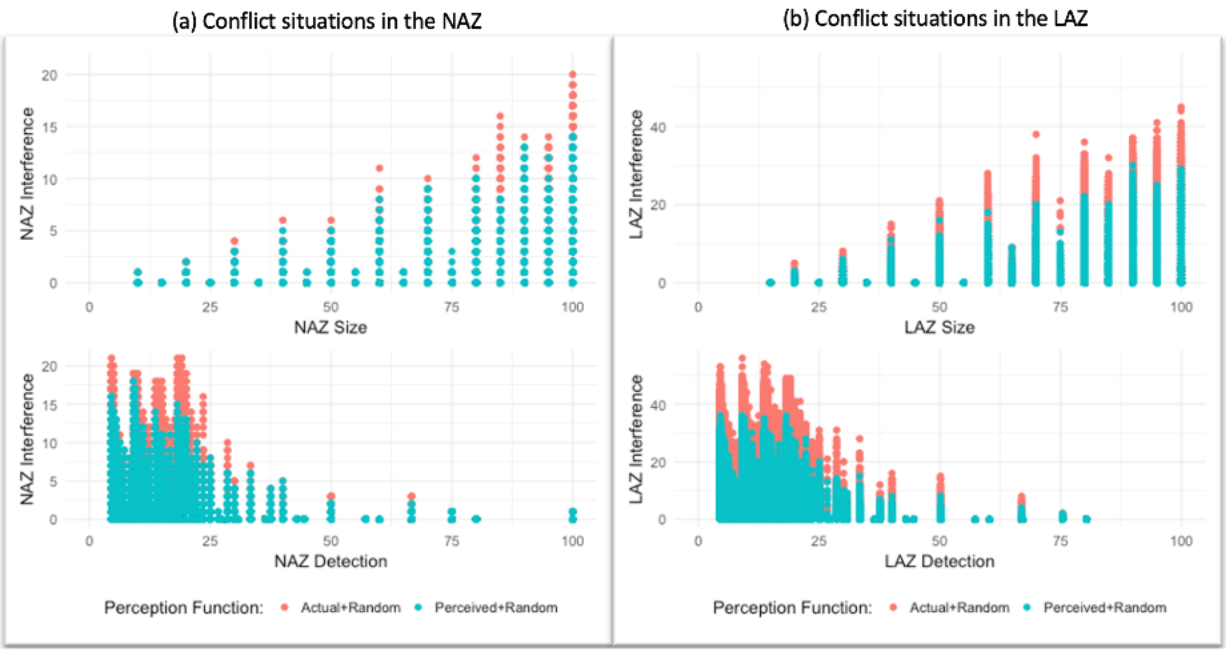

Figure 44: Stage 1 - Self-governance 1695-1710MHz model - Number of conflict events in the restricted areas NAZ (right) and LAZ (left) of the sharing scheme

maximum possible size, where the detection rate causes an immediate peak in the number of events from the first time period[3].

Another initial signaling element in our model is the detection effectiveness of the system. In Figure 46, we observe how this factor shapes the environment, where additional efficacy implies a sizable number of sensing and detecting elements in the system. We note that the effectiveness factor negatively impacts the average number of events in the NAZ (upper graph) and LAZ (lower graph) areas. However, it is not as significant as the impact of the initial definitions of the boundaries of the restricted zones. In this case, all the scenarios have at least some interference events. Furthermore, the number of events is inversely proportional to the system's effectiveness (i.e., as effectiveness increases, there are fewer conflict events). This behavior agrees with other self-governing signaling examples in the literature (see, for instance, Leeson [59]).

In our model, a well self-governed 1695-1710MHz band is one where the system reaches a "stable" state. Stability represents a condition in which the incumbent and the new entrants reach an agreement on the size of the restricted zones without a government, in any form, intervening in the negotiation process. Further, when the system is in a stable state, the number of conflict situations (i.e., interference events) due to SUs' unauthorized transmissions is minimal, hence limiting the impact on the normal operations of the PU. On the other hand, a poorly governed spectrum sharing scheme is one where the size of the restricted zones keeps changing, and the PU is "forced" to maintain the largest restricted areas for its protection against conflict situations.

In Figure 47, we find the evolution of the size of the restricted zones as a function of the initial boundaries (left graph) and detection effectiveness (right graph). We observe that negotiations on the size of restricted areas take place in all scenarios regardless of their initial configurations. All simulations representing a case where there is a change in the initial boundaries of the restricted zones (left graph) converge to a stable state in which the agents reach an agreement on proper area boundaries. Additionally, we notice that when

[3] The peaks shown in Figures 45 and 46 are correlated with the immediate effects after an increase in the size of the restricted areas. This effect is evident in the case of the NAZ since no SU transmissions are allowed in this area at any given time.

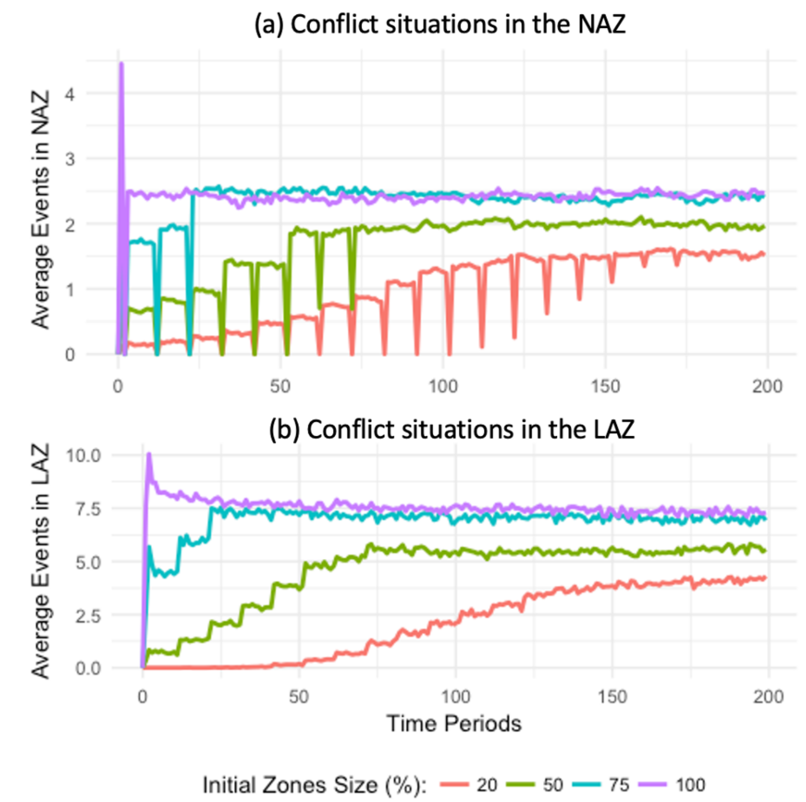

Figure 45: Stage 1 - Self-governance 1695-1710MHz model - Effects of the initial definitions (boundaries) of the restricted zones NAZ (upper) and LAZ (lower)

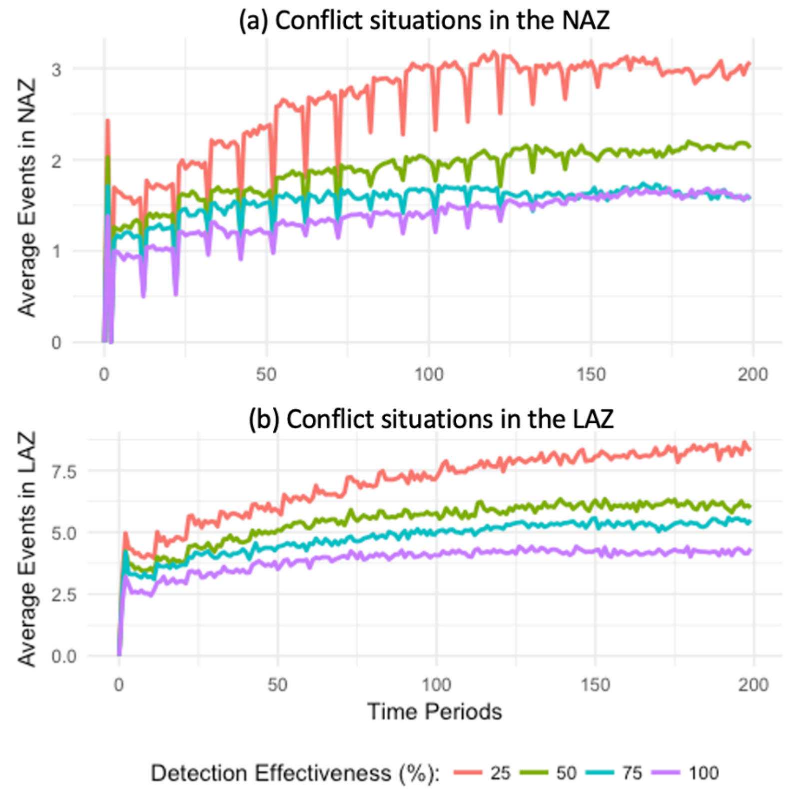

Figure 46: Stage 1 - Self-governance 1695-1710MHz model - Effects of the initial definitions of the detection "effectiveness" of the system in the number of conflict situations in the restricted areas NAZ (upper) and LAZ (lower)

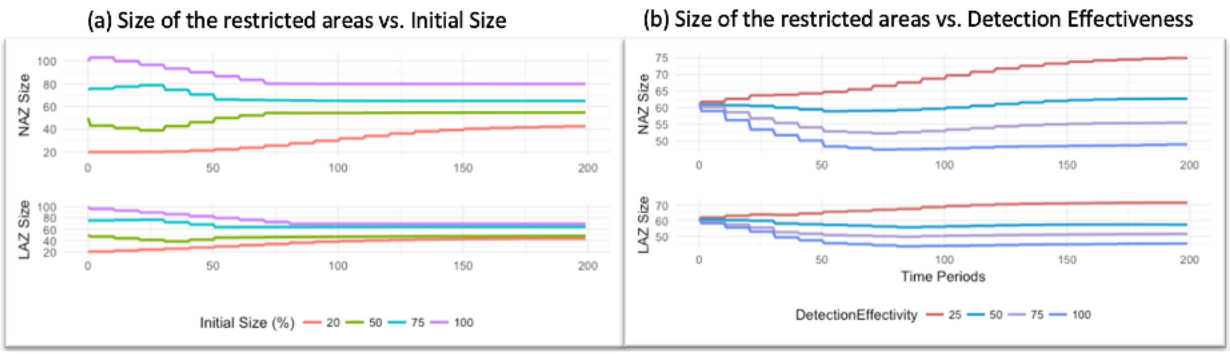

Figure 47: Stage 1 - Self-governance 1695-1710MHz model - Evolution of the SU/PU negotiation process of updating the LAZ and NAZ size

the initial size is over 50% of the maximum allowed, they are reduced to more manageable boundaries. When analyzing the detection effectiveness of the system (right graph), we observe that this factor also has an impact on the negotiation process. In the particular case of effectiveness, when it is very low, we can expect only an increase in the LAZ and NAZ. However, for values over 50%, we can see a reduction in the areas, which is even more evident at very high effectiveness rates. When considering the effectiveness of the system alone (i.e., the equipment capabilities to detect interference events), we observe that the entire system also reaches a stable state. In other words, there are no further (significant) changes in the boundaries of the restricted zones.

The other component that dictates the stability of the system is the number of conflict events. In this context, it is important to observe how the amount of enforceable events correlates to factors such as the initial signals provided by the PU and SUs. In Figure 48, we describe the relationship between the initial gestures and the total number of events. In this figure, the x-axis represents the initial size of the restricted zones, the y-axis shows the initial effectiveness of the detection method, and the proportion and hue of the "bubble" represent the total number of events. These outcomes show that the combination of a very high detection rate and the smallest initial size results in the lowest total number of enforceable events in the system. We find the lowest total number of events in all cases representing

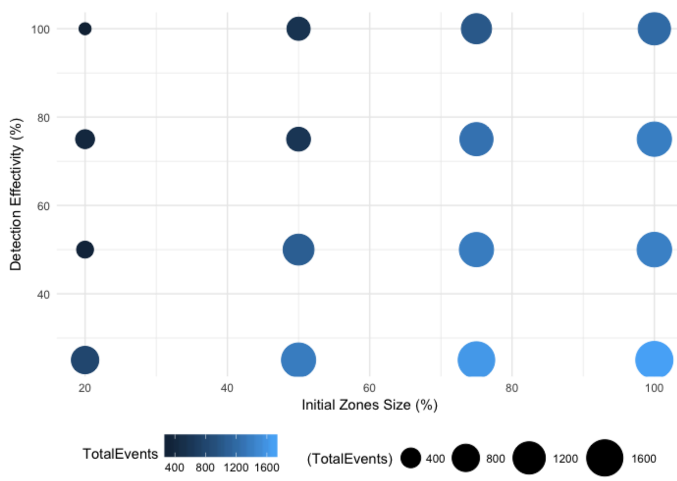

Figure 48: Stage 1 - Self-governance 1695-1710MHz model - Relationship between the total number of events, the initial size of the restricted areas, and detection rate (effectiveness)

smaller restriction areas. For larger area sizes, we observe an interesting phenomenon: even when the detection effectiveness increases, the number of events is not reduced in the same proportion. This demonstrates again that in self-enforcement scenarios, signaling between users has a greater impact than the effectiveness to catch "bad" agents.

7.2 Stage 2: Radio Environment Maps to construct local and dynamic ABM environments

The main goal of Stage 2 is to incorporate an Interference Cartography (IC) or spectrum map as part of the environment of a multi-tier spectrum sharing model. In this light, we first evaluate the representation of a spectrum map using simulated measurements. Then, we verify the performance of the interpolation techniques used to complete the available (simulated) measurements.

7.2.1 Map representation

The primary outcome of our REM simulator is a dataset representing the location of each MCD in the map and the corresponding signal value (e.g., RSS) for that location. In addition, our simulator produces a map representation of the "real" signal values and their corresponding error (i.e., $Error = Real - Interpolated$) at each cell location. We believe that all the generated data is a valuable input for the ABMs we develop in the following research stages of this dissertation.

In Figure 49, we observe a typical representation of a REM-simulated map. The IC map is composed of a variable number of transmitters (shown in red) and receivers or sensors (shown in Blue). Our simulator also creates a visual illustration of the generated wireless metric (e.g., SNIR) within the region of interest (e.g., urban map).

We test multiple combinations of IC map parameters to verify the performance of our system. In Figure 50, we observe the map representation generated by our REM simulator. First, the "real" values of the map correspond to the estimated (simulated) measurements for each cell in the map (upper graph). They are calculated using the transmitter's characteristics and the path-loss evaluation at each cell point on the map. As previously mentioned, this map can be dynamically generated using different combinations of transmitter characteristics and propagation models. In Figure 50 (middle graph), we find the interpolated map. This is the actual IC representation of the REM. It results from a collection of measurements obtained from the MCDs or sensors and a given interpolation technique (e.g., linear interpolation) used to complete the map. Finally, to evaluate the quality of the interpolation techniques, a data-set of the individual error at each cell location is also generated. This is the absolute error at each cell location, and it represents the difference between the real (simulated) measurements and the interpolated values (see the lower part of Figure 50)[4].

[4] In Appendix B, we observe the variograms of the multiple maps we create in Stage 2 as a function of the wireless measurements.

Figure 49: Stage 2 - REM Simulator - Visual illustration of the transmitters, receivers, and SNIR in a constructed IC or spectrum map

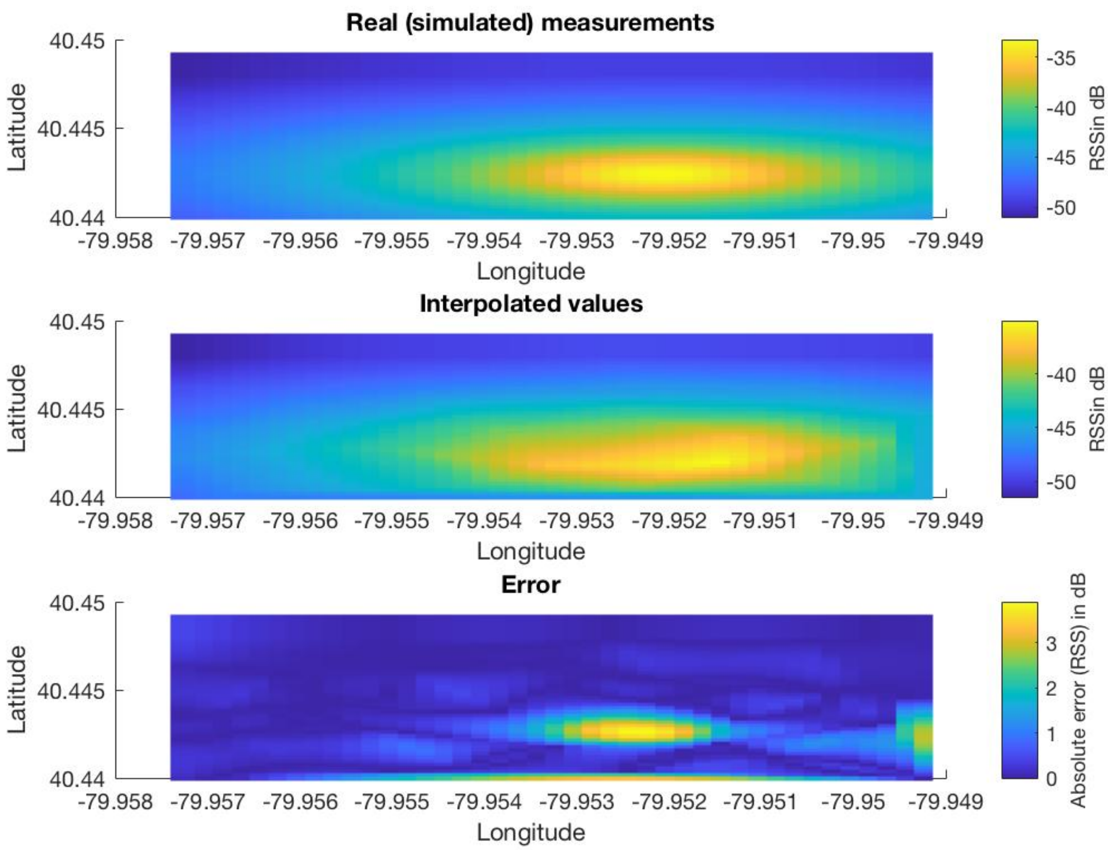

Figure 50: Stage 2 - Map representation of the REM simulated results

7.2.2 Interpolation performance

The primary aspect to evaluate the quality of the IC is to assess the error between the real and the interpolated values. We utilize the Root Mean Square Error (RMSE) between the simulated (measurements) and the resulting IC map as our main evaluation criterion.

Figures 51, 52, and 53 show the results of the performance evaluation of each interpolation technique as a function of the map description and the number of available sensors. The first thing to note is that the number of sensors has a significant impact on the RMSE only when the number of sensors is below the threshold of fifteen (15) MCDs. This is the outcome of the simulator regardless of the type of map. When the number of sensors is greater than the previously explained threshold, the results converge to a stable state. Therefore, for all interpolation algorithms and maps, a new sensor does not significantly reduce the RMSE.

When comparing the different interpolation techniques, we note that all spatial statistic-based methods (i.e., nearest neighbor, natural neighbor, and linear interpolation) have a similar performance. When comparing direct (spatial statistics-based) and indirect (transmitter-based) methods, we observe a clear difference. As depicted in Figures 51, 52, and 53, direct methods[5] produce lower interpolation errors in all (map) scenarios.

The REM simulator includes the development of three maps varying in size[6]. When analyzing the performance of the different interpolation techniques concerning the type of map, we find that an increase in the size of the map increments the RMSE. However, the general trend remains constant in all constructed maps. Some reasons for this difference include the increase in the number of cells in the map and the distance between transmitters and receivers. Note that our results are similar to other outputs in the REM literature. In particular, when we compare the performance of different interpolation techniques for the construction of spectrum maps (see for example [85]).

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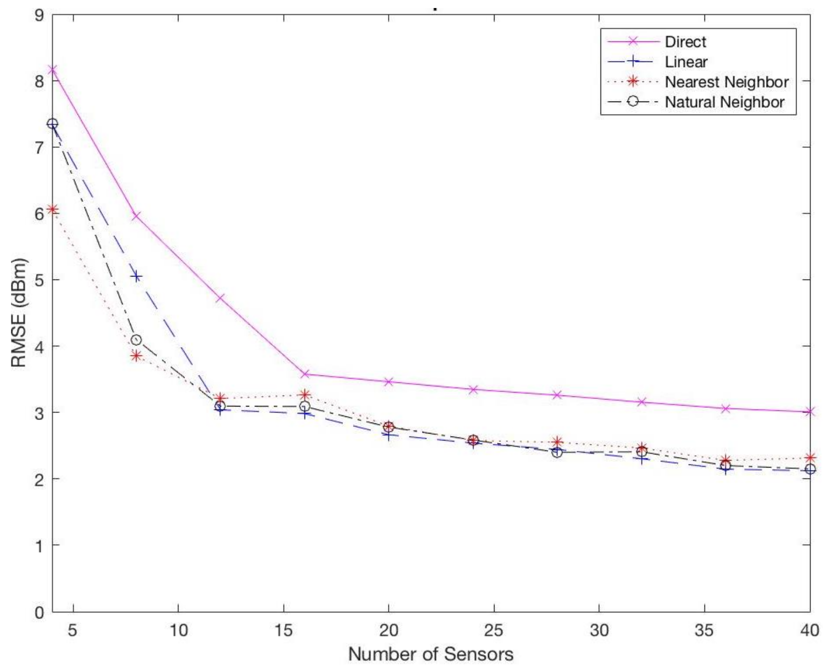
5 It is worth mentioning, that the only indirect method included in the simulator is RSSD.

6 From smallest to largest we have: urban, semi-urban, and rural.



5

Figure 51: Stage 2 - Interpolation performance evaluation - Urban environment (map)

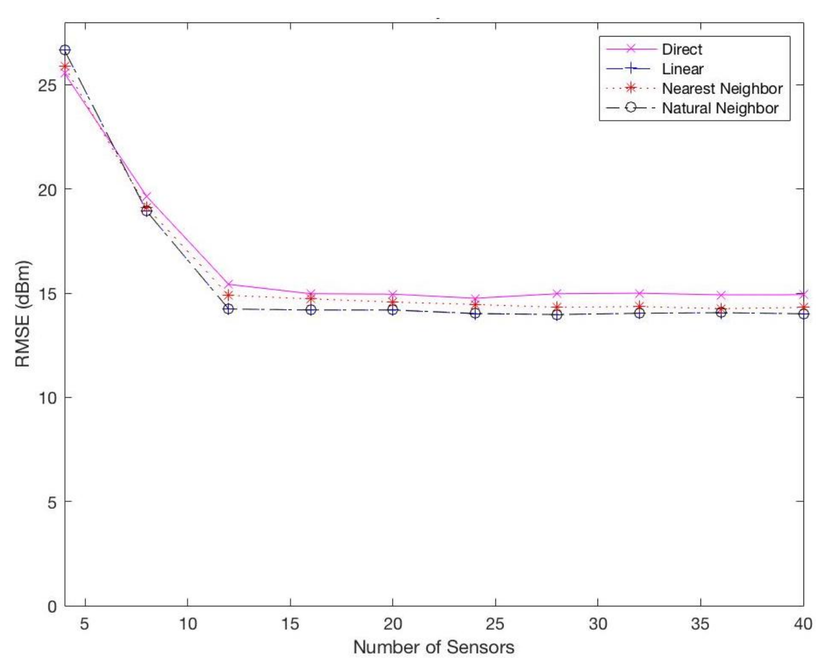


Figure 52: Stage 2 - Interpolation performance evaluation - Suburban environment (map)

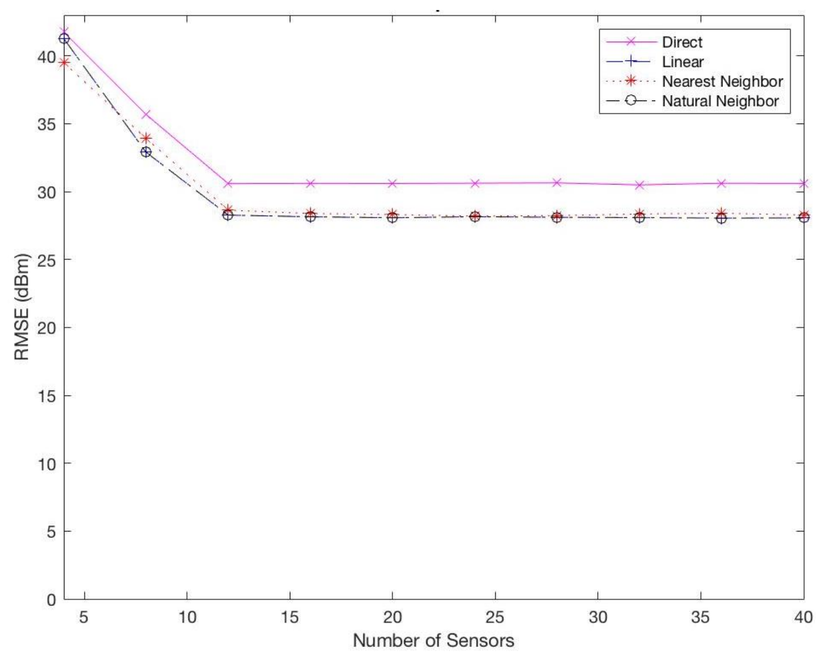


Figure 53: Stage 2 - Interpolation performance evaluation - Rural environment (map)

7.2.3 Transmitter location performance

The REM simulator incorporates two types of interpolation techniques. First, direct methods estimate the missing values from the available measurements in the system. These methods are not unique to the construction of REMS. Indeed, a variety of applications (e.g., image processing) use these interpolation methods. The only outcome of these techniques is the set of missing data points (i.e., missing measurements). Second, we consider the indirect algorithm of Received Signal Strength Difference (RSSD). Besides the interpolated values for the missing cells, this method also produces an estimated location of the transmitter(s). In Figure 54, we show the RMSE for the estimated transmitter location as a function of the number of sensors and the map representation. These results are similar to other outcomes in the literature, where the location error is inversely proportional to the number of available MCDs. Similar to the performance of the interpolation techniques, the area of the map has an impact on the ability to estimate the exact location of the transmitter. Hence, in rural scenarios, the RMSE is higher than the smaller REM area in suburban and urban conditions.

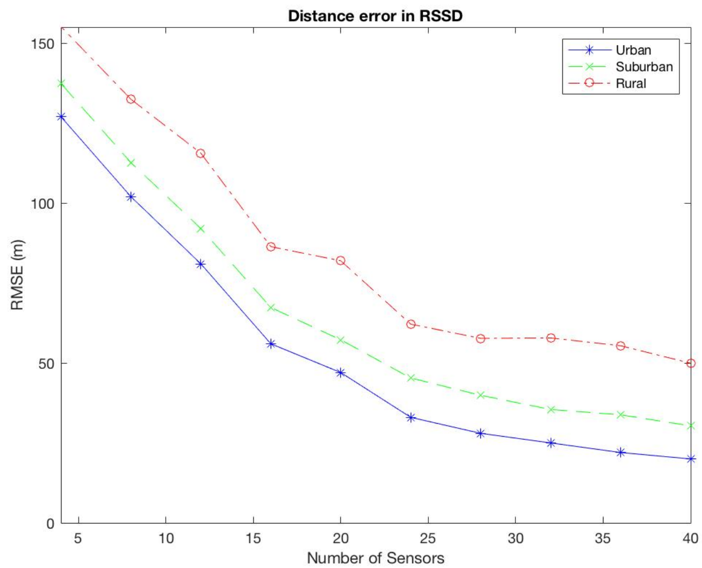


Figure 54: Stage 2 - RMSE of the transmitter estimated location

7.2.4 Propagation models performance

Due to the lack of wide-spread measurements, we rely on simulations to generate the measurements of the IC map. To calculate (simulate) these measurements, we rely on well-known wireless propagation models, such as Free Space Path Loss (FSPL), Longley-rice, and Rain[7]. These propagation models are used in both, the simulation of measurements and the construction of the "real-values" map. The results of the RMSE evaluation for each propagation model in an urban[8] environment as a function of the number of sensors are included in Figure 55. First, we observe how different models result in different error situations. For instance, the Rain model has a higher RMSE compared to free-space and Longley-Rice, being the latter the model with the best performance. The overall evaluation performance of the propagation models is within other performance evaluations presented in

[7] Due to the modularity of the REM simulator, additional wireless propagation models can also be included.

[8] The results for suburban and rural maps hold the same tendency in terms of the propagation model being used and the corresponding RMSE.

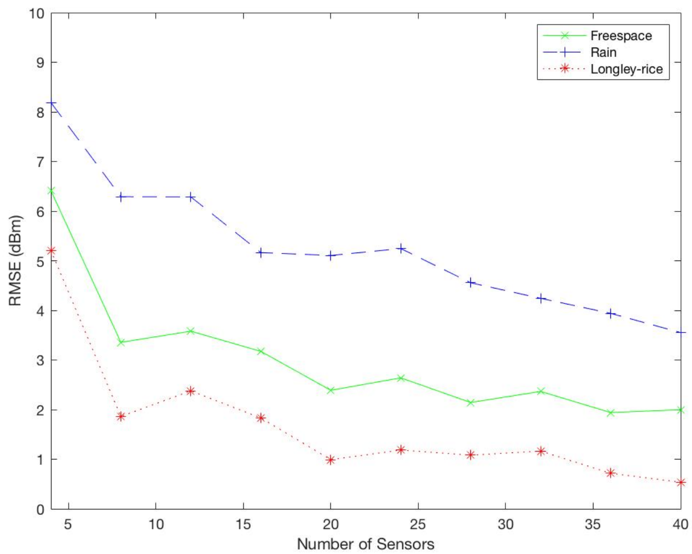


Figure 55: Stage 2 - Performance evaluation of the utilized propagation models

the literature of REM simulations [214].

7.3 Stage 3: A local and multi-tier spectrum sharing scenario under different governance systems

In this section, we present the results of our multi-tier, localized, and governance-based model for spectrum sharing agreements (*model 2.0*).

7.3.1 Number of conflict situations

In our governance-based model, usage conflicts can still occur. In particular, usage conflicts due to inaccuracies with the IC map of the REM (i.e., *Type A*), or events due to the potential overlapping of wireless signals among users in different tiers (i.e., *Type B*). Thus, the main objective behind including various governance systems is to reduce the number of conflict situations in the band.

In Figure 56, we observe the evolution in the average number of conflict situations as a function of the agents' interactions (i.e., time). The presented graphs include each governance system in the *Best Case Scenario* for both types of conflict situations: *Type A* (left graph) and *Type B* (right graph). Regardless of the governance system in place, a small number of events are present in the system. The presence of these conflict situations triggers the mitigation actions in the governance systems. For instance, the system may increase the size of the PU's protection areas by increasing the interference threshold. In the case of centralized governance (blue line), it appears that the mitigation strategies do not have a substantial impact on the number of events since, for both types of conflicts, the average number of events is constant throughout the agents' interactions. In self-governance (green line), we observe a consistent number of events throughout the agents' interactions. However, note that for *Type B* events, these are not as frequent as with the centralized method. In polycentric governance (orange line), we observe the most promising results. For both types of conflicts situations, the introduction of polycentric governance leads to a significant reduction in the number of events after the initial agents' interactions[9].

Regarding the distribution in the number of conflict events in the *BCS*, we note that the median number of conflict situations per interaction in the system is low, with a median of less than one event (see Figure 57). Even though the governance systems have distinct outcomes regarding the reduction of the number of conflict situations, the overall distribution[10] is very close to zero, with a few outliers all located under the 1-event mark .

In Figure 58, we find the evolution in the number of conflict events in the *Worst Case Scenario*. We note that the total number of events is considerably larger than the *BCS*, this is particularly evident for *Type A* events (left graph). In the case of *Type B* conflict situations (right graph), there is also an increment in the number of events, particularly for the centralized governance setting. However, we notice that the overall number of events is still considerably low in the *WCS*. When studying the difference in each governance mech-

[9] After approximately 1/3 of all the interactions, the number of events drops close to zero (0).

[10] For both types of events: *Type A* (left graph) and *Type B* (right graph).

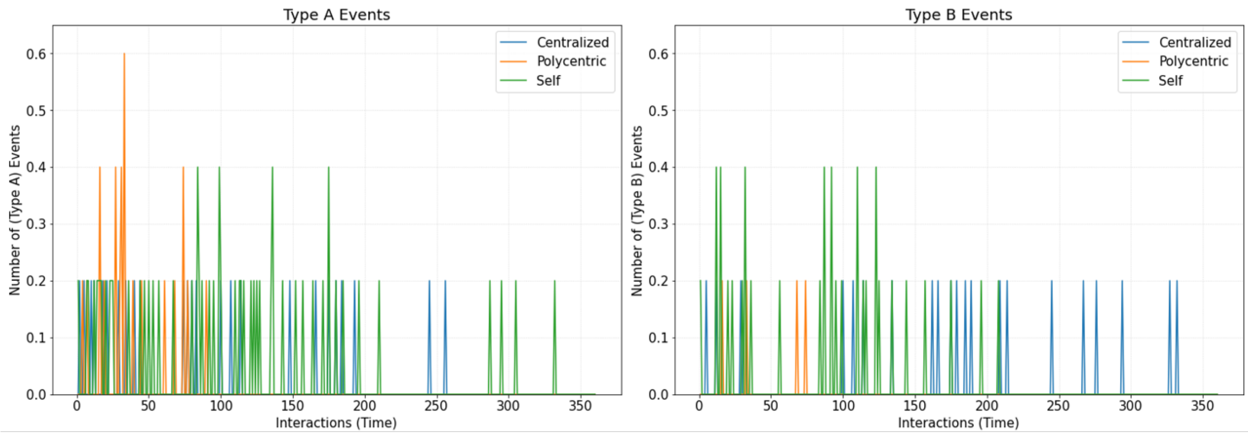


Figure 56: Stage 3 - Evolution of the number of *Type A* (left) and *Type B* (right) conflict events for the *Best Case Scenario*

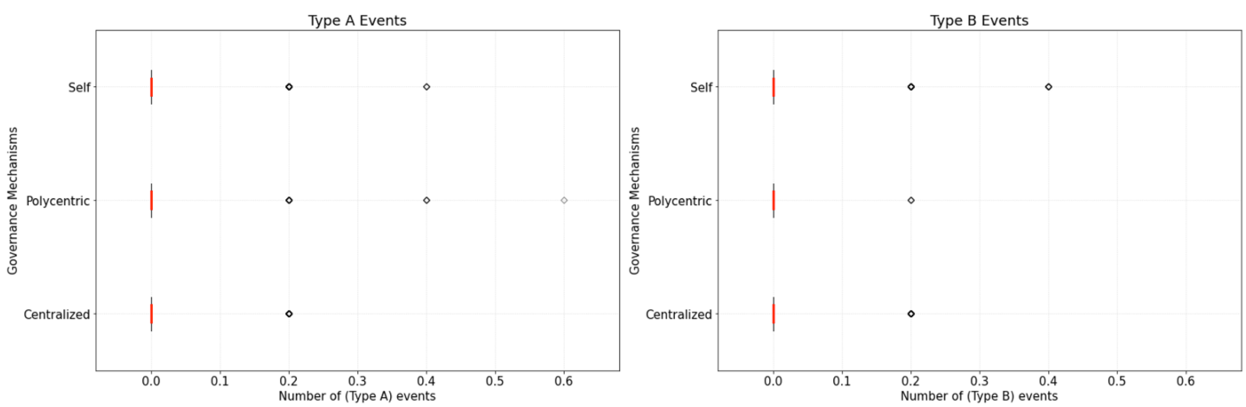


Figure 57: Stage 3 - Distribution of the number of *Type A* (left) and *Type B* (right) conflict events for the *Best Case Scenario*

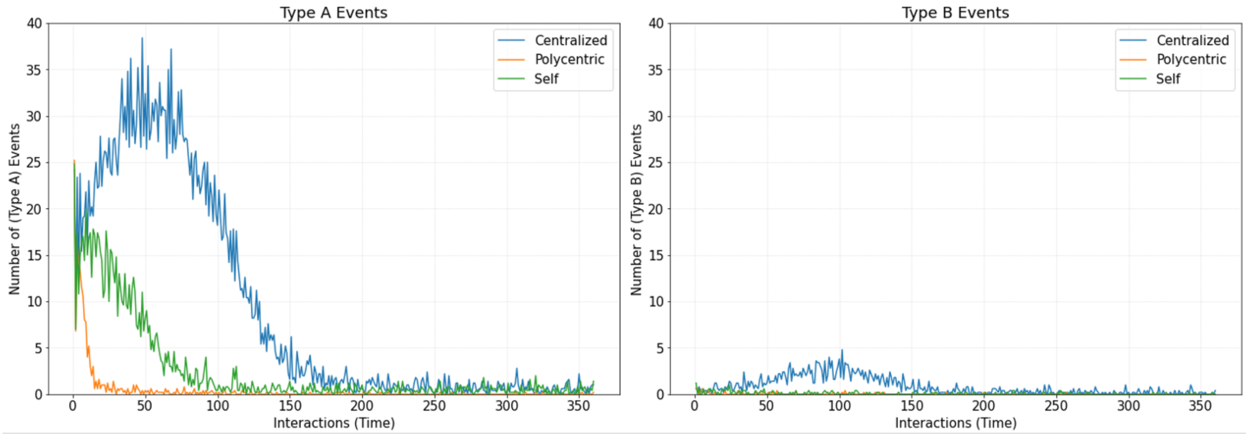


Figure 58: Stage 3 - Evolution of the number of *Type A* (left) and *Type B* (right) conflict events for the *Worst Case Scenario*

anism, we see two distinct outcomes for each type of conflict situation. For *Type A* events (left graph), we observe a reduction of events for all governance systems. This is particularly evident in the case of distributed approaches, where the number of events is minimized after the initial interactions of the model. In centralized governance, there is also a reduction in the number of conflict events. However, this reduction is not as immediate as in decentralized methods. For *Type B* events (right graph), the number of conflict situations is similar for all types of governance systems but centralized governance.

In the distribution of the number of conflict situations (see Figure 59), we observe an increase in the number of *Type A* (left graph) events regardless of the governance system. We also note how the overall number of events is considerably smaller under distributed governance approaches. This reduction is unmistakable in polycentric systems, where the overall distribution[11] is under five (5) events per interaction and a median of almost zero (0) conflict situations. For *Type B* events, the increase in the number of events in the *WCS* is not as evident than for *Type A* events. In this case, we also observe the biggest increase in the number of events for the centralized governance approach.

[11] Excluding the outliers of the distribution.

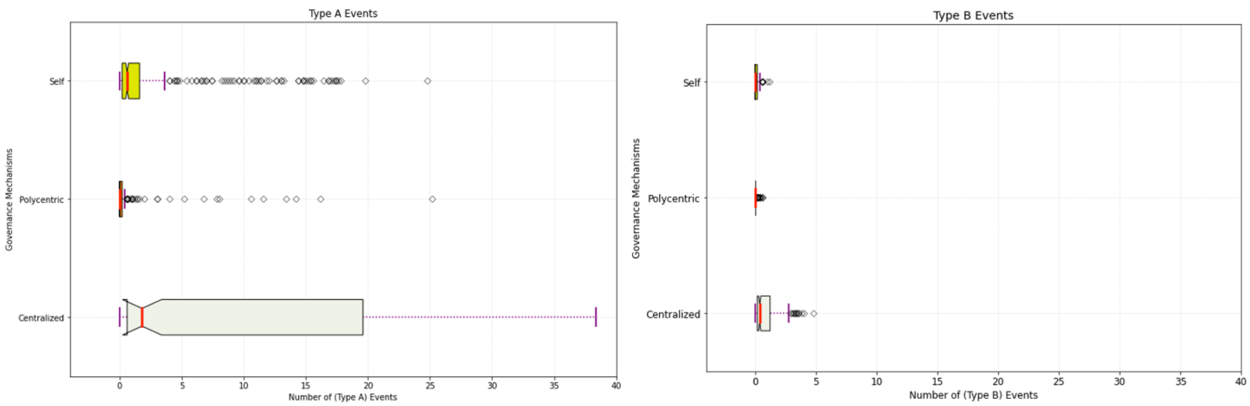


Figure 59: Stage 3 - Distribution of the number of *Type A* (left) and *Type B* (right) conflict events for the *Worst Case Scenario*

Even though we observe a considerable reduction in the number of events for all governance systems, this decrease can be the product of a reduction in the number of available resources in the sharing agreement. In other words, this decrease may be related to limitations in the available opportunities that the secondary users have to transmit, as we discuss in the following sections.

7.3.2 Transmission efficiency of secondary users

Besides reducing the number of conflict events, a crucial element in the success of spectrum sharing scenarios is the provision of incentives to the secondary users. In our model, we measure this efficiency as the ability of SUs to use the available resources, i.e., whether they can transmit the information using the shared wireless medium. For this purpose, we define two variables in our model. First, the SU decides if it has data to transmit using its assigned *transmission probability* and a random uniform variable (see Figure 60 and Expression 7.1). If the SU *has data to transmit*, it checks the RSS value stored in the REM and decides whether it is authorized to use the shared medium, completing in this way its transmission process. As explained in Equation 7.2, the SU transmission efficiency is the product of these two factors: *SU has data to transmit?* and can it transmit the data?.

$$SU_{Data\ to\ transmit?} = \begin{cases} Yes, & \text{if } Random\ variable <= Transmission\ probability \\ No, & \text{Otherwise} \end{cases} \tag{7.1}$$

$$SU_{Transmission\ Efficiency} = \frac{data\ to\ transmit}{data\ transmitted} \tag{7.2}$$

In Figure 61, we explore the evolution of transmission efficiency for the secondary users in each governance system. When comparing both experimental scenarios (i.e., *BCS* and *WCS*), we see an important difference. In the *Best Case Scenario* (left graph), there are no significant differences in the evolution of the SU transmission efficiency for each governance system. Most of the time, the SUs can transmit all of their generated data[12] regardless of the governance system. Since a few conflict situations are present in the system, not many limitations are imposed on the new entrants; thus, we observe a high SU transmission efficiency in all governance systems. In the case of *WCS*, we observe a clear difference between the distinct governance mechanisms and the ability of the SUs to use the resources. In centralized governance, the SU transmission efficiency drops close to zero (0). In other words, the SUs in the band generated data to transmit, but the conditions of the system did not allow them to transmit it. In self-governance, the situation is not as "extreme" as the centralized system; however, most of the time, the transmission efficiency of the SUs is less than 20%. In polycentric governance, after the initial phases of interactions, the SU transmission efficiency averages 90%. In other words, the secondary users can utilize the shared resources most of the time. Even though we observe a reduction in the number of events in all governance systems, we notice that in centralized and self-governance this outcome is partially due to a reduction in the number of active SUs.

Figure 62 depicts the overall distribution of the transmission efficiency of the secondary users in the *BCS* and *WCS*. In the *BCS* (left graph), the median usage efficiency is close to 100% in all governance systems. However, when the band conditions are at their "worst",

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Note that in some interactions, many users did not produce data to transmit and, consequently, the efficiency for those cases is zero (0).

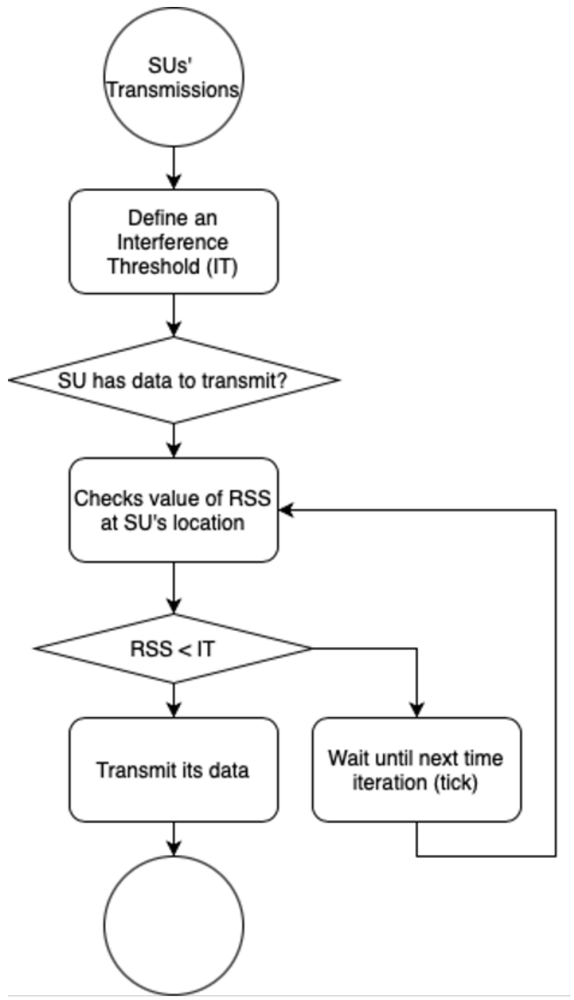

Figure 60: Stage 3 - Flow diagram of the secondary user transmission decision process

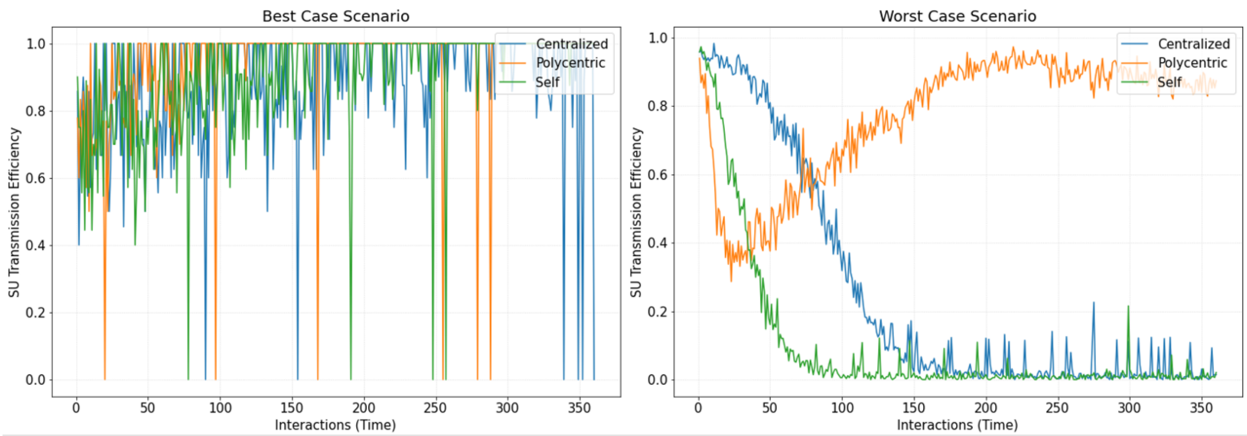

Figure 61: Stage 3 - Evolution of the average SU transmission efficiency for the *Best Case Scenario* (left) and *Worst Case Scenario* (right)

the SU transmission efficiency drops in all governance systems (right graph). In polycentric governance, this decrease is not as noticeable as with centralized and self-governance, with a median usage of the resources of approximately 84%. In the case of centralized and self-governance, the median SU transmission efficiency is approximately 5%. Note that for self-governing approaches, a more important outcome for the agents is reaching agreements regarding the conditions of the band (see Section 7.3.3). These agreements show the ability of the agents to maintain a continuous dealing relationship[13].

7.3.2.1 Information (knowledge) problem in centralized systems As argued by Hayek, one of the fundamental components to construct a rational economic order is that systems need to "...possess all the relevant information..." [190]. The main challenge with this data is that knowledge of the circumstances never exists in a concentrated or integrated form. This knowledge is constituted as dispersed bits of incomplete and frequently contradictory information that many separate individuals possess. The sort of knowledge in this scenario is knowledge of the kind which by its nature cannot enter into statistics and

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It is worth noticing that these agreements are not necessarily the most efficient in terms of resource allocation.

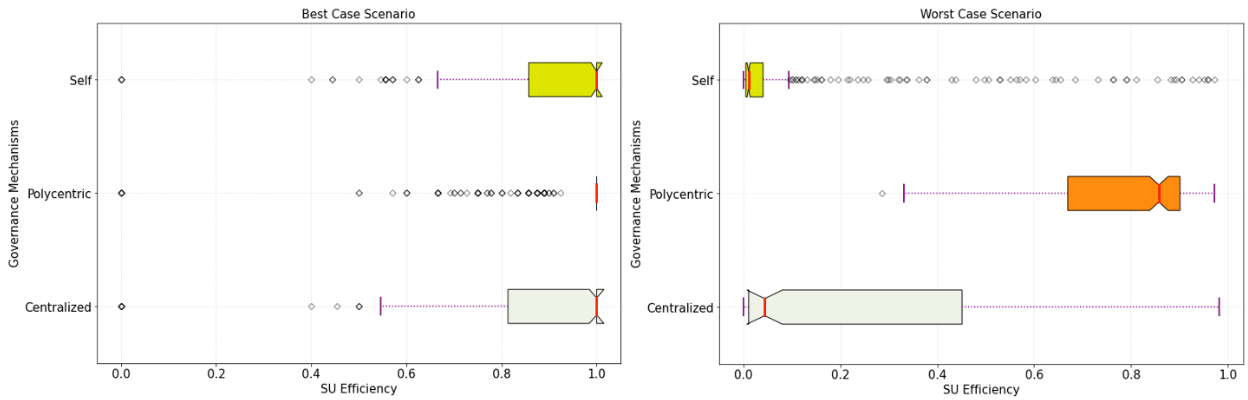

Figure 62: Stage 3 - Distribution of the SU transmission efficiency for the *Best Case Scenario* (left) and *Worst Case Scenario* (right)

therefore cannot be conveyed to any central authority in statistical form [215].

In our model, we capture this problem of information access (i.e., incomplete information) as a *detection uncertainty*. Since the central authority needs to group the local data from many sources, the knowledge problem may lead to incomplete information, which results in missed conflict events. Thus, the *detection uncertainty* variable in our ABM dictates the proportion of events not being detected by the central authority due to incomplete knowledge.

In Figure 63, we find the number of conflict situations as a function of different *detection uncertainty* rates in a centralized scheme. As we observe in the evolution (left) and distribution (right) of the number of conflict situations, when the *detection uncertainty* is 0.25[14], the number of events is at its highest level. As the number of missing information decreases (i.e., a reduction in the *detection uncertainty*), there is a reduction in the number of conflict situations. Even when the central authority can successfully identify all the available information (i.e., *uncertainty detection* = 100%), there is still a considerable number of conflict situations in the system.

The lack of complete information implies that the central *coordinator* is neither able to capture all the events in the system nor to apply the required measures to minimize

[14] Due to missing or incomplete information, the central entity can detect only 25% of the conflict situations.

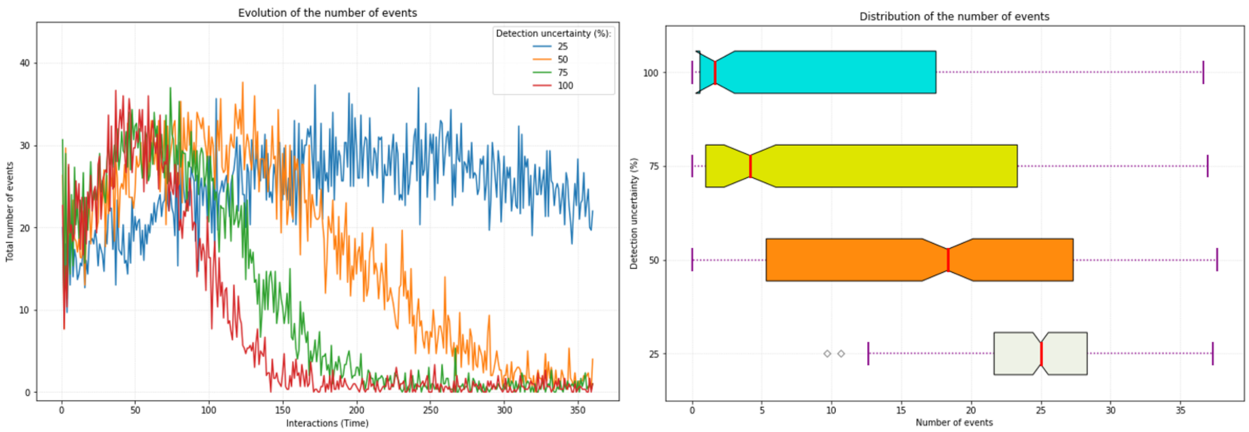

Figure 63: Stage 3 - Effects of the variable *Uncertainty detection* in the average number of conflict events in centralized governance scenarios

such events. Consequently, the efficiency in the use of resources by the secondary users is higher in situations where the *detection uncertainty* is low (see Figure 64). When the *coordinator* collects approximately 25% of the available data (i.e., *detection uncertainty* = 25%), the SU transmission efficiency is over 40% for all agents' interactions. Contrary, when the system can collect all the available information, the central *coordinator* can implement conflict mitigation strategies more frequently. This set of actions both reduces the number of events and the available SU transmission opportunities.

7.3.3 Impact of the governance mechanisms in the sharing parameters

Depending on the implemented governance mechanism, different control measures are applied as a means to minimize the number of conflict situations. These measures include modifications to system-wide parameters such as the Interference Threshold (IT) value[15], and modifications to the transmission characteristics of the SUs. Among these individual measures, we find the reduction of the transmission power, a switch in the frequency bands

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A change in the Interference Threshold (IT) is directly proportional to the size of the protection zone of higher-tier users. A large IT signifies a large protection area.

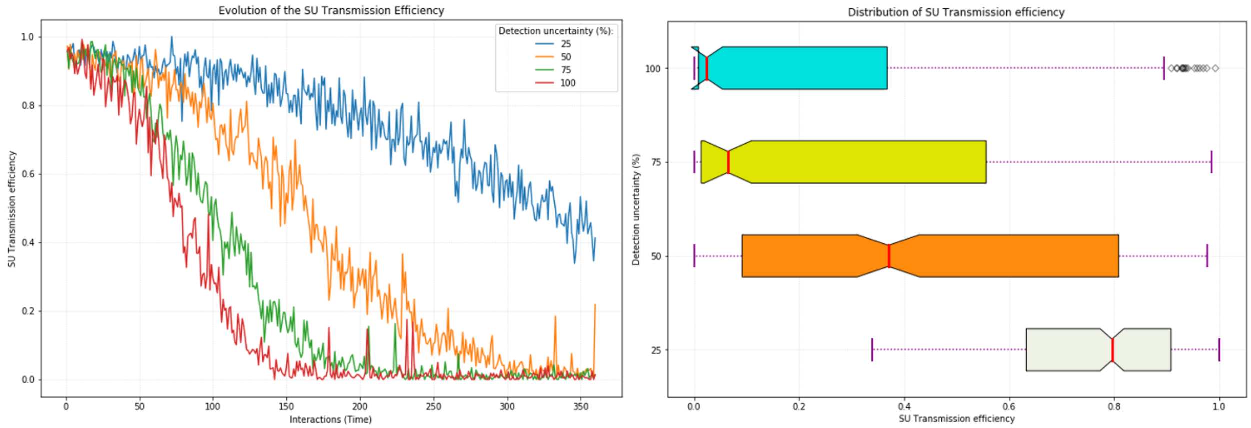

Figure 64: Stage 3 - Effects of the variable *Uncertainty detection* in the SU transmission efficiency in centralized governance scenarios

(i.e., channels), and a change in the *margin of error* value. In this section, we analyze the relationship between these measures and the distinct governance systems.

7.3.3.1 Evolution of the Interference Threshold (IT) In all governance mechanisms, it is possible to increase or reduce the interference threshold of the system. A change in the IT results in a change in the size of the protection areas for higher-tier users. In centralized governance, the central *coordinator* increases the interference threshold any time a *Type A* conflict situation occurs. In self-governance, the primary user is in charge of controlling its protection criteria. Thus, the PU increases and reduces the size of the interference threshold according to the continuous dealing process. Finally, the different local *coordinators* in polycentric governance are allowed to change the value of the IT within its jurisdiction (i.e., within the local coordination zone).

The evolution of the interference threshold in the *Best Case Scenario* (left graph) and *Worst Case Scenario* (right graph) are depicted in Figure 65. When the system is under its best conditions (i.e., *BCS*), the number of conflict situations is considerably low. Consequently, the actions taken in the different governance systems are also minimal. For all governance approaches, the value of the interference threshold tends to be reduced[16]. In polycentric and centralized governance, the slope in the reduction is smaller than self-governance, which shows the steepest increase of the system. In addition, a key result for self-enforcing approaches is that the interference threshold reaches a stable state with little or no changes at all. This result signals that the agents reach an agreement regarding the IT parameter.

In the *Worst Case Scenario* (right graph), the interference threshold presents a completely different outcome than in the *BCS*. In centralized governance, the interference threshold has a significant increase at the beginning of the interactions and then it stabilizes, but at a high value (around -95dB). This implies the presence of very large protection zones and, consequently, the reduction of usage opportunities for the SUs. In self-governance, we also observe a significant increase in the IT. However, this increase is not as substantial as in centralized systems and by the end of the agents' interactions it stabilizes around -86dB. Similar to the *BCS*, this stabilization process is a positive result for self-governance[17]. Finally, in polycentric governance, the value of the IT has a decreasing trend before it stabilizes around -65dB. This is translated into the high number of transmission opportunities available for the SUs.

7.3.3.2 Evolution of the SU's transmission parameters The IT value is the only global parameter modified by the distinct governance systems. In what follows, we analyze the SU's transmission parameters that are also modified as part of the efforts to reduce the number of conflict situations.

In polycentric and self-governance, agents can switch frequency bands. The change in this transmission parameter does not imply a limitation in the transmission opportunities for new entrants. Instead, it seeks to balance the number of SUs in each of the available channels (*c1* and *c2*). The number of conflict situations in the *BCS* is relatively low; thus, we observe only a few instances where SU's changed frequency bands. In the *WCS* (Figure 66), we observe a higher number of SUs going from *c1* to *c2* and vice versa. This is particularly evident in

16 It is worth mentioning that in Figure 65 the values on the x-axis are negative (< 0). Hence, the figure depicts a line with a positive slope.

17 It implies that participants in different tiers are able to reach an agreement regarding the IT of the system.

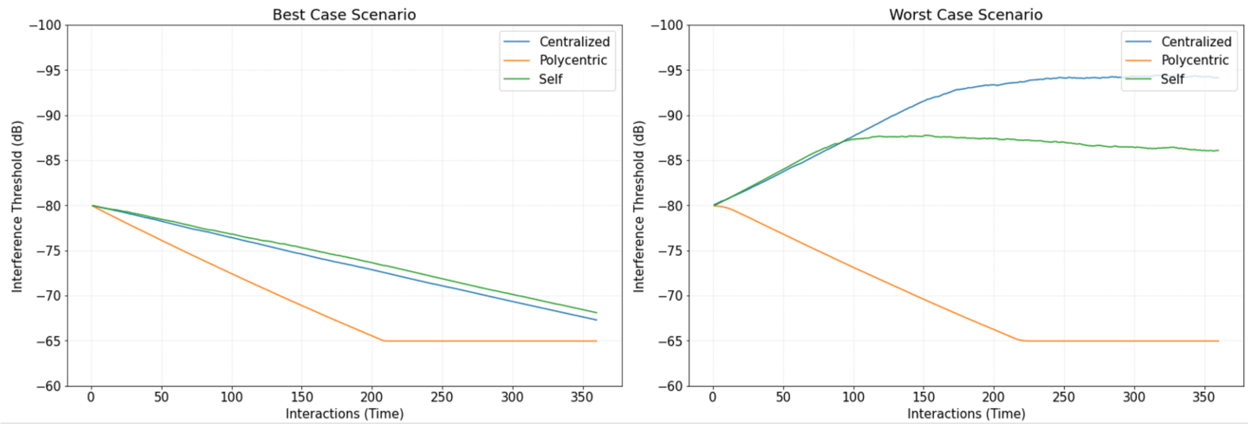

Figure 65: Stage 3 - Evolution of the interference threshold in the *Best Case Scenario* (left) and *Worst Case Scenario* (right)

self-governance, where the SUs elect to switch channels to send “trust” signals more than 150 times. Even though this is also the case in polycentric governance, the number of channel transitions is not as significant as self-governance. Finally, since centralized systems do not use this strategy, the number of channel changes is only one (1)[18].

As mentioned above, in *Model 2.0*, we assume that all participants are cooperative agents[19]. Thus, agents in the different tiers are making their best effort to comply with the rules of the sharing contract and avoid conflict situations. Among these efforts, agents try to minimize the number of conflict events due to inaccuracies with the REM's IC map. For this purpose, each agent emulating an SU possesses a *margin of error* variable. The goal of increasing this variable is to overcome errors in the REM and avoid unauthorized transmissions in the vicinity of active primary users, as is shown in expression 7.3

$$SU_{SU_{transmission}} = \begin{cases} Transmit, & \text{if } RSS + (margin\ of\ error) <= IT \\ Do\ not\ transmit, & \text{Otherwise} \end{cases} \tag{7.3}$$

18 At the beginning of the simulation process, every SU is assigned a channel for its use.

19 The only type of conflict situation in the system is *Type I*.

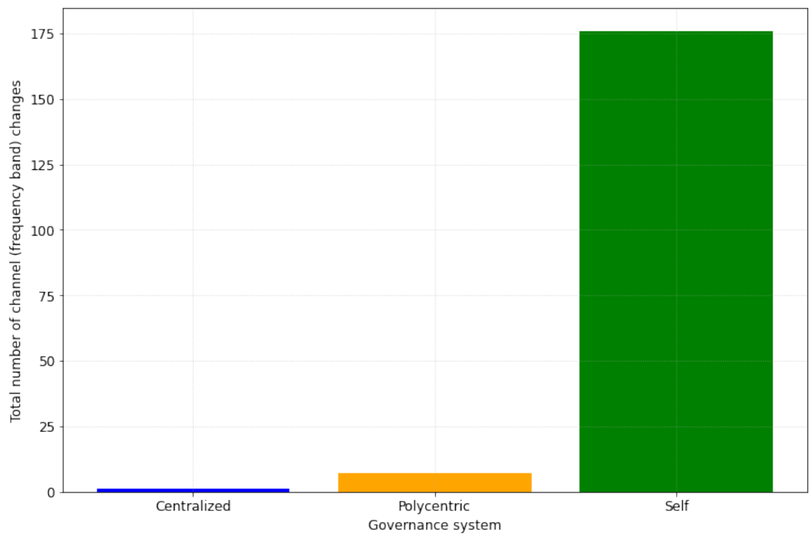

Figure 66: Stage 3 - Average number of channel (frequency band) changes in the *Worst Case Scenario*

The evolution of the average SUs' *margin of error* for the *Best Case Scenario* (left graph) and *Worst Case Scenario* (right graph) is depicted in Figure 67. When the system is under its best conditions (i.e., *BCS*), there is minimal change in the *margin of error* of the secondary users. This behavior is consistent across all governance mechanisms. A modification in the margin of error is a characteristic of distributed governance; thus, in centralized governance, agents do not modify its value. In self-governance, the *margin of error* has a moderate increase, and then it stabilizes. Again, this stabilization is another crucial milestone for self-governing approaches and their continuous dealing mechanism. In polycentric governance, we observe a significant increase of the SUs' *margin of error*. This result implies a substantial adjustment to the conditions of the band by the SUs and, consequently, an important reduction in the number of conflict situations.

In the *WCS* (right graph), there is a considerable adjustment in the behavior of the secondary users, where the average *margin of error* for the new entrants is much higher than in the *BCS*. In self-governance, there is a substantial increase in the *margin of error* than the *BCS*, then it reaches a stable point. In polycentric governance, we observe a more significant

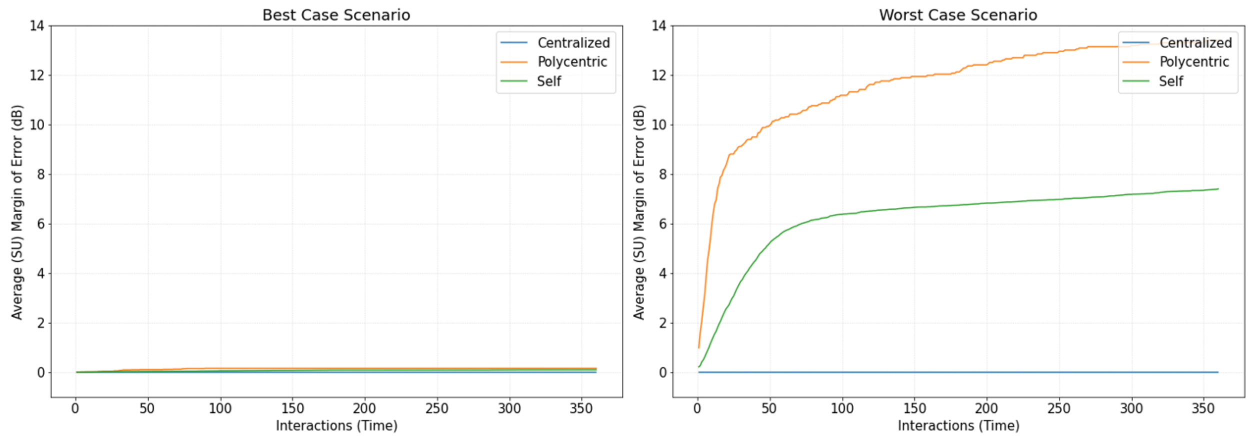

Figure 67: Stage 3 - Evolution of the model parameter SUs' *margin of error* in the *Best Case Scenario* (left) and *Worst Case Scenario* (right)

increase in the *margin of error* than self-governance. These results show the adaptability of the SUs to the conditions of the band and the benefits of localized coordination.

The final action to minimize the number of conflict situations in the system is to limit the transmission power of the SUs. The main goal of this measure is to avoid signal overlapping and potential usage conflicts for a receiver in the PU's network. Note that all the governance systems in our models make use of this strategy.

In Figure 68, we show the evolution of the average SUs' transmission power[20] for the *Best Case Scenario* (left graph) and *Worst Case Scenario* (right graph). When the system is under its best conditions (i.e., *BCS*), there is not a significant difference among the governance systems. This is also shown in the SU transmission power distribution depicted in Figure 69, where the median transmission power in the *BCS* (left graph) is very similar across the distinct governance systems.

When analyzing the SUs' transmission power in the *WCS* (right graph of Figure 68), we observe that the governance systems lead to different outcomes. In centralized governance, due to the high number of conflict situations, the local *coordinator* keeps reducing the trans-

20 It is necessary to point out that the transmission power of the secondary users is only measured when such users are currently active (i.e., transmitting).

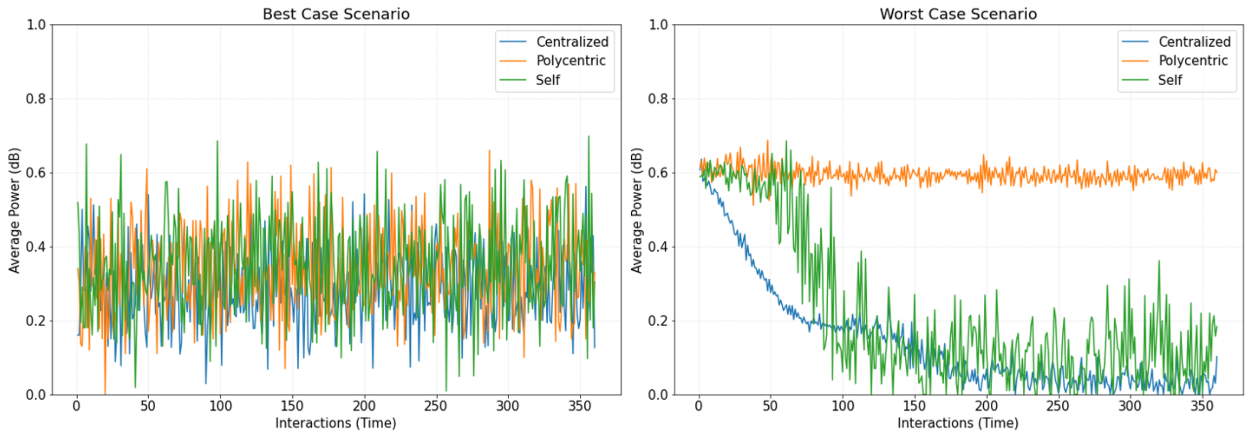

Figure 68: Stage 3 - Evolution of the average SU transmission power in the *Best Case Scenario* (left) and *Worst Case Scenario* (right)

mission power of the SUs to its minimum. Since the number of conflict situations is not completely reduced, the SUs' find few opportunities to transmit. Consequently, the average SUs' transmission power is close to zero (0). In self-governance, the transmission power is significantly more variable than in the other governance systems. One explanation for this outcome is the continuous interactions of the agents and their corresponding actions until the system stabilizes. In polycentric governance, the secondary users maintain a constant transmission power through agents' interactions. This behavior is also seen in the median transmission power (see Figure 69 (right graph)). As we observe, the median transmission power for the new entrants of the band is higher in both the polycentric and self-governance approaches than centralized systems.

7.3.4 Impact of the experiment setup variables

To conclude the analysis of the results of Stage 3, we analyze the impact of the different experimental setup variables and their corresponding levels (see Section 6.3.3). As mentioned above, to evaluate the performance of *Model 2.0*, we select five (5) important model parameters as our experiment setup variables. We select these variables due to their

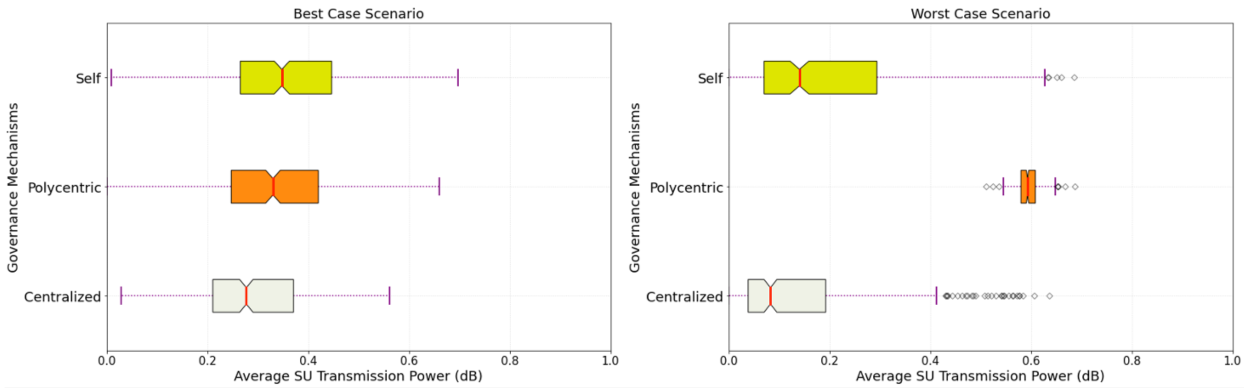

Figure 69: Stage 3 - Distribution of the SU transmission power in the *Best Case Scenario* (left) and *Worst Case Scenario* (right)

importance in the sharing agreements. Thus, these variables include the number of primary users, the number of secondary users, *sensor density*, average *fading deviation*, and *SU load* (see Table 23).

First, we analyze the relationship between the number of conflict events and the model parameters in centralized governance (see Figure 70). When analyzing each of the parameter transitions from *BCS* (blue bar) to *WCS* (orange bar), we observe a substantial increase in the number of events for all model inputs but *sensor density*. The *sensor density* result is in line with the results obtained for the IC map simulation (see Section 6.24)[21]. When there is an increase in secondary users, we observe the biggest difference in conflict situations. In this case, we observe that the number of conflict situations increases approximately 700%. This outcome is also true for the average *fading deviation*. The final parameter that has a significant impact on the number of conflict situations is the *SU load*.

In polycentric (Figure 71) and self-governance (Figure 72), we observe a similar outcome to centralized governance. A change in the model parameters (from *BCS* to *WCS*) causes a considerable increase in the number of conflict situations for all parameters, except for

21

We found that only under a given threshold of MCD coverage, the sensor density in the system starts generating larger errors in the IC map.

Variable	**Scenario**	
	BCS	**WCS**
Number of primary users	5	10
Number of secondary users	10	100
Sensor density	0.8	0.4
Average *fading deviation*	0.5	4
SU load	0.2	0.7

Table 23: Stage 3 - Experiment setup for the *Best Case Scenario* and *Worst Case Scenario*

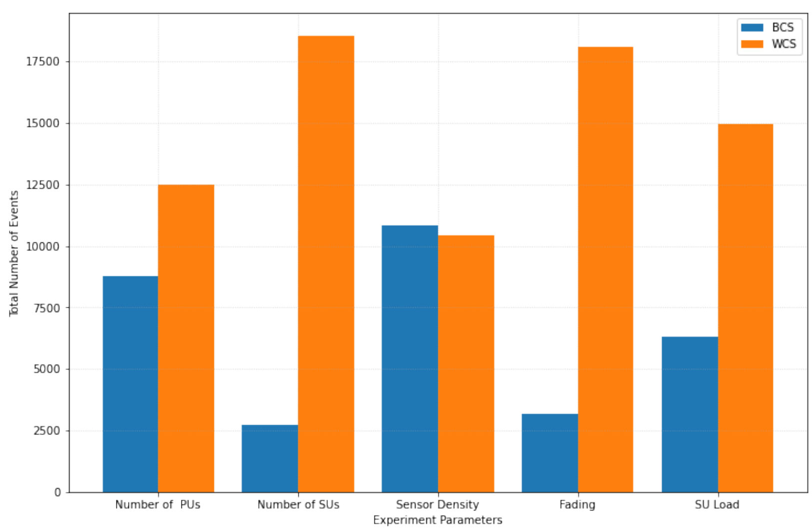

Figure 70: Stage 3 - Relationship between the number of conflict situations and the model parameters in centralized governance

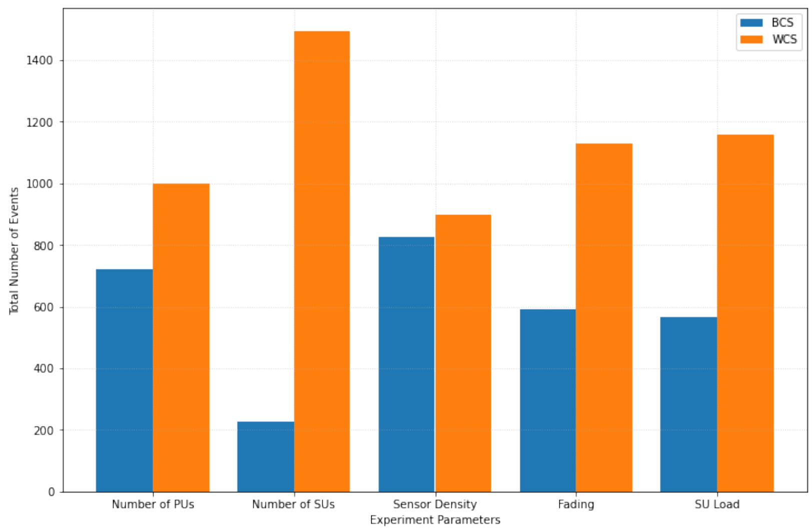

Figure 71: Stage 3 - Relationship between the number of conflict situations and the model parameters in polycentric governance

sensor density. For the number of primary users, even though there is an increase in conflict situations, this change is not as noticeable as other model parameters. Once again, a change in the number of SUs, their corresponding load (i.e., *SU load*), and the IC errors (i.e., average *fading deviation*) show the most substantial difference in the number of events when going from the best (i.e., *BCS*) to the worst (i.e., *WCS*) sharing agreement conditions.

7.4 Stage 4: Smarter agents in spectrum sharing scenarios

In the final stage of this work, we study the impact of developing "smarter" agents. For this purpose, we enhance the internal decision-making abilities of the SUs. The goal is to predict the emergence of conflict situations using past experiences (historical data) and ML classification models.

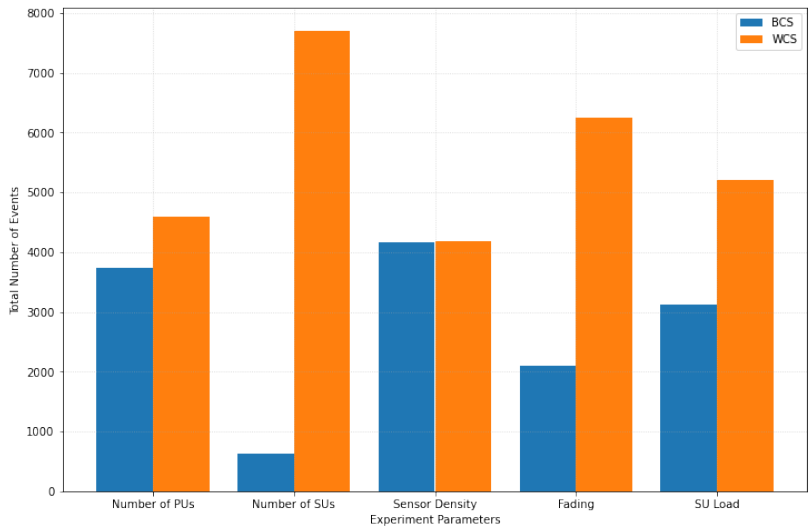

Figure 72: Stage 3 - Relationship between the number of conflict situations and the model parameters in self-governance

7.4.1 Local machine learning approach

We start this analysis at the agent-level or local ML approach. In this scenario, each secondary agent is responsible for collecting and storing its past executions, creating and fitting an ML model, and using the fitted ML model to predict the emergence of conflict situations[22]. We divide the analysis of the local application of ML into its utilization within the three governance mechanisms implemented in the model.

To test the impact of ML techniques at the agent-level, we consider five widely-used machine learning classifiers: Logistic Regression (LR) Classifier, Support Vector Machine (SVM), Nearest Neighbor (NN) Classifier, Random Tree Forest (RF), and Gradient Boosting Classifier (xGBoost or xGB). In previous sections, we explored how the number of conflict situations in the *Best Case Scenario* is considerably low. In addition, the number of *Type B* events in the system for both, the *BCS* and *WCS*, is also very low compared to the *WCS*

[22] In Appendix H, we observe an example of the preliminary data exploration process regarding the data used to build the different ML models included in our ABM.

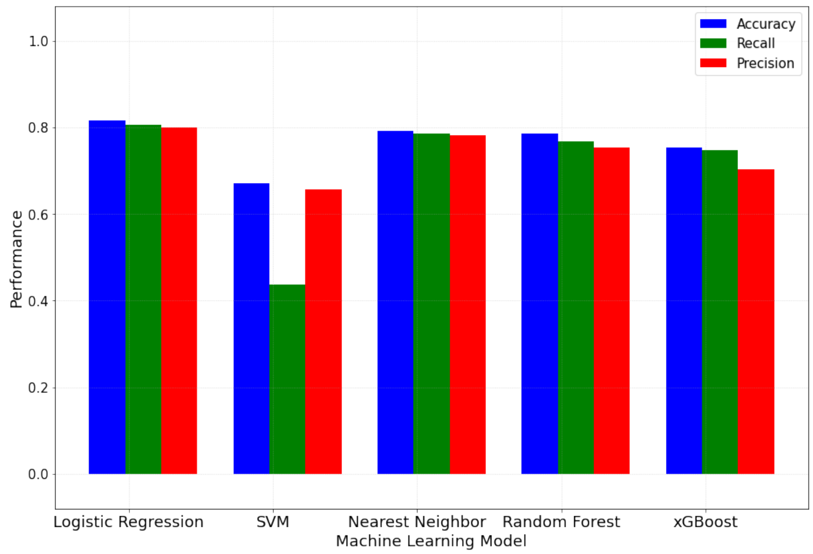

Figure 73: Stage 4 - Performance evaluation of the machine learning models built in centralized governance systems

of *Type A* events. Therefore, for the analysis of the application of ML techniques in ABM, we only consider the *Worst Case Scenario* (i.e., high number of users (both PUs and SUs), low *sensor density*, high average *fading deviation*, and high *SU load*) for *Type A* events. We believe this is the scenario in which the system would benefit the most from "smarter" agents.

7.4.1.1 Centralized governance In previous sections, we analyzed how the implementation of centralized governance leads to a higher number of conflict situations. Consequently, the development of enhanced SU agents could be very beneficial under this governance approach.

First, we study the performance of the different models built for the ML-based ABM (*Model 3.0*). In this light, we analyze the classification performance metrics (i.e., accuracy, precision, and recall.) for each of the implemented ML techniques.

Figure 73 depicts the performance evaluation of the ML models constructed in the centralized governance approach. All models except for Support Vector Machine (SVM) have

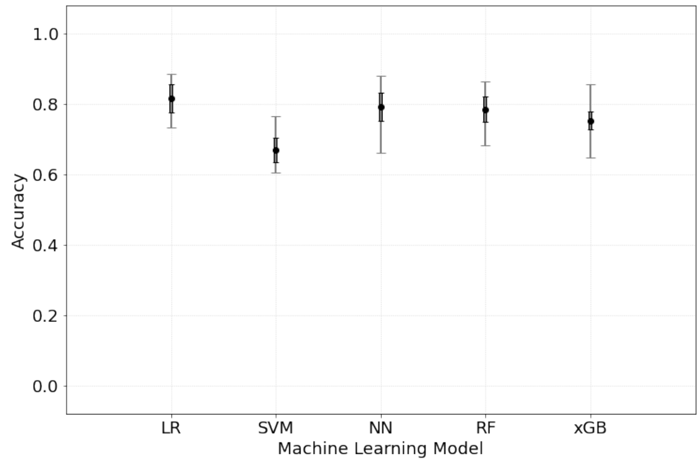

Figure 74: Stage 4 - Accuracy performance evaluation of the machine learning models built in centralized governance systems

similar performance, with their evaluation metrics ranging from 70% to 80%. Note that the models present higher accuracy (blue bar) compared to precision (red bar) and recall (green bar). These results show good performance levels for all the selected ML techniques, which allows us to utilize them with a high degree of confidence. If we further analyze the accuracy of each model (see Figure 74), we also find encouraging results. The accuracy of the ML models is considerably high (between 0.68 and 0.91) throughout our simulations. In the case of SVM, the accuracy performance of the models is slightly inferior[23]. Nonetheless, the performance is still over 50%, which makes it a useful model for future predictions.

Figure 75 shows the evolution of the number of conflict events for different scenarios: the simple coordination implemented in the governance-based ABM (i.e., *WCS without ML* (blue dotted line)), and the scenarios with different ML techniques. We observe a reduction in the number of conflict events in the system when using any ML technique. Further, all ML models have similar results regarding the evolution of the number of conflict events.

[23] An average of 0.64 with a variation between 0.6 and 0.76.

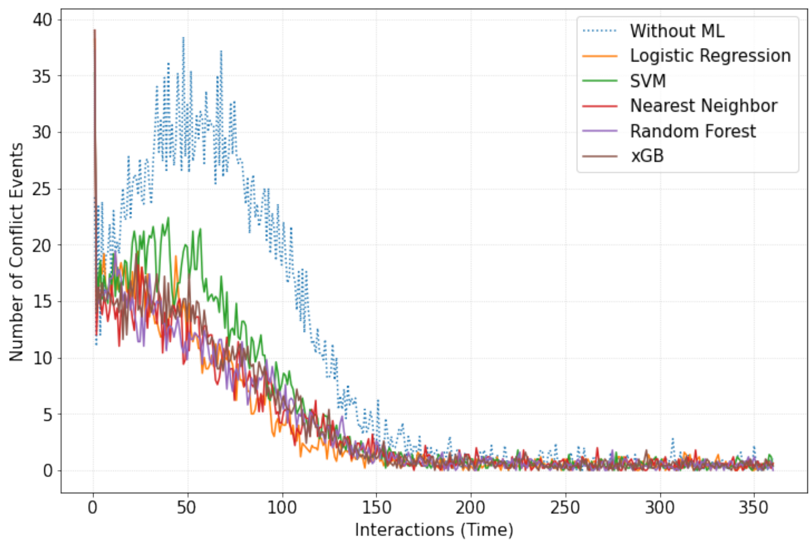

Figure 75: Stage 4 - Evolution of the number of conflict events - Scenarios with machine learning (algorithms) and settings without machine learning (simple coordination) - Centralized governance

The previous outcome is confirmed when analyzing the distribution of all the events in the system (Figure 76). The median number of conflicts for models without ML is slightly higher than all the cases that include ML. This median number of events per interaction is close to zero (0). The difference between using ML and simple coordination is in the higher part of the distribution, with Q3 and maximum values much higher for the scenario without ML compared to ML scenarios. Thus, in 75% of agent's interactions (i.e., Q3), the utilization of ML leads "cuts" the number of events per interaction in half or more.

The number of conflict events is not the only parameter that dictates the performance of the sharing agreement. In this analysis, we also study the efficiency in the use of the available resources. In Figure 77, we show the evolution in the SU transmission efficiency for simple governance coordination (i.e., *WCS without ML* (blue dotted line)) and the usage of ML models. The efficiency in the ML-enhanced models is lower than in the scenarios where only coordination is implemented. In other words, the ML models contribute to avoiding conflict situations but limit the availability of resources for the SUs. We observe this result

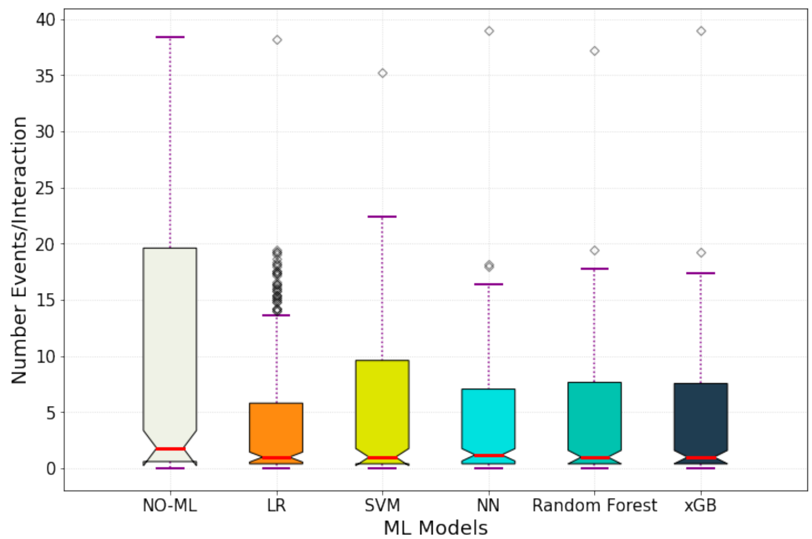

Figure 76: Stage 4 - Distribution of the number of conflict events - Scenarios with machine learning (algorithms) and settings without machine learning (simple coordination) - Centralized governance

across all the ML algorithms implemented in *Model 3.0*.

The overall distribution for the SU transmission efficiency also depicts the relationship between the models that include ML and simple coordination (see Figure 78). Simple coordination models have a slightly higher median SU transmission efficiency values than models that rely on ML. This is also true for other distribution metrics (e.g., Q3 and maximum), where the setting without ML results in higher efficiency than the scenarios with an ML model. Among the ML techniques, we observe that *xGB* and *SVM* have a slightly better performance in terms of SU transmission efficiency than the other ML algorithms.

7.4.1.2 Polycentric governance In polycentric governance approaches, we also modify the internal decision-making models of secondary users through ML algorithms.

In Figure 79, we observe the performance evaluation for the ML models utilized by the different agents in the sharing agreement. To evaluate these techniques, we also use the accuracy (blue bar), precision (red bar), and recall (green bar) of the classification methods.

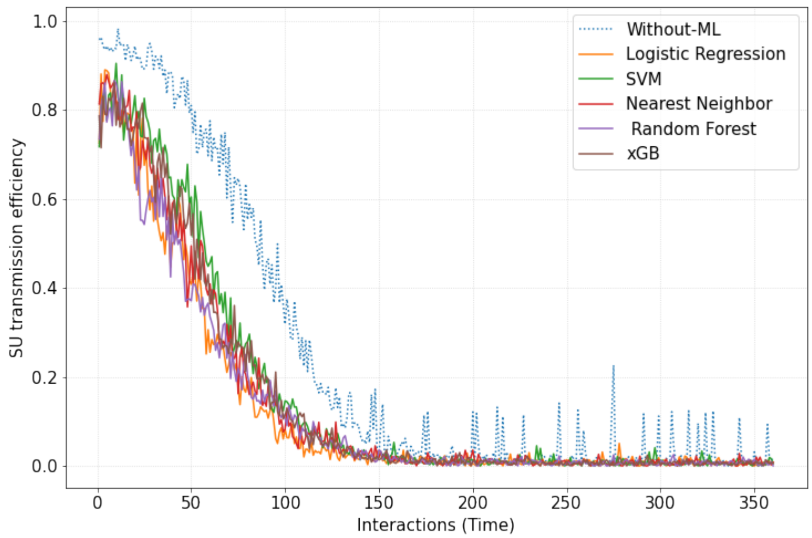

Figure 77: Stage 4 - Evolution of the average SU transmission efficiency - Scenarios with machine learning (algorithms) and settings without machine learning (simple coordination) - Centralized governance

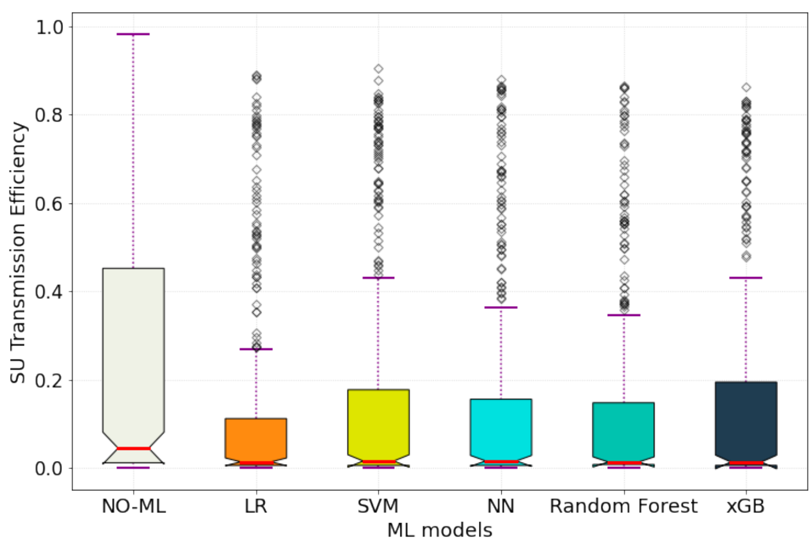

Figure 78: Stage 4 - Distribution of the SU transmission efficiency - Scenarios with machine learning (algorithms) and settings without machine learning (simple coordination) - Centralized governance

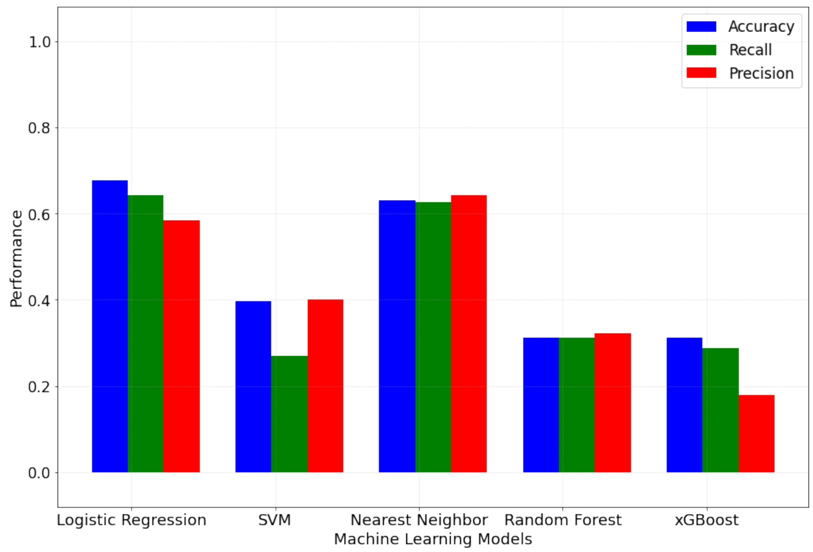

Figure 79: Stage 4 - Performance evaluation of the machine learning models built in polycentric governance systems

In the case of polycentric governance, only Logistic Regression and Nearest Neighbor present a performance over 50% for all their metrics. The remaining techniques have non-optimal performance evaluations, all being below 40%. One explanation for this result is the diversity of data being generated. In other words, since simple coordination in polycentric governance significantly reduces the number of events, some agents do not observe and collect data about multiple conflict situations. Consequently, based on the design of the ML-based ABM, they may not be required to implement ML models, or the data used to create these models do not have high diversity.

A detailed performance evaluation of the ML models' accuracy is presented in Figure 80. Similar to other evaluation metrics, only Logistic Regression and Nearest Neighbor have an overall accuracy distribution over 60%. The remaining ML methods have accuracy distributions below 0.4. In addition, we observe a more compact accuracy distribution for the different models we built. This is also related to the number of secondary users implementing ML models in polycentric approaches, as we explore in the following sections.

In Figure 81, we find the evolution in the average number of events per interaction as

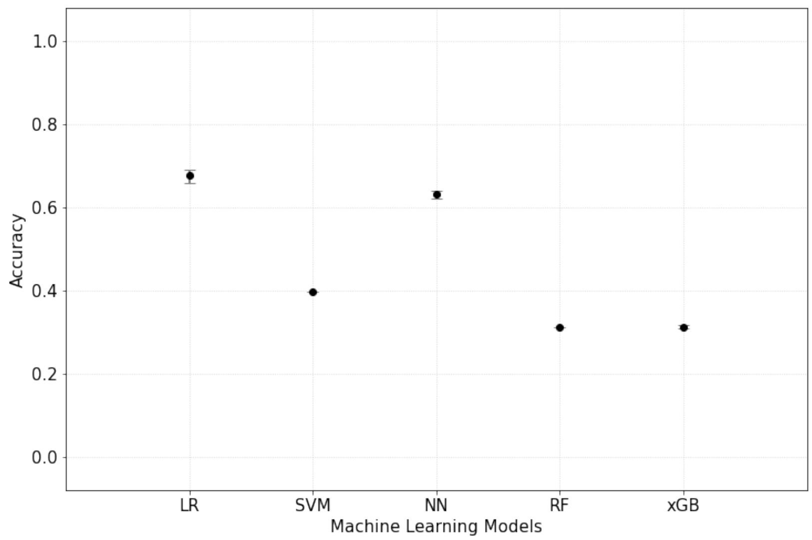

Figure 80: Stage 4 - Accuracy performance evaluation of the machine learning models built in polycentric governance systems

a function of whether the system includes ML techniques. When comparing the simple coordination or the absence of ML models (blue dotted line) with the utilization of ML techniques, we see that the number of conflict situations during the initial interactions of the system is larger for the simple coordination setting. However, after this initial period, simple coordination and the application of ML models show similar outcomes. They all reduce the number of conflict situations in the system, on average, to a stable state close to zero (0) conflict events per interaction.

If we analyze the distribution of conflict events for simple coordination models and scenarios using ML (see Figure 82), we notice that there is no significant difference among them. The median number of conflict situations per interaction is close to zero (0) for all scenarios. Additionally, all other distributions metrics (e.g., Q3 and maximum) are also close to zero (0) conflict events in each interaction. The only difference between scenarios with ML and without ML is the distance from the distribution to the largest outliers. This result is also related to the number of conflict events and SUs using ML models under polycentric governance.

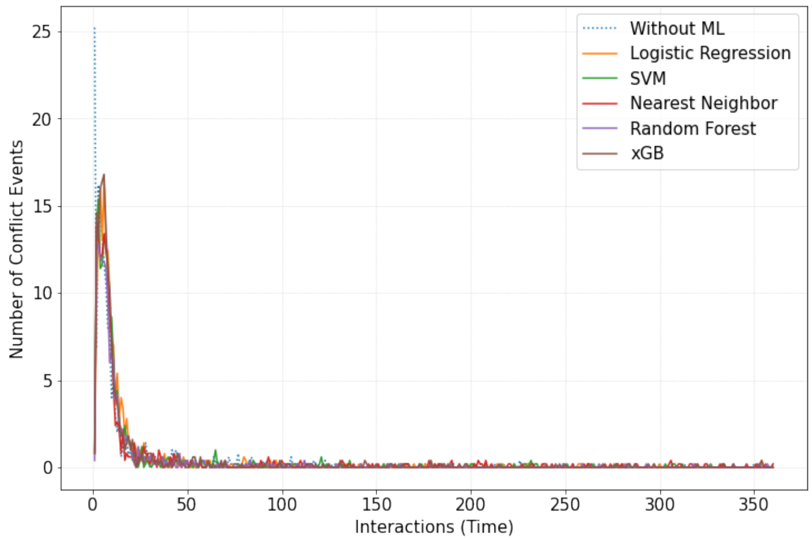

Figure 81: Stage 4 - Evolution of the average number of conflict events - Scenarios with machine learning (algorithms) and settings without machine learning (simple coordination) - Polycentric governance

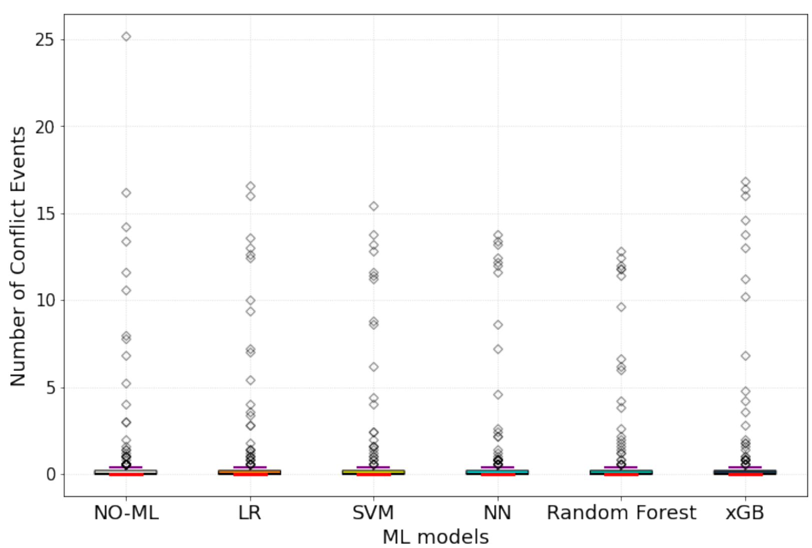

Figure 82: Stage 4 - Distribution of the number of conflict events - Scenarios with machine learning (algorithms) and settings without machine learning (simple coordination) - Polycentric governance

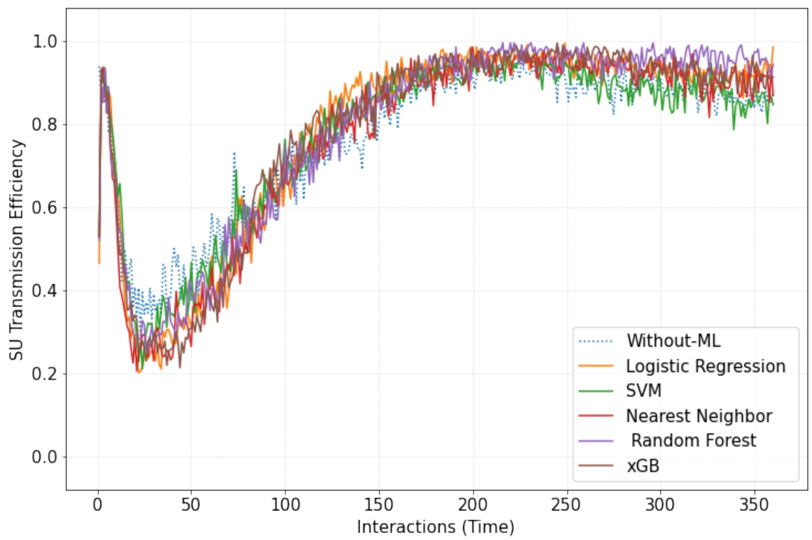

Figure 83: Stage 4 - Evolution of the SU transmission efficiency - Scenarios with machine learning (algorithms) and settings without machine learning (simple coordination) - Polycentric governance

In Figure 83, we present the results for resource usage efficiency as a function of the application of ML techniques. Similar to the number of conflict situations, there is no significant difference between the simple coordination approach (i.e., *WCS without ML*) and the implementation of ML models. In all scenarios, the resulting resource use efficiency is very high after the initial agents' interactions. This result is also shown in the distribution of the SU transmission efficiency (see Figure 84). All scenarios, including those without ML, have very high transmission efficiency. Note that some ML models, such as Logistic Regression, Random Forest, and xGBoost, present a slightly higher median efficiency than the simple coordination setting.

7.4.1.3 Self-governance The performance evaluation for the implemented ML models in self-governing approaches are depicted in Figure 85. In the case of the accuracy (blue bar) of the algorithms, we observe a similar performance for all of them, with an average score of approximately 78%. In the case of precision, we observe how all models, but SVM,

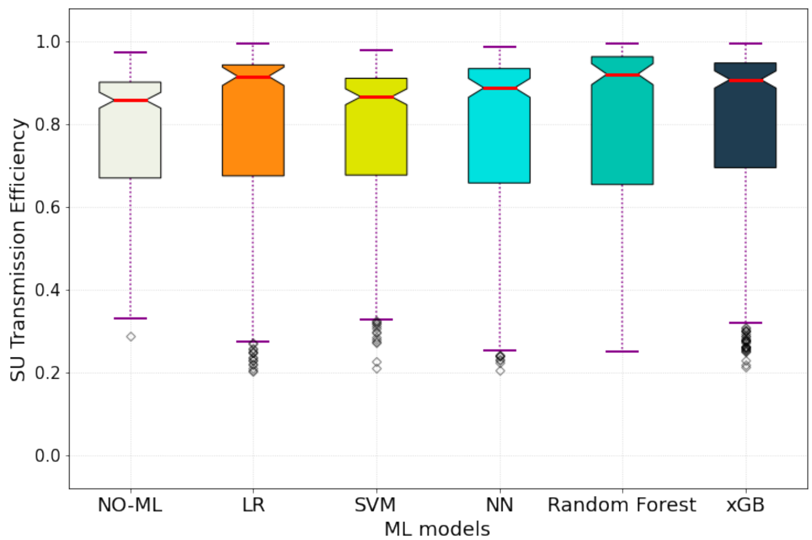

Figure 84: Stage 4 - Distribution of the SU transmission efficiency - Scenarios with machine learning (algorithms) and settings without machine learning (simple coordination) - Polycentric governance

have relatively high precision scores over 65%. Regarding the recall scores, we observe that all models, except for xGBoost, have recall scores over 60%.

Figure 86 shows the distribution of the accuracy scores for the ML models used in self-governance systems. The average accuracy for these ML models ranges between 65% and 82%. This is also true for other metrics in the accuracy scores distribution. For instance, the minimum accuracy scores obtained in the self-governance scenario is over 62% for all models.

In Figure 87, we find the evolution in the number of conflict situations as a function of the implementation of ML techniques in the model. When simple coordination is implemented, the number of events at the beginning of the dealing relationship is higher compared to the application of ML techniques. After the first rounds of negotiations, there is no significant difference for scenarios with and without ML. Regarding the different ML models being used, there is also no significant difference in the number of events throughout the agents' interactions. We observe similar results in the distribution of the total number of events

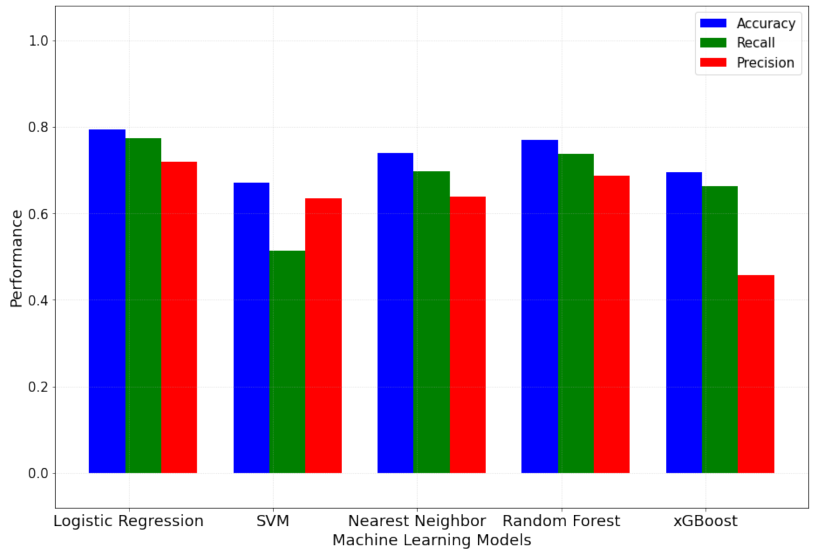

Figure 85: Stage 4 - Performance evaluation of the machine learning models built in self-governance systems

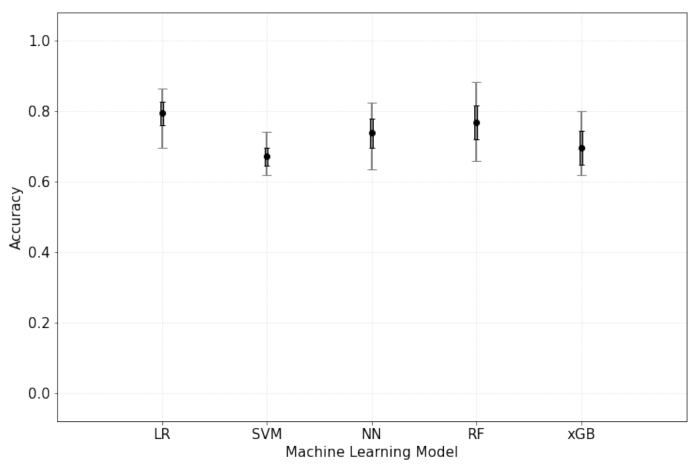

Figure 86: Stage 4 - Accuracy performance evaluation of the machine learning models built in self-governance systems

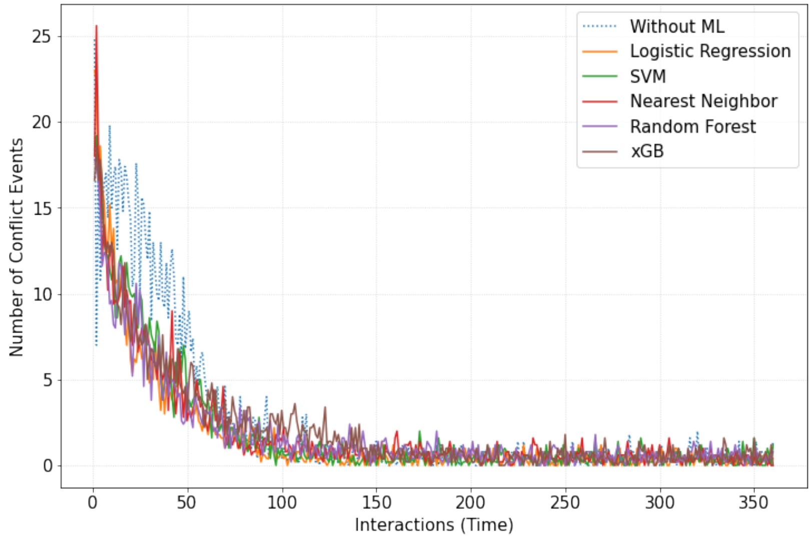

Figure 87: Stage 4 - Evolution of the number of conflict events - Scenarios with machine learning (algorithms) and settings without machine learning (simple coordination) - Self-governance

when comparing simple coordination and the usage of ML techniques (see in Figure 88). The median number of events per interaction for both the scenarios with and without ML is close to zero (0). Further, the difference between simple coordination and the enhancement of models using ML is only shown in the number and magnitude of the outliers in the distribution.

In Figure 89, we show the SU transmission efficiency in self-governance systems for scenarios with and without ML. In the initial interactions of the system, self-governance coordination leads to higher efficiency compared to the inclusion of ML models. However, after these initial negotiations, all scenarios present a similar SU transmission efficiency. With regards to the type of ML technique being used, there is no substantial difference among the models we built. This outcome is also shown in the distribution of the resource efficiency in self-governance scenarios (see Figure 90). In all scenarios, the transmission efficiency distribution for the SU follows the same structure. The median efficiency in the system is very low regardless of the application of ML and the type of ML classifier.

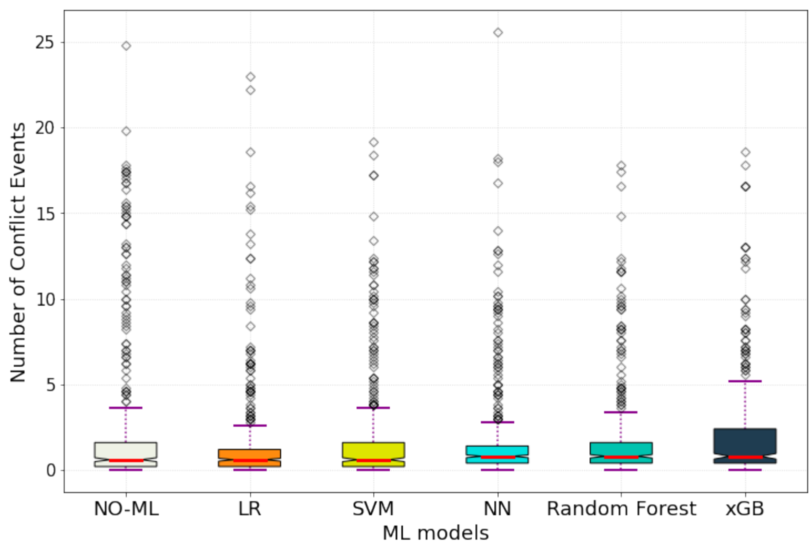

Figure 88: Stage 4 - Distribution of the number of conflict events - Scenarios with machine learning (algorithms) and settings without machine learning (simple coordination) - Self-governance

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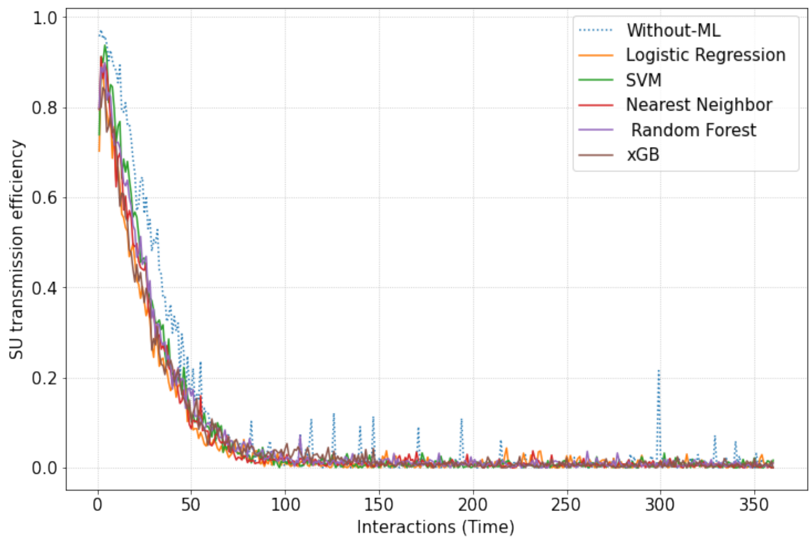

Figure 89: Stage 4 - Evolution of the average SU Transmission efficiency - Scenarios with machine learning (algorithms) and settings without machine learning (simple coordination) - Self-governance

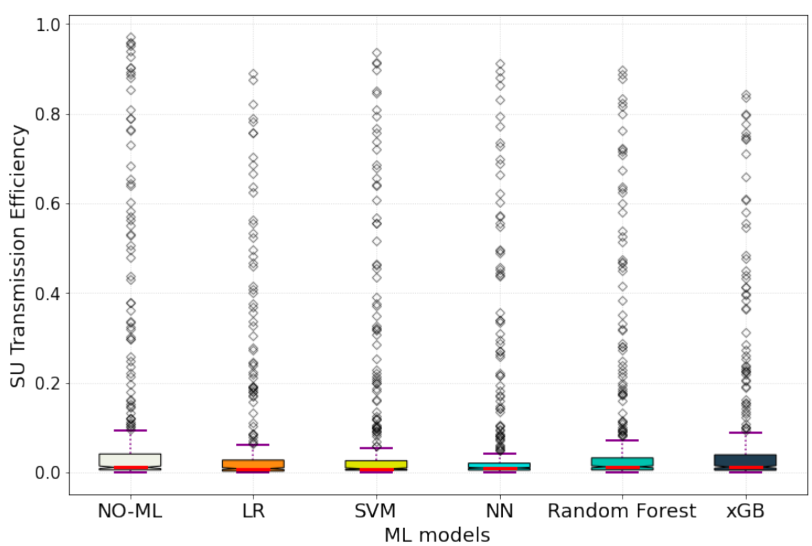

Figure 90: Stage 4 - Distribution of the SU transmission efficiency - Scenarios with machine learning (algorithms) and settings without machine learning (simple coordination) - Self-governance

7.4.1.4 Number of secondary users implementing ML techniques

In the local ML approach, each agent is responsible for gathering data, fitting an ML model, evaluating the model, and using it to avoid conflict situations. However, not every agent benefits from the implementation of an ML model (see Section 6.4). *Model 3.0* contemplates two conditions in which an agent does not consider ML algorithms for its future interactions. First, if during the data-gathering phase, the agent's total number of conflict situations is relatively low, the agent gathers the data, but it does not build an ML algorithm. This design choice is implemented due to the sensitivity of ML models to the data used to construct them. Thus, if the data does not have enough examples of both types of outcomes (i.e., conflict or not conflict), the models tend to make biased decisions. Second, if the fitted models do not have an optimal performance evaluation (e.g., accuracy below 50%), the agents decide not to use them as part of their decision-making models.

In Figure 91, we present the distribution of the number of secondary users implementing ML techniques in each governance system. In centralized governance, we observe the highest number of secondary users implementing ML models. In this case, the average number of SUs using ML is 34 out of 100 new entrants. However, the variance in the distribution for centralized systems is considerably vast. Thus, the number of SUs using ML ranges from 20 to over 40 throughout our experiments and simulations. The other governance setting where a substantial number of SUs implement ML techniques is self-governing. In this case, the average number is around 20%, with a range of users between 10% to 27%. In polycentric governance, we observe a very different outcome. Localized coordination has a positive impact in reducing the number of events in the system. Therefore, due to our model design, just a few participants are required to build ML models, specifically between 1% to 3% of SUs agents.

7.4.2 Global machine learning approach

The other approach to include ML models in ABM is at the coordinator-level (i.e., global ML application). In this process, SUs gather data about their current environment and transfer this information to the *coordinator*. The *coordinator* builds, fits, evaluates, and

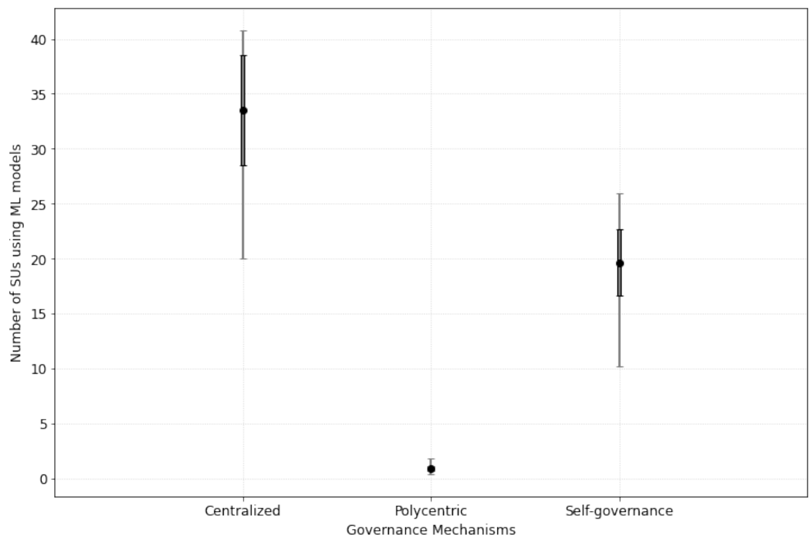

Figure 91: Stage 4 - Distribution of the number of secondary user agents implementing ML models in the different governance mechanisms

passes back (to the SUs) the fitted ML models. A fundamental difference with the local approach is that all SUs utilize the ML model for their future interactions[24]. Further, all SUs in the band utilize the same ML model (built by the *coordinator*).

Since a (central or local) *coordinator* is in charge of building the ML models, only centralized and polycentric approaches are part of the global ML application[25]. In the following sections, we analyze the results obtained when applying ML globally in the governance systems of interest.

7.4.2.1 Polycentric governance In polycentric governance, each local area *coordinator* gathers data from its jurisdiction (i.e., SUs located within the local coordination area), builds and evaluates a single classification model, and transfers this model back to the SUs in its jurisdiction. The model in conjunction with the (unseen) data gathered by each SU is used

24

In the case of the local application of ML, not all agents build machine learning models. For the agents using ML, each SU is responsible for building a local model tailored to its local observations.

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In self-governance, there is no central or third-party entity involved in the decisions of the agents.

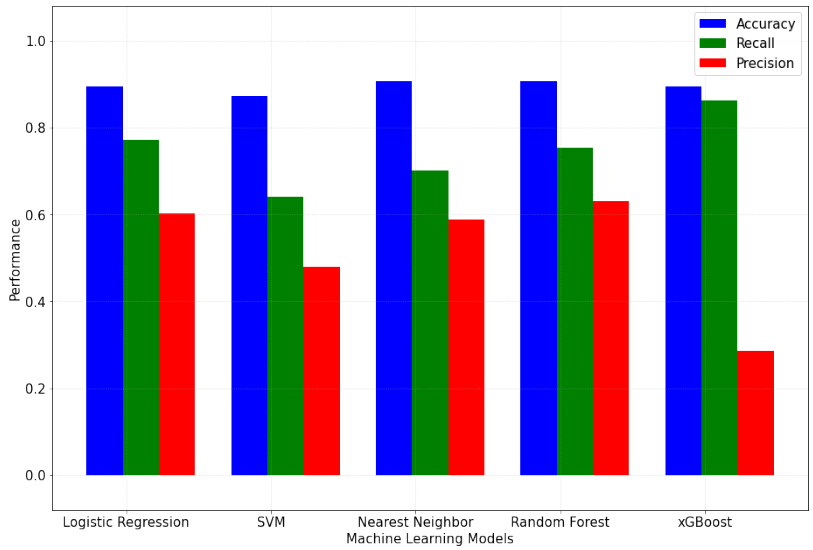


Figure 92: Stage 4 - Performance evaluation of the (global) machine learning models built in polycentric governance systems

to predict and avoid conflict situations.

We begin this analysis by evaluating the performance of each of the classifiers implemented in the system (see Figure 92). We assess this performance in terms of accuracy (blue bar), precision (red bar), and recall (green bar). The accuracy of all models is considerably high, with an average of around 90%. Recall scores are also optimal, which have values over 65% regardless of the ML model we use. In the case of precision, not all the models have the same performance. Logistic regression, nearest neighbor, and random forest techniques have a relatively high recall score over or around 0.6 (60%). The remaining ML models present a precision evaluation below 50%.

In Figure 93, we present the evolution in the number of conflict situations for scenarios using (global) ML models and simple coordination (i.e., *without ML* (blue dotted line)). In the scenarios where we do not add ML algorithms, the number of events is higher during the initial interactions. After this initial period, the number of events is similar or lower than cases without ML. When analyzing the performance of the different ML models we implement, we observe that *xGB* and *SVM* produce a similar outcome than the no inclusion

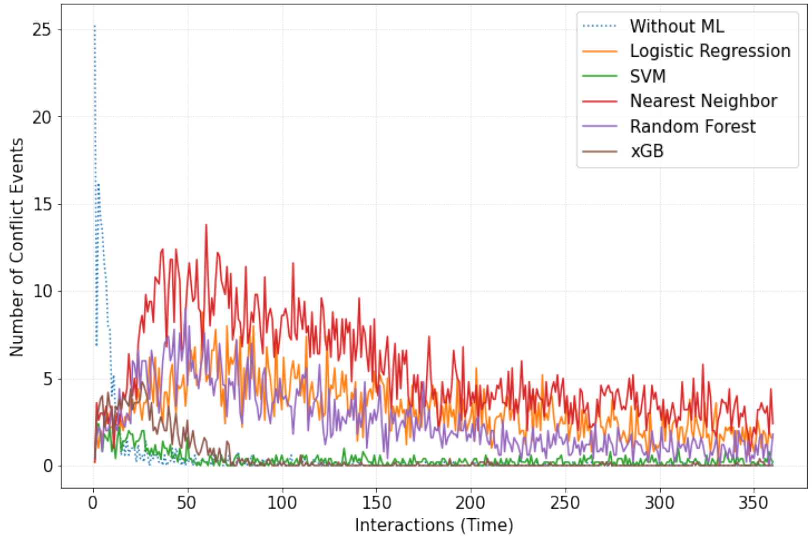


Figure 93: Stage 4 - Evolution of the average number of conflict events - Scenarios with (global) machine learning (algorithms) and settings without machine learning (simple coordination) - Polycentric governance

of ML. This is not the case for Logistic Regression, Nearest Neighbor, and Random Forest models. These techniques lead to a higher number of conflict situations throughout the agents' interactions, being NN the model with the poorest performance in the system.

Figure 94 illustrates the distribution in the number of events as a function of the addition of ML techniques. We observe that the simple coordination scenario (i.e., *WCS without ML*) leads to fewer conflict situations in the band compared to most (global) ML models. The only ML techniques with a similar performance than simple coordination are *SVM* and *xGB*. For the remaining models, we observe a higher median number of conflict events per interaction.

Figure 95 details the SU transmission efficiency for the scenarios where (global) ML techniques were added to the ABM. During the initial interactions, the simple coordination approach (i.e., *WCS without ML*) leads to a lower SU transmission efficiency. After this initial period, the SU transmission efficiency when the system does not include ML is similar to the settings that include ML models. Regarding the ML algorithms we use, we observe that Logistic Regression and Nearest Neighbor have the highest SU transmission efficiency. These

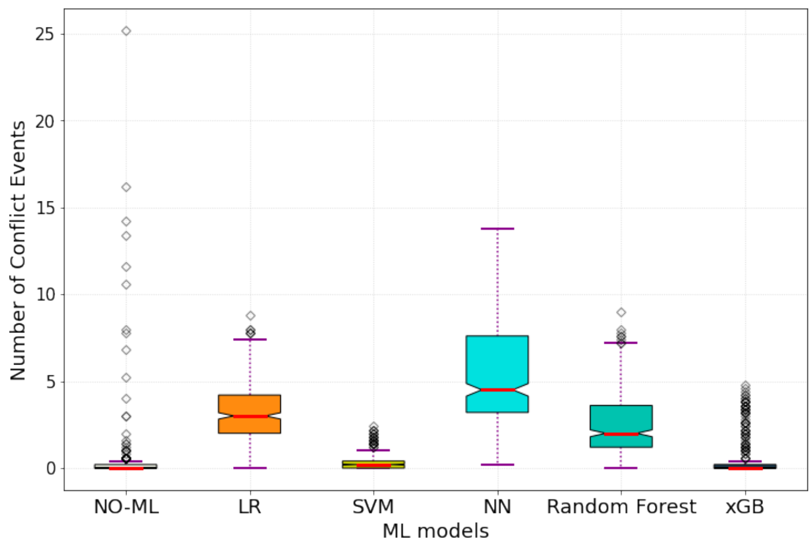


Figure 94: Stage 4 - Distribution of the number of conflict events - Scenarios with (global) machine learning (algorithms) and settings without machine learning (simple coordination) - Polycentric governance

outcomes are also shown in the overall distribution of SU transmission efficiency (see Figure 96). When the system implements a *LR* or a *NN* algorithm, the model have higher median efficiency. In the case of Logistic Regression, this median efficiency is close to 100%. In the case of simple coordination, we note that it generates similar or higher median efficiency compared to the remaining ML models.

7.4.2.2 Centralized governance In centralized governance, the central *coordinator* collects data from all the SUs in the sharing agreement. Then this central entity builds, fits, and evaluates a single ML model. This model is then transferred back to the SUs for their usage. The goal is to utilize the coordinator-built model in conjunction with unseen situations (new interactions) to avoid conflict situations in the sharing band.

In Figure 97, we show the performance evaluation for each ML technique available in the model. We observe that all ML models have very similar performance scores. Thus, their accuracy (blue bar) is approximately 80% or higher and their recall (green bar), and

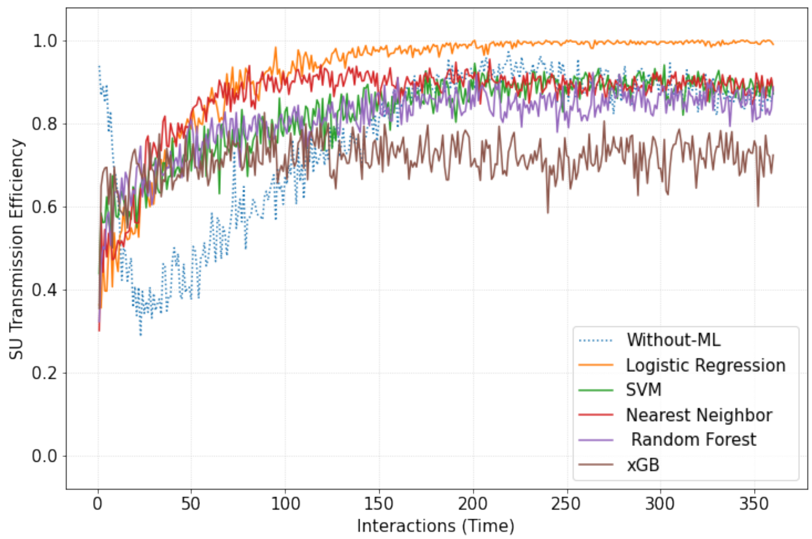


Figure 95: Stage 4 - Evolution of the average SU transmission efficiency - Scenarios with (global) machine learning (algorithms) and settings without machine learning (simple coordination) - Polycentric governance

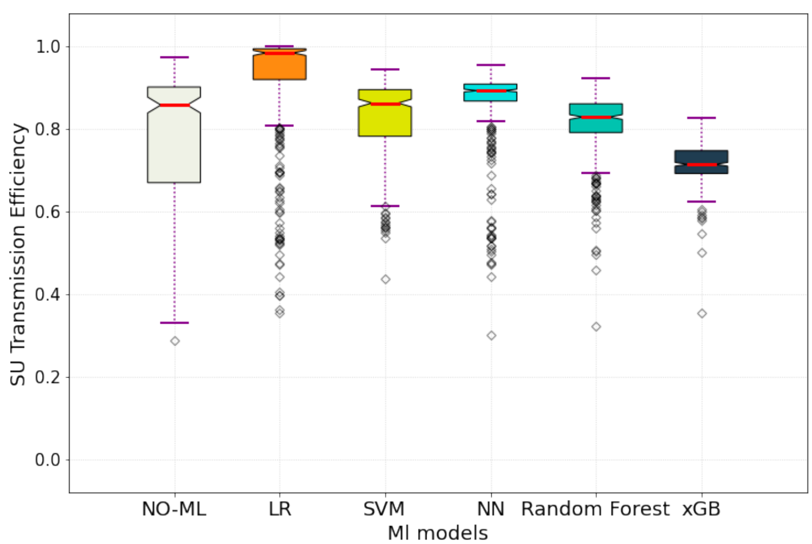


Figure 96: Stage 4 - Distribution of the SU transmission efficiency - Scenarios with (global) machine learning (algorithms) and settings without machine learning (simple coordination) - Polycentric governance

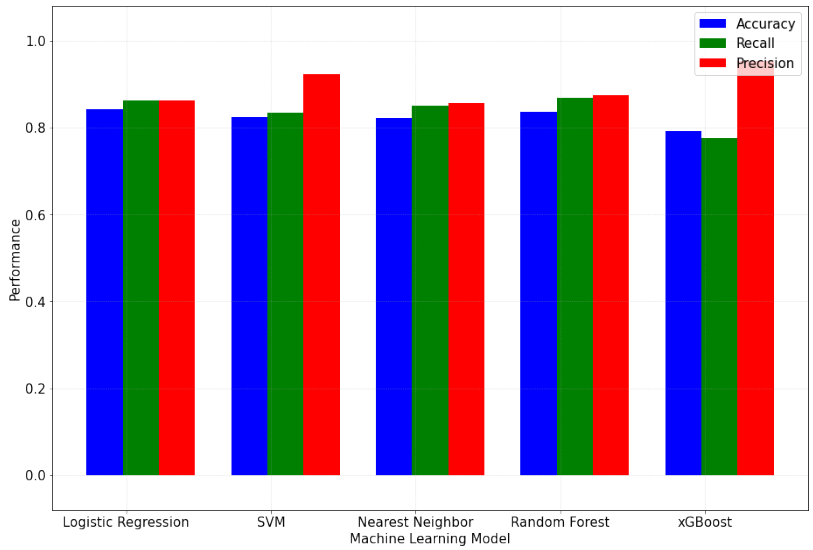


Figure 97: Stage 4 - Performance evaluation of the (global) machine learning models built in centralized governance systems

precision (red bar) scores reach, on average, 83%.

Figure 98 presents the evolution of the number of events in the settings with and without ML models. During the initial agents' interactions, we observe that the scenario without ML (blue dotted line) generates a significantly higher number of conflict situations than the settings with ML, being this difference in the order of 30 to 1. However, after the initial agents' interactions, the number of conflict events in simple coordination is almost equal to the ML-related scenarios. Regarding the different ML algorithms, we note that there is no significant difference among them. All models reduce the number of conflict situations to a minimum from the initial interactions. We observe similar results in the distribution of the number of events (see Figure 99). The addition of ML algorithms contributes to reduce the overall number of events in the system. However, note that the median number of events per interaction is very similar in all scenarios[26].

When analyzing the number of resources available for the secondary users (i.e., SU trans-

[26] This is not the case for the other metrics in the distribution. For instance, Q3 and the maximum are considerably higher for the simple coordination scenario than the ML-based settings.

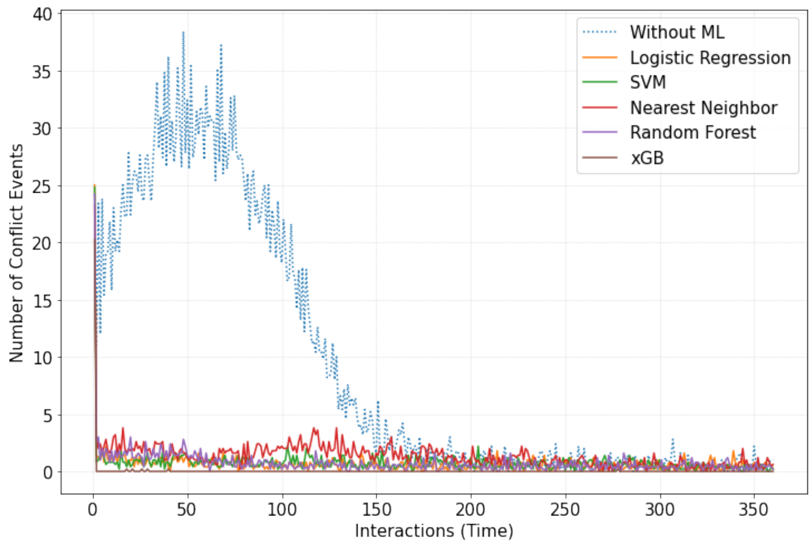


Figure 98: Stage 4 - Evolution of the average number of conflict events - Scenarios with (global) machine learning (algorithms) and settings without machine learning (simple coordination) - Centralized governance

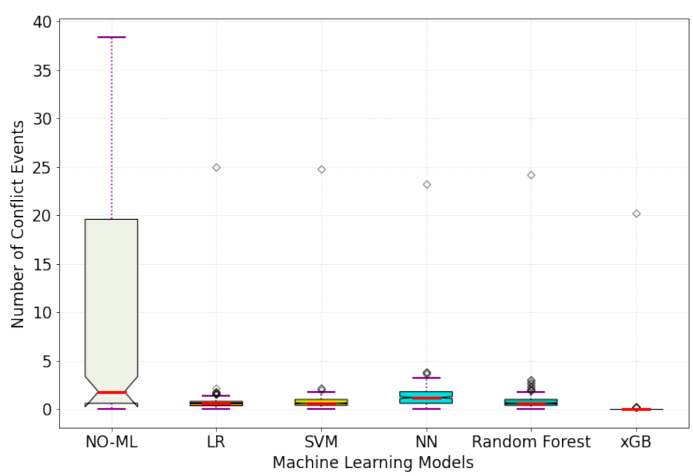


Figure 99: Stage 4 - Distribution of the number of conflict events - Scenarios with (global) machine learning (algorithms) and settings without machine learning (simple coordination) - Centralized governance

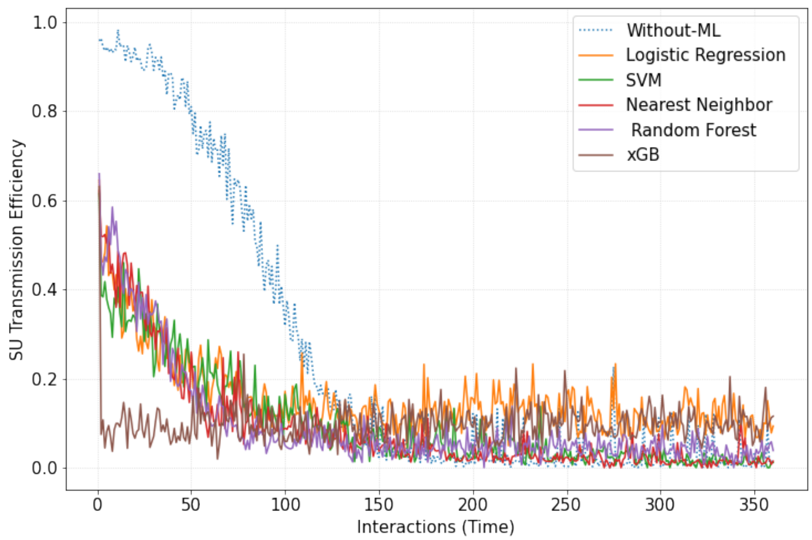


Figure 100: Stage 4 - Evolution of the average SU transmission efficiency - Scenarios with (global) machine learning (algorithms) and settings without machine learning (simple coordination) - Centralized governance

mission efficiency), we observe a completely different outcome compared to the number of events (see Figure 100). The efficiency of simple coordination is much higher than the implementation of (global) ML models, at least in the initial interactions of the system. When analyzing the different ML techniques, we see that all models but *xGB* have higher efficiency during the initial phases of the model and, after the initial agents' interaction, this efficiency rapidly drops[27]. We observe a similar outcome in the distribution of the SU transmission efficiency (see Figure 101). We note that the ML-related scenarios generate a slightly higher median efficiency than simple coordination settings. However, simple coordination generates a higher Q3 and maximum efficiency than the models with ML. Regarding the different ML algorithms, we observe that *LR* and *xGB* generate the highest SU transmission efficiency.

[27] In *xGB* scenarios, the efficiency remains low throughout the agents' interactions.

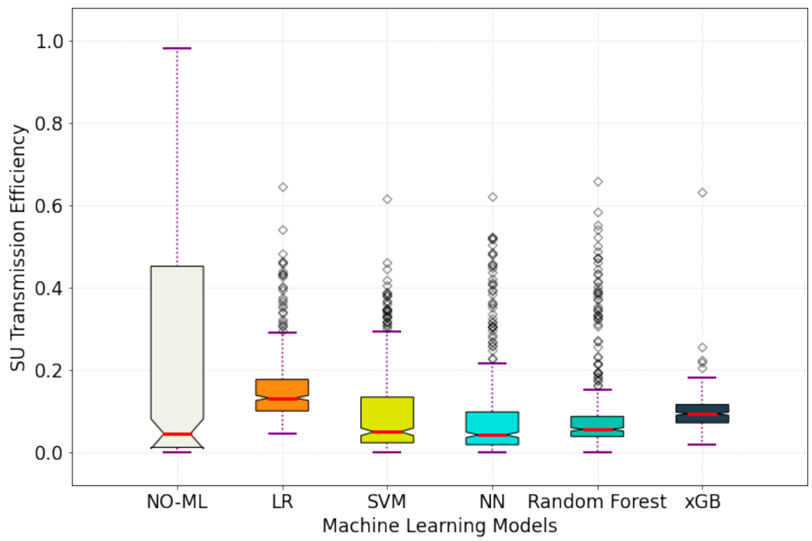


Figure 101: Stage 4 - Distribution of the SU transmission efficiency - Scenarios with (global) machine learning (algorithms) and settings without machine learning (simple coordination) - Centralized governance

7.4.3 Comparison of the local and global machine learning approaches

To conclude the analysis of Stage 4, we study the difference between simple coordination (i.e., *WCS* without ML), the local ML approach, and the global ML approach.

First, we study the number of events (see Figure 102). In centralized governance (left graph), we find that the lack of an ML model (blue line) leads to the largest number of conflict situations. In the local (green line) and the global (orange line) ML application, we observe that the global approach is more efficient in reducing the number of conflict situations, where the number of conflict events is rapidly minimized[28]. In polycentric governance (right graph), we note that the overall number of events is much lower than the centralized approach. Additionally, both simple coordination and local ML outperform global ML in reducing the number of conflict situations.

[28] Simple coordination and local ML also reduce the number of events; however, the reduction is not as immediate as with global ML.

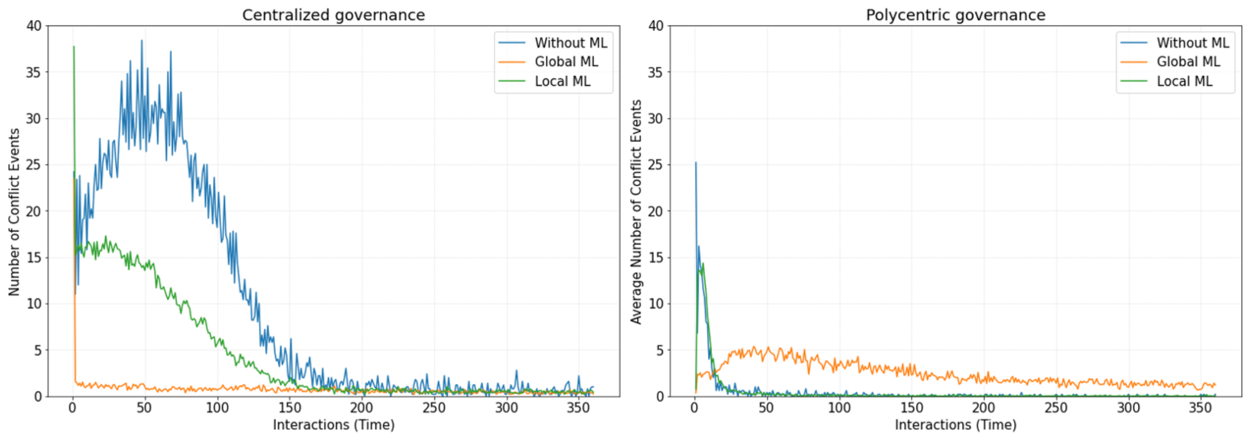


Figure 102: Stage 4 - Evolution of the average number of conflict events - Simple coordination (without ML), local, and global machine learning scenarios in centralized (left) and polycentric (right) governance systems

Figure 103 presents the distribution of the number of events as a function of the addition of (local and global) ML algorithms. In centralized governance (left graph), all approaches produce a similar median number of conflict situations per interaction. However, the maximum and Q3 values of the distribution are substantially higher in simple coordination than settings that include ML models. Regarding the local vs. the global application of ML, we observe that the local application leads to a higher maximum (and Q3) number of events than the global use of ML. In polycentric governance (right graph), the simple coordination or no application of ML generates a similar number of conflict events than the local ML application, with a median close to zero (0) conflict situations per interaction. Contrarily, the global ML approach generates more conflict events than both the no addition of ML and the local use of ML.

In Figure 104, we show the SU transmission efficiency in each of the ML approaches available in the ABM. In centralized governance (left graph), we can divide the analysis into two stages. First, during the initial agents' interactions, simple coordination leads to higher resource efficiency than local and global ML approaches. When comparing the local vs the global ML systems, we observe that the local approach has higher efficiency.

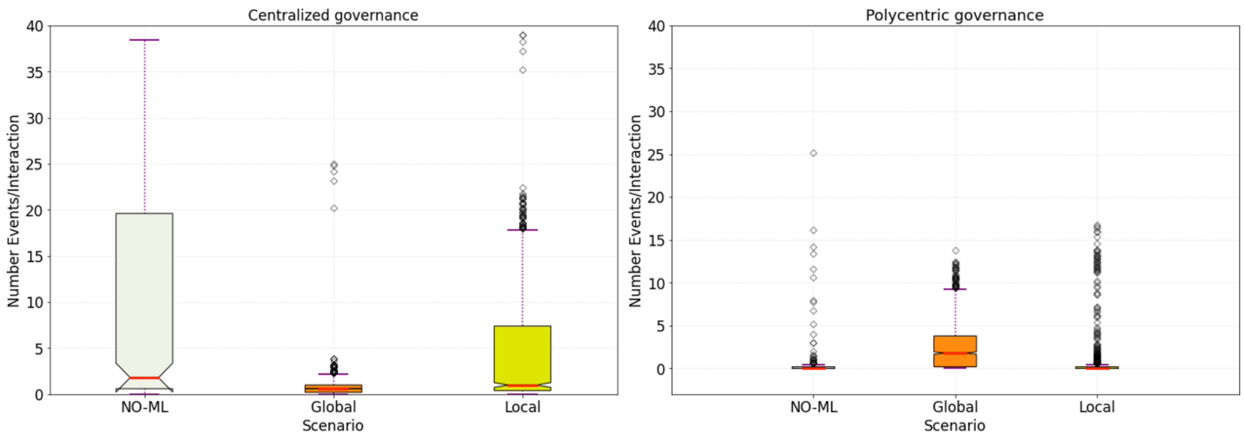


Figure 103: Stage 4 - Distribution of the number of conflict events - Simple coordination (without ML), local, and global machine learning scenarios in centralized (left) and polycentric (right) governance systems

Second, after the initial agents' interactions, all approaches lead to lower SU transmission efficiency. In polycentric governance (right graph), we also divide the evaluation into two stages. First, during the initial agents' interactions, the global ML approach leads to higher SU transmission efficiency than the local ML and simple coordination scenarios. In the second stage (i.e., after the initial interactions), we observe that all the methods have a similar SU transmission efficiency, with values around 90%.

Figure 105 shows the distribution of the SU transmission efficiency for each ML approach available in *Model 3.0*. We observe a significant difference in the SU transmission efficiency between centralized (left graph) and polycentric (right graph) systems, where polycentric governance leads to higher efficiency in all scenarios. In centralized governance, all ML settings result in a similar median efficiency of approximately 3%. We note a difference between these methods in the other distribution metrics, where simple coordination presents a larger maximum (and Q3) efficiency values than scenarios with (local and global) ML techniques. In polycentric approaches, we observe that the local ML has a slightly better median efficiency performance. However, all methods have similar median SU transmission efficiency scores (around 85%) and comparable overall distributions.

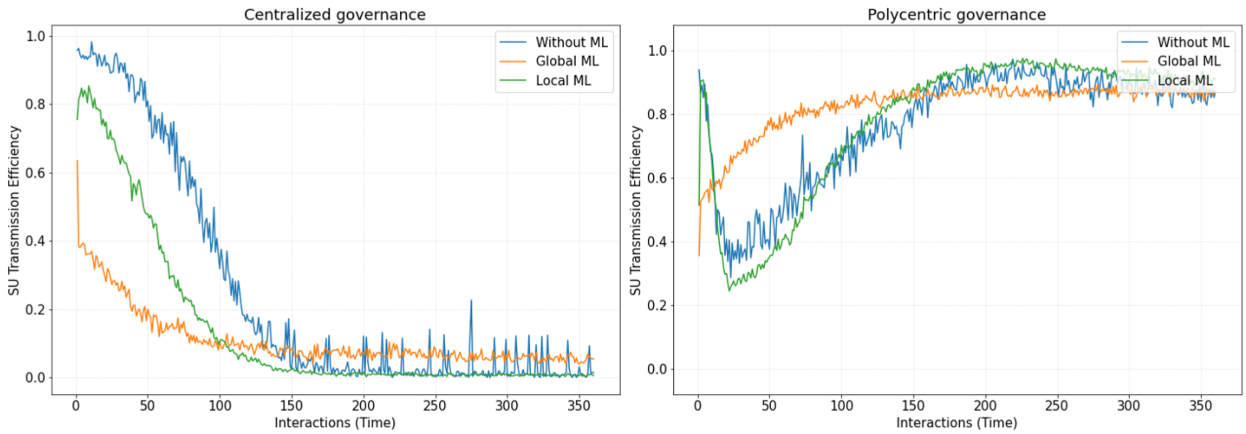


Figure 104: Stage 4 - Evolution of the average SU transmission efficiency - Simple coordination (without ML), local, and global machine learning scenarios in centralized (left) and polycentric (right) governance systems

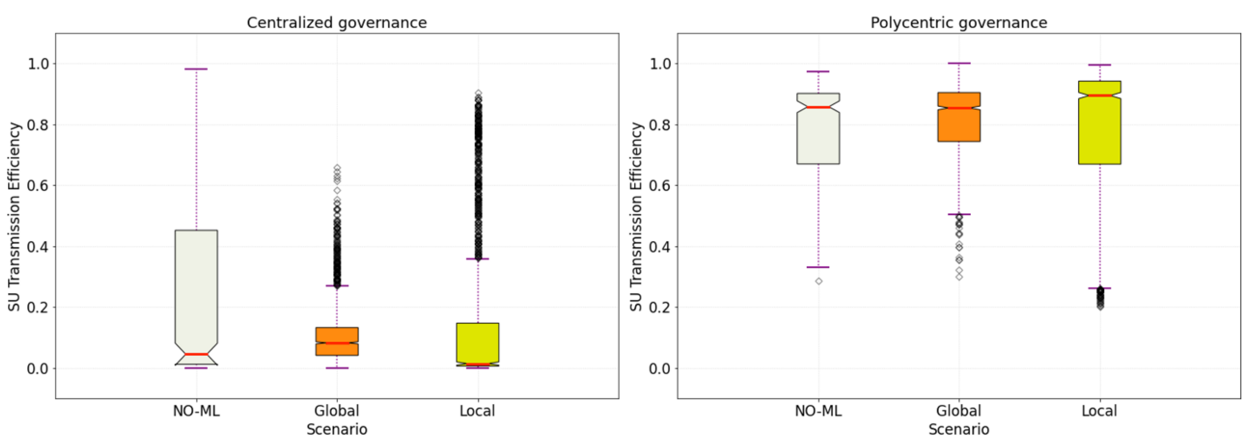


Figure 105: Stage 4 - Distribution of the SU transmission efficiency - Simple coordination (without ML), local, and global machine learning scenarios in centralized (left) and polycentric (right) governance systems

8.0 Analysis

In the previous chapter, we presented the results obtained in the different stages designed to create smarter localized spectrum sharing models based on different governance approaches and the addition of ML algorithms. In this chapter, we take a step further and discuss what these results imply in the general spectrum sharing context, what they signify in terms of our research hypotheses and questions, and how they account towards formulating recommendations and guidelines for future work.

8.1 Main findings

In this section, we highlight the main findings gathered from the results presented in Section 7 for each of the experimental stages.

8.1.1 Stage 1: Including alternative (localized) governance mechanisms in spectrum sharing agreements (two-tier model)

In Stage 1, we tested the application of distributed governance systems in a spectrum sharing scheme. In particular, we tested the viability of self-governing systems in the two-tier sharing scheme of the 1695-1710MHz band. To test this viability, we relied on the construction of an Agent-Based model (i.e., *Model 1.0*) that captures the conditions of the band and the behavior of the participants in the agreement.

The results presented in Section 7.1, show that the behavior modeled for the SUs is correctly captured in the government-centric part of our ABM. Second, the results agree with the literature regarding the performance of command-and-control schemes, in particular, the fact that the success of centralized schemes is directly related to the number of available resources. In the case of our model, this refers to the situation where agents are quickly sanctioned with very high penalties, which considerably diminishes their discount rates.

In the centralized scheme, a central agency is in charge of defining and enforcing the rules. Consequently, an external agent is responsible for determining not only the size of the restricted areas but also the detection effectiveness within them. In this situation, we found that to guarantee a successful result, the system needs to achieve a high detection rate in both, the NAZ and LAZ. With low "catching" rates of 50% and 25%, the number of events is almost double than in cases with 75%, or higher, detection rates. These results are an example of the high amount of resources needed by the central agency to monitor and control the created restricted areas.

The most important aspect of self-government is the successful interaction of primary and secondary users. We showed that the size of the boundaries around the incumbent user, and hence the ability to detect "bad guys" within the system, stems only from the negotiation process of independent agents. Further, the system successfully allocates the shared resources according to the predefined set of rules in the band irrespective of the initial conditions, such as the initial gestures of trust. Thus, spectrum sharing through a self-governing arrangement is possible under a wide variety of realistic circumstances.

Regarding the process of self-governance, we showed that once the initial boundaries are assigned into the categories of limited and unlimited use, the trust signal of reducing the size for the starting point has a more substantial impact on the governance of the spectrum. When starting with the smallest size, we can expect little or no conflicts within the system, which is consistent with the continuous dealing principle, that is, good gestures by primary users are "paid" by the secondary users, and vice versa. Our analysis also shows that perception characteristics, as represented by differences in perception functions of the secondary users, have a great impact on self-governance. When users know the detection rate, more "infractions" are committed when the detection rate is relatively low. On the other hand, when the agents only have a perception of this rate, the number of events is considerably reduced. Nonetheless, the sole perception of a rate leads to interference events whereas in full knowledge scenarios, especially with higher detection rates, this is not the case. In this regard, one of the main benefits of adopting self-governance frameworks is that sharing schemes can switch from static and centralized definitions to local and dynamic agreements. Such agreements reflect the local conditions of the sharing process, provide enough protection to the incumbent, and add significant value and incentives to the new entrants.

These results show that a self-governance structure is possible in spectrum sharing scenarios under the right circumstances. In the context of Stage 1, these circumstances include a set of well-defined participants, communication channels, sharing conditions, and, most importantly, a common goal to define optimal protection zones. Additionally, the band provides clear definitions of the different interactions between agents and the associated rewards for a "good" behavior. As mentioned above, self-governance is not a "one-size-fits-all" solution. Indeed, other spectrum-sharing scenarios might not benefit from a self-governing approach. For instance, if there is no common incentive among the agents to reach a continuous and stable dealing process, there are no clear definitions for the different agents, or there is an absence of clear communication channels between agents.

8.1.2 Stage 2: Radio Environment Maps to construct local and dynamic ABM environments

The main goals of Stage 2 are to test the simulation process of the IC map component of an REM, and to include these simulation results (measurements) as the environment of an ABM. The general objective is to build dynamic ABMs that provide local information (e.g., spectrum situation parameters) for the agents interacting in such a dynamic environment.

The results of our simulated REM are very encouraging. The model is very flexible in its definition. Hence, it allows us to simulate multiple transmitters, sensors, map representations, propagation models, interpolation techniques, and signal measurements. We mimic the traditional process to create the IC map of an REM by simulating "real" measurements and interpolating the remaining values with well-known techniques. Further, these interpolation methods include techniques widely tested in other domains (e.g., nearest neighbor) and interpolation solutions exclusively designed for Radio Environment Maps (e.g., RSSD).

Regarding the map representation and the corresponding connection with ABM, our REM simulator produces three very valuable outcomes; 1) the created Interference Cartography (IC) map; 2) a "real-world" map, which corresponds to all the received (simulated) signal values across the whole map (not only in the MCDs' locations); and 3) an error (i.e., RMSE) measure resulting from the difference of the wireless values in the real-world map and the created IC map. Additionally, when indirect interpolation methods, such as Received Signal Strength Difference, are utilized, the locations of the PU transmitter(s) are also a valuable outcome of our REM simulator. Due to the connection between the REM simulator and our ABM, all these outcomes are passed between the REM and dynamic ABM. Therefore, we can successfully enhance the functionalities of REMs for their application in different spectrum sharing contexts, while providing agents in *Models 2.0* and *3.0* with more dynamic and localized information about their spectrum situation.

We find that regardless of the interpolation technique being used, the number of Measure Capable Devices (MCDs) or sensors have a negligible impact on the interpolation error for values over 15 sensors. This outcome is common across the different types of maps being created in the simulator (e.g., rural). Additionally, we found that indirect interpolation methods (e.g., nearest neighbor) produce fewer errors in the extrapolation of spectrum values than indirect techniques (e.g., RSSD).

A key component in our REM simulator is the creation of different types of maps varying in size, namely urban, semi-urban, and rural. When analyzing the interpolation error as a function of the type of map, we find that as the size of the map or region of interest increases, the average interpolation error also increases. However, all the results follow the same trend in terms of the RMSE of the interpolation techniques and the number of sensors in the map.

The IC map constructed in Stage 2 is based on the measurements (simulations) at different locations within the REM area. In this light, different propagation models are used to estimate the wireless values at such locations. This provides the REM simulator with additional dynamic characteristics that benefit the development of dynamic Agent-Based Models. When we analyze the performance of these propagation models, we observe that the FSPL and Rain models produce the fewest errors in the IC map.

The main result of Stage 2 is the successful simulation of a multi-parameter Interference Cartography (IC) map. In addition, as shown in Section 7.2, the results obtained in the different simulations are similar to other examples presented in the literature regarding the construction of spectrum maps for REMs. Finally, due to the multi-dimensionality of the

REM simulator, not only the IC map values are integrated into the ABM, but also additional useful information such as the location of transmitters of the PUs is available for the sharing agents.

8.1.3 Stage 3: A local and multi-tier spectrum sharing scenario under different governance systems

The main goal of Stage 3 is to develop an ABM spectrum sharing model that better captures local behaviors (i.e., *Model 2.0*). For this purpose, we expand the resource access strategies and governance frameworks. Thus, we include a multi-tier access arrangement and a polycentric governance approach.

In *Model 2.0*, we analyze *Type I* conflict events. In other words, we study conflict situations where the stakeholders participating in the sharing agreement cooperate to avoid such conflicts. These conflict situations are further classified into two types: *Type A* and *Type B* events. From the results of Stage 3, we find that *Type A* events are more common than *Type B* events. This is true regardless of the conditions of the sharing agreement (e.g., *BCS* or *WCS*).

To thoroughly study the results of Stage 3, we divided the analysis into two very distinct situations, namely a *Best Case Scenario (BCS)* and *Worst Case Scenario (WCS)*. In the *BCS*, all the conditions of the band are favorable (e.g., number of participants in the band is low). Under these parameters, the number of conflict situations in the system is significantly reduced. On the other hand, in the *WCS*, the conditions of the band are at its "worst possible" (e.g., a large number of participants). This change in the band parameters results in a significant number of conflict events in the sharing agreement regardless of the governance system in place.

A fundamental design element of our model is the evaluation of different governance systems. The goal of each governing approach is to minimize the number of conflict situations between agents in different tiers. As previously mentioned, when the band is under its "worst" conditions (i.e., *WCS*), we see a significant number of conflict situations. Although all governance systems can reduce the number of conflict situations, polycentric governance has the best performance in that context. This reduction occurs much faster than in centralized and self-governance approaches, which leads to a reduced number of events overall.

The second criterion used to evaluate the performance of the sharing agreement is the efficiency in the use of resources by the secondary users (i.e., SU transmission efficiency). All governance mechanisms indeed lead to an overall decrease in the number of events per interaction. However, in the case of centralized and self-governance approaches, this reduction impacts the SU transmission efficiency. Thus, the overall median efficiency is close to zero (0) for these governing systems. This is not the case in polycentric governance, where the median efficiency is considerably higher than the other governance organizations. In the *WCS*, polycentric governance leads to a better outcome in both, the number of events and the resource efficiency, when compared to centralized and self-governance approaches (see Figure 106)[1].

A critical outcome of self-governing systems is the ability of the agents, and solely the agents, to create and maintain long-lasting dealing relationships. Thus, one metric to measure the success of these organizations is usually the stability of the reached agreements [216]. This is the case in our sharing model (*Model 2.0*), where the different band participants can agree on parameters such as interference thresholds, available resources, margin or error, and the number of users per channel.

To test the performance of our multi-tier governance-based model (i.e., *Model 2.0*), we define five relevant spectrum-sharing characteristics: the number of primary users, number of secondary users, number (density) of sensors to build the IC map, average fading deviation of the wireless measurements, and the SU average load (i.e., required resources by each SU). To test the impact in the number of conflict situations, we compare the results in a change from *BCS* to *WCS* for each input parameter. We find that the SU behavior has the most substantial impact on the number of conflict situations. This outcome is present in both the number of SUs and the *SU load*. The influence in the number of conflict situations due to a change in the input variable *fading deviation* is also significant. This results in more IC map inaccuracies that are directly related to *Type A* conflict situations. Finally, it is worth noting

[1] For the *BCS*, due to the few conflict events in the system, all governance systems lead to the same outcome, namely almost zero (0) events and a high SU transmission efficiency.

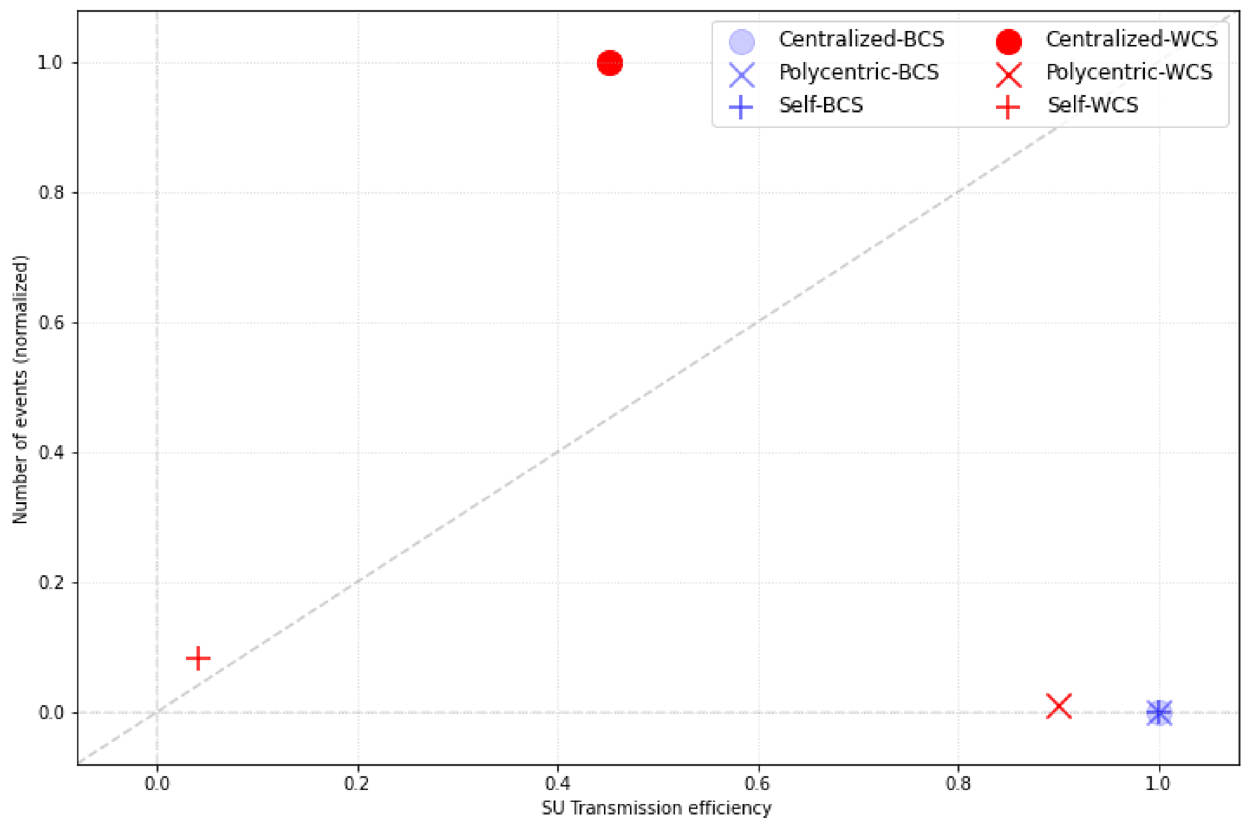


Figure 106: Stage 3 - Trade-off comparison between the average SU transmission efficiency and total number of events (normalized) - Governance-based model (*Model 2.0*)

that similar to the results obtained in Section 7.2, the change in *sensor density* for values over 10% does not imply a significant difference in the number of conflicts in the system.

To summarize, we designed, developed, and tested a new spectrum sharing model (*Model 2.0*). This updated model includes a more flexible multi-tier spectrum access scheme and governance framework. Polycentric governance implies the development of (nested) local coordination areas in the sharing agreement. The results from Stage 3 show that this division allows us to capture local behaviors in a better way. This multi-level governance system outperforms the other governance organizations by reducing the number of conflict situations and providing enough transmission opportunities to the new entrants.

8.1.4 Stage 4: Smarter agents in spectrum sharing scenarios

Besides the inclusion of governance systems designed to capture local behaviors (e.g., polycentric and self-governance), another option for the reduction of the number of conflict situations is to develop "smarter" participants (i.e., agents). In Stage 4, we successfully build a new spectrum sharing ABM (i.e., *Model 3.0*), which enhances the decision-making capabilities of the SUs by adding ML techniques.

The main objective of *Model 3.0* is to gather data about past executions to construct and fit an ML classification model that allows SUs to predict the potential emergence of conflict events. For this ML-based model, we design two approaches. First, a local approach, where the agent needs to execute all the required tasks (e.g., gathering the data and building the model). Second, a global approach, in which the agent is only responsible for the data-gathering phase. Then, the *coordinator*[2] is responsible for developing the corresponding classification and prediction models.

In the centralized governance and local ML-approach scenario, we find that the overall performance of the ML models we built is relatively high. Thus, the distribution of accuracy scores for all the models we tested is over 60%. The construction and use of these models by the SUs leads to a considerable reduction in the number of events compared to simple coordination (i.e., *WCS without ML*). However, in the case of the SU transmission

[2] Local or central depending on the type of governance system in place.

efficiency, the scheme without ML outperforms all scenarios where ML techniques were part of the model, as shown in Figure 107. We observe that the experiment where we implement the *xGB* classifier produces the fewest conflict situations while maintaining the highest SU transmission efficiency among the scenarios with less than 40% of conflict situations[3].

In the polycentric governance and local ML approach, we find that the performance of the implemented ML models is relatively low. Thus, all performance metrics (e.g., precision) are below the 70% marker, particularly for *SVM*, *RF*, and *xGB*. This outcome has two possible explanations. Since the simple polycentric coordination (i.e., *without ML*) considerably reduces the number of events, the agents using ML tend to observe a disproportionate amount of "no-conflict" cases; therefore, the data used to build (fit) the ML models may lack diversity. Additionally, since many secondary users experience a reduced number of events, just a few of them are required to build ML models to improve their capabilities.

In polycentric governance scenarios, when analyzing the number of events and the SU efficiency, we observe that settings without ML and with local ML have very similar performances (see Figure 108). Thus, the median number of events per interaction is considerably low (almost zero (0)) with high SU transmission efficiencies (around 90%) for all ML models and scenarios.

In the self-governance and local ML approach, the overall performance for all the implemented ML algorithms is slightly below 80%. We also find that there is no considerable difference neither in the number of conflict events nor in the SU transmission efficiency when adding ML models in the system. In both scenarios, the number of events and the SU transmission efficiency are low (see Figure 109). We observe that the simple coordination scenario (i.e., *WCS without ML*) produces the fewest number of conflict situations. However, it also presents a very low SU transmission efficiency, which is also the case for the scenarios with the addition of ML.

In Figure 110, we show the comparison of the model schemes without ML, with local ML, and global ML as a function of the number of conflicts and the SU transmission efficiency. In centralized governance, we observe that the scenario with simple coordination leads to a

[3] The simple coordination (i.e., *WCS without ML*) produces the highest median efficiency. However, it also generates the highest number of events per interaction.

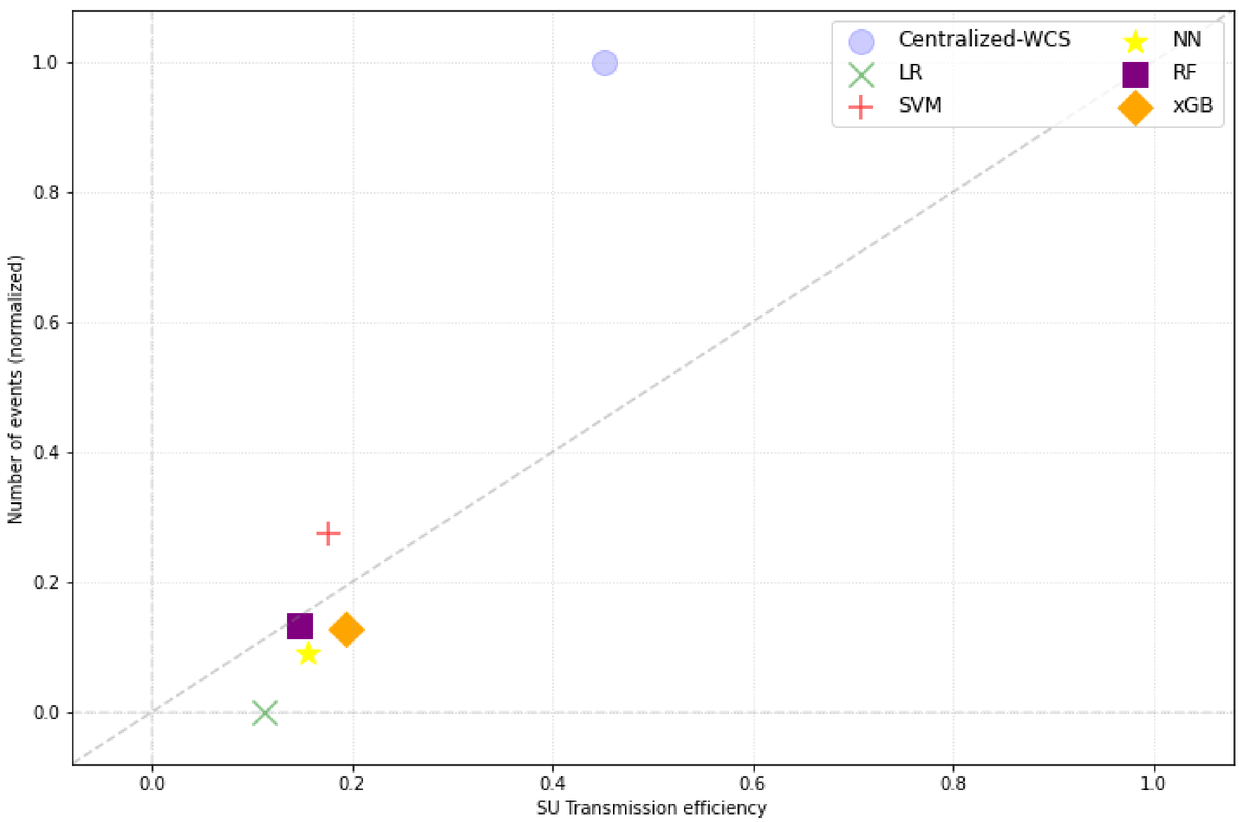


Figure 107: Stage 4 - Trade-off comparison between the average SU transmission efficiency and total number of events (normalized) in the centralized governance and (local) ML scenario - ML-based model (*Model 3.0*)

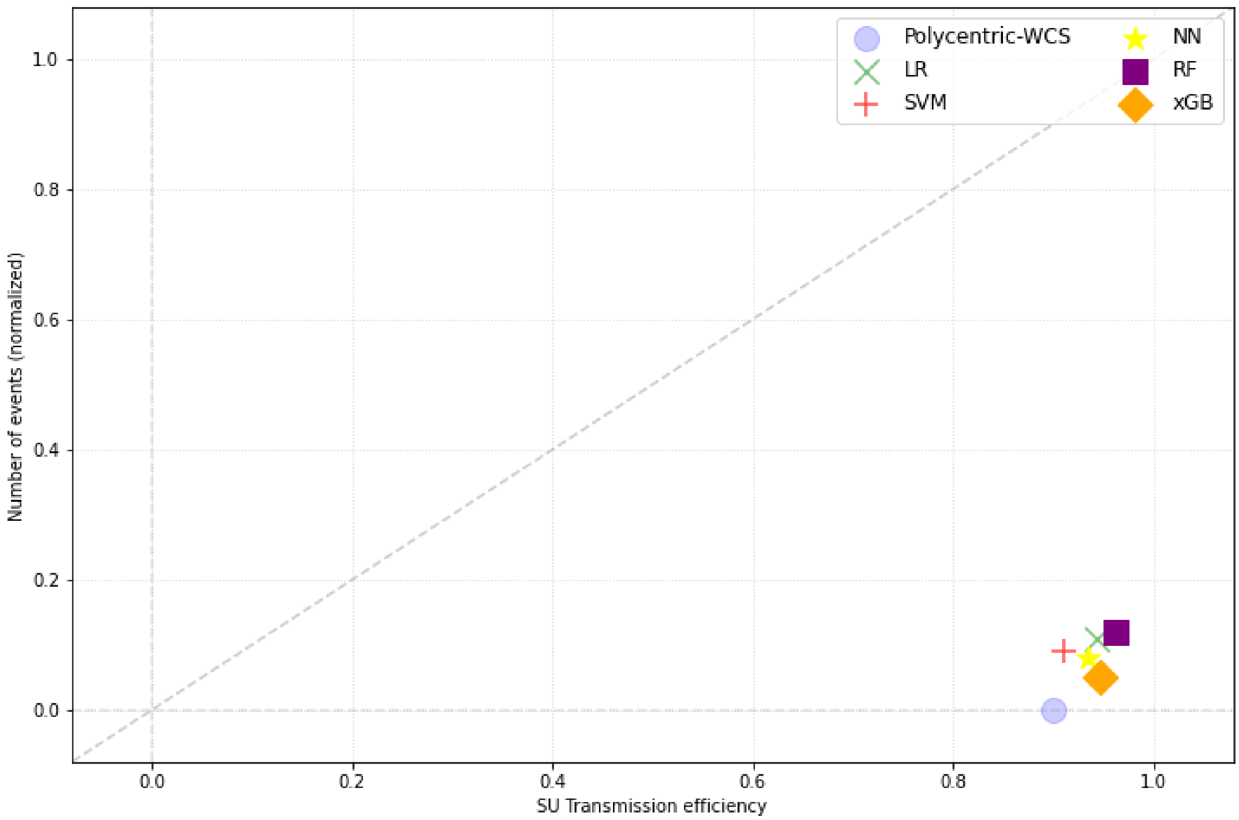


Figure 108: Stage 4 - Trade-off comparison between the average SU transmission efficiency and total number of events (normalized) in the polycentric governance and (local) ML scenario - ML-based model (*Model 3.0)*

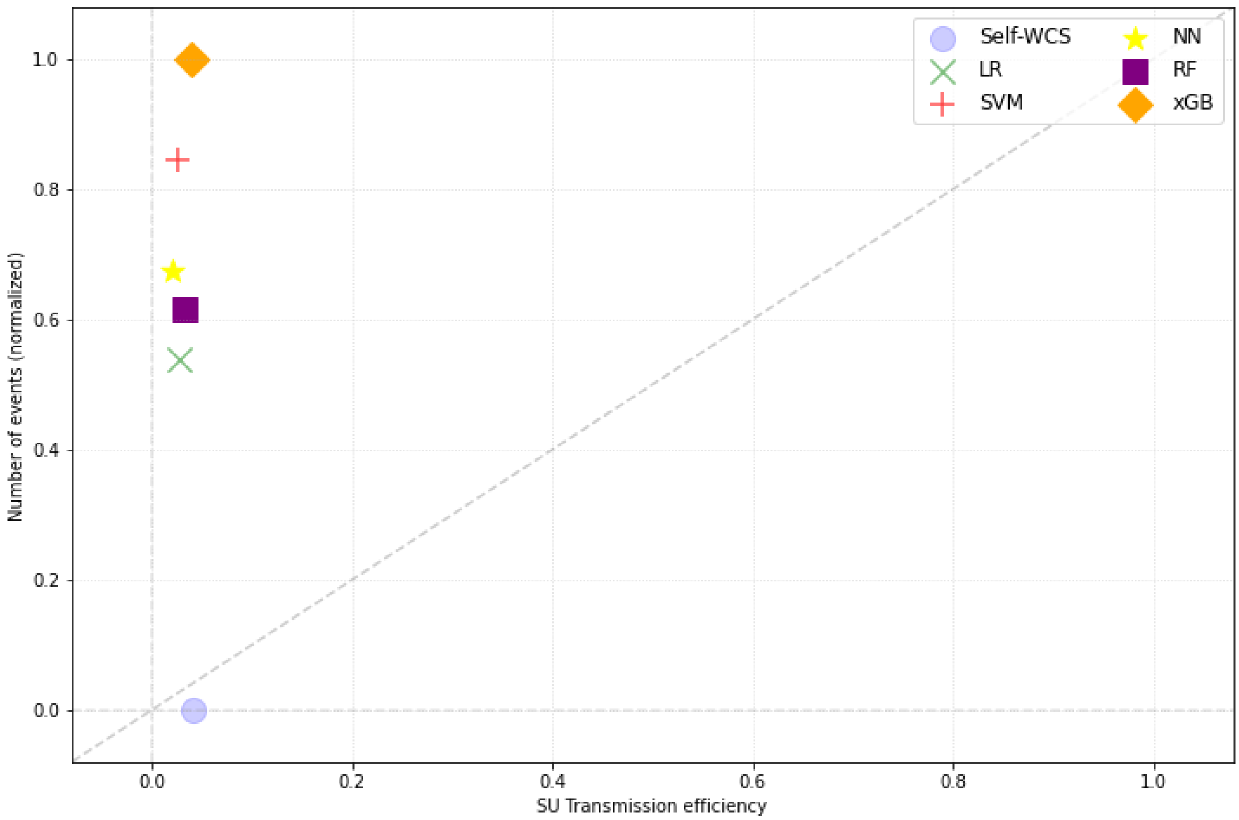


Figure 109: Stage 4 - Trade-off comparison between the average SU transmission efficiency and total number of events (normalized) in the self-governance and (local) ML scenario - ML-based model (*Model 3.0)*

higher number of events than models in which ML is applied. When evaluating the schemes where ML is included, we find that the global approach results in the fewest number of conflict situations (almost zero (0)). Regarding the SU transmission efficiency, we find that the scenario without ML leads to higher efficiency compared to both the local and global applications of ML.

Figure 111 shows the comparison of the model schemes without ML, with local ML, and global ML as a function of the number of conflicts and the SU transmission efficiency. In polycentric governance, the models without ML and local ML present the lowest number of conflict situations compared to models with global ML. Even though all scenarios have similar SU transmission efficiency scores (a median value of 88%), the local application of ML presents the highest median efficiency in the sharing agreement.

We successfully included endogenous Machine Learning as part of our Agent-Based Model to create *Model 3.0*. We can create ML models to classify and predict the possible emergence of conflict situations using past executions of the system. We find that the results vary according to the governance system. In centralized governance, we observe a reduction in the number of events in both approaches for the addition of ML. In polycentric organizations, the application of ML techniques does not produce a significant difference in the system. Thus, all models and scenarios lead to similar outcomes for the number of conflicts and the SU transmission efficiency. Finally, in self-governance, we observe that simple coordination (i.e., *without ML*) produces similar results to the scenarios where ML techniques enhance the ABM.

We successfully develop two approaches for the addition of ML to ABM. When comparing the results of the schemes without ML, with local, and global ML in *Model 3.0*, we also observe divergent results for the different governance systems. In centralized approaches, the local ML approach results in fewer events than the global ML and the coordination approaches. However, in terms of SU usage efficiency, this is not the case. The simple coordination models present a higher efficiency when compared to local and global ML. In polycentric governance, the global application of ML models results in the lowest number of conflict situations per interaction. However, the local ML approach leads to the highest efficiency in the system. For polycentric governance approaches, the simple coordination

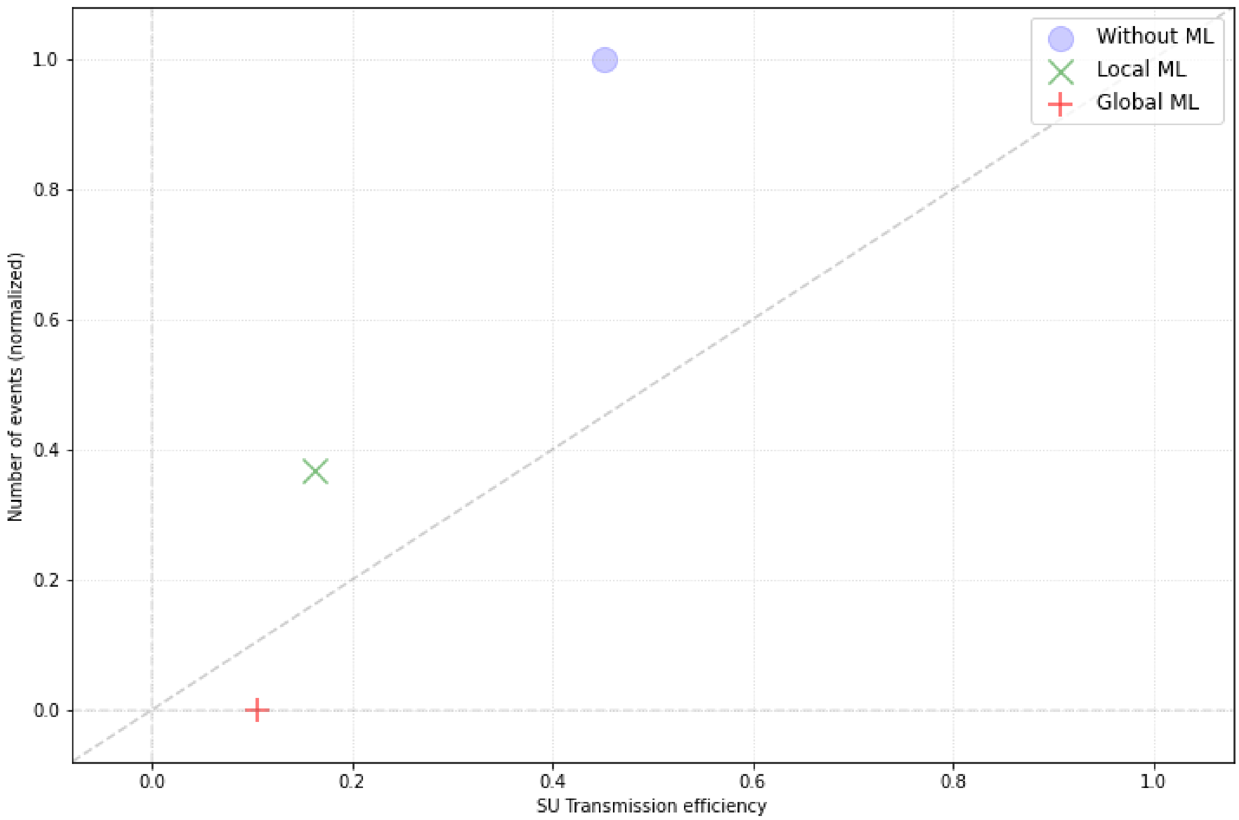


Figure 110: Stage 4 - Trade-off comparison between the average SU transmission efficiency and number of events (normalized) in centralized governance, local, and global ML scenarios - ML-based model (*Model 3.0*)

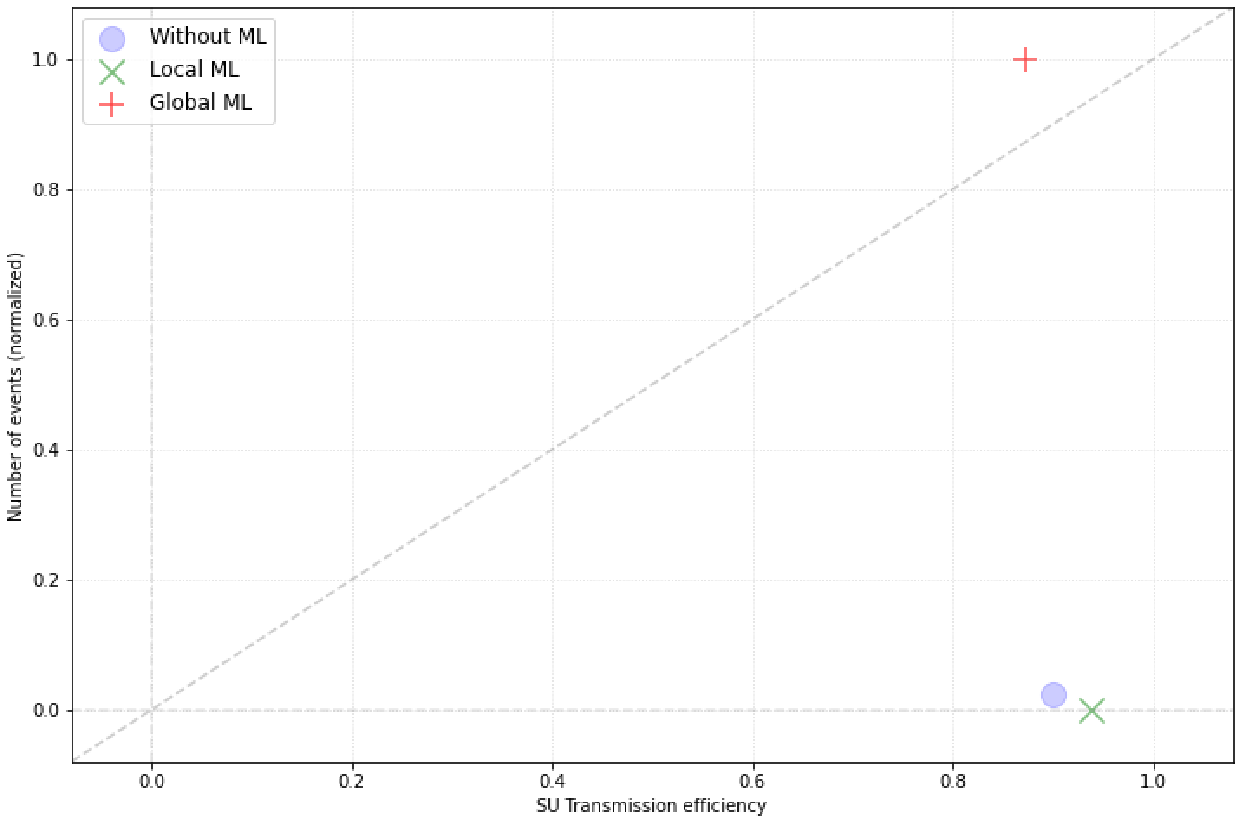


Figure 111: Stage 4 - Trade-off comparison between the average SU transmission efficiency and number of events (normalized) in polycentric governance, local, and global ML scenarios - ML-based model (*Model 3.0*)

(i.e., without ML) represents a middle point between local and global solutions regarding both, the number of conflict events and the SU transmission efficiency.

8.2 Hypotheses testing and statistical validation

In this section, we present the factors that we have explored to test the hypotheses relevant to the dissertation stages of this work. To reject the null hypothesis, we have performed a paired (see Expression 8.1) or unpaired (see Expression 8.2) t-test with the available data. The results that we present in what follows correspond to a 90% confidence interval (i.e., $\alpha = 0.1$) on the difference between the factors compared for each hypothesis. Note that we apply this test for the factors and parameters that rely on aggregate measures from the experiment repetitions.

$$\begin{aligned} n_x &= n_y \\ Confidence\ interval &= 100(1-\alpha)\% \\ d &= (\mu_x - \mu_y) \\ d \pm t_{[1-\alpha/2,k-1]} &\sqrt{\frac{S_x^2}{n_x} + \frac{S_y^2}{n_y}} \end{aligned} \tag{8.1}$$

$$\begin{aligned} n_x &\neq n_y \\ Confidence\ interval &= 100(1-\alpha)\% \\ d &= (\mu_x - \mu_y) \\ d \pm t_{[1-\alpha/2,v]} &\sqrt{\frac{S_x^2}{n_x} + \frac{S_y^2}{n_y}} \\ v = &\left[\frac{(S_x^2/n_x + S_y^2/n_y)^2}{\frac{1}{n_x+1}(S_x^2/n_x)^2 + \frac{1}{n_y+1}(S_y^2/n_y)^2}\right] - 2 \end{aligned} \tag{8.2}$$

In Table 24, we show our results of the t-test and analysis for hypothesis **H1**. We compare the average number of conflict events under the *Best Case Scenario* and *Worst Case Scenario* as a function of the average fading (i.e., Interference Cartography error) for each governance system. Our results show that, with a 90% confidence interval, the number

Hypothesis			H1
Relevant factors		**T-test result**	**Conclusion**
Number of conflict events in Centralized governance with average fading equal to 4.0	Number of conflict events in Centralized governance with average fading equal to 0.5	9.1928 ± 1.1048	The number of conflict events is higher in Centralized governance and average fading equal to 4.0
Number of conflict events in Polycentric governance with average fading equal to 4.0	Number of conflict events in Polycentric governance with average fading equal to 0.5	0.4656 ± 0.2106	The number of conflict events is higher in Polycentric governance and average fading equal to 4.0
Number of conflict events in Self-governance with average fading equal to 4.0	Number of conflict events in Self-governance with average fading equal to 0.5	2.5500 ± 0.4425	The number of conflict events is higher in Self-governance and average fading equal to 4.0

Table 24: T-test results and analysis for hypothesis H1

of conflict situations is higher in scenarios with a higher number of errors in the IC map of the REM. This allows us to reject the null hypothesis.

The goal of **H2** is to compare the performance of distributed governance systems vs. the classical centralized approach in spectrum sharing scenarios. To test, analyze, and evaluate H2 in a better way, we divide it into two hypotheses, namely H2.1, and H2.2.

Table 25 shows the results of the t-test and analysis for hypothesis **H2.1**. We compare the average number of conflict events per interaction under the *BCS* and *WCS* for different types of conflicts (i.e., *Type A* and *Type B*), and the application of a local ML solution. Our results show that the number of conflict situations, for most scenarios, is higher under centralized governance than self-governance. This allows us to reject the null hypothesis.

In Table 26, we find the results of the t-test and analysis for hypothesis **H2.2**. We compare the average number of conflict events per interaction under the *BCS* and *WCS* for different types of conflicts (i.e., *Type A* and *Type B*), and the application of both local and global ML methods. From the testing analysis, we observe that, in all scenarios, the number

Hypothesis			**H2.1**
Relevant factors		**T-test result**	**Conclusion**
Number of Type A conflict events in Centralized governance in the Best Case Scenario	Number of Type A conflict events in Self-governance in the Best Case Scenario	0.0167 ± 0.009	The number of Type A events is higher in the *BCS* for centralized governance
Number of Type A conflict events in Centralized governance in the Worst Case Scenario	Number of Type A conflict events in Self-governance in the Worst Case Scenario	6.6261 ± 1.1901	The number of Type A events is higher in *WCS* for centralized governance
Number of Type B conflict events in Centralized governance in the Best Case Scenario	Number of Type B conflict events in Self-governance in the Best Case Scenario	0.0031 ± 0.0058	The result of the test is not conclusive in the confidence interval
Number of Type B conflict events in Centralized governance in the Worst Case Scenario	Number of Type B conflict events in Self-governance in the Worst Case Scenario	0.3728 ± 0.0526	The number of Type B events is higher in the *WCS* for centralized governance
Number of Type A conflict events in Centralized Governance and Local ML approach	Number of Type A conflict events in Self-governance and Local ML approach	7.4301 ± 0.2951	The number of Type A events is higher in the Local ML approach & centralized governance

Table 25: T-test results and analysis for hypothesis H2.1

of conflict events is higher in centralized governance than in polycentric governance. This allows us to reject the null hypothesis.

Another crucial parameter that allows us to study the performance of spectrum sharing scenarios is the ability of secondary users to utilize the available resources. In hypothesis **H3**, we test the impact of distributed governance systems vs. classical centralized approaches in this SU transmission efficiency. For testing, analyzing, and evaluating this hypothesis, we divide it into two hypotheses, namely H3.1 and H3.2.

In table 27, we show the results of the t-test and analysis for hypothesis **H3.1**. We compare the SU transmission efficiency under the *Best Case Scenario*, *Worst Case Scenario*, and the application of local ML. Our results show that, in most scenarios, the average SU transmission efficiency is higher in centralized governance than in self-governance. Consequently, it is not possible to reject the null hypothesis.

Table 28 depicts the results of the t-test and analysis for hypothesis **H3.2**. We compare the SU transmission efficiency as a function of the *Best Case Scenario*, *Worst Case Scenario*, local ML approach, and global ML approach. Our results show that, in all scenarios, the average SU transmission efficiency is higher in polycentric governance than in centralized governance models. This allows us to reject the null hypothesis.

In Stage 4, we successfully integrate ML and ABM. The goal of this integration is to reduce the number of conflict events through the creation of smarter agents. However, the addition of ML into ABM entails the construction of more complex agents with additional computational requirements. In hypothesis **H4**, we compare the performance evaluations of the governance-based model (i.e., *Model 2.0*) and the ML-based model (i.e., *Model 3.0*) for centralized governance systems.

In Table 29, we show the results of the t-test and analysis for hypothesis **H4**. We compare the number of conflict events in centralized governance scenarios as a function of whether (local and global) machine learning techniques are included in the model. Our results show that, in all scenarios, the number of conflict situations is higher when we do not use endogenous machine learning in the models. Consequently, we can reject the null hypothesis.

A fundamental evaluation criterion for the models in which machine learning algorithms

Hypothesis			**H2.2**
Relevant factors		**T-test result**	**Conclusion**
Number of Type A conflict events in Centralized governance in the Best Case Scenario	Number of Type A conflict events in Polycentric governance in the Best Case Scenario	0.0022 ± 0.0007	The result of the test is not conclusive in the confidence interval
Number of Type A conflict events in Centralized governance in the Worst Case Scenario	Number of Type A conflict events in Polycentric governance in the Worst Case Scenario	8.7294 ± 1.1247	The number of Type A events is higher in the *WCS* for centralized governance
Number of Type B conflict events in Centralized governance in the Best Case Scenario	Number of Type B conflict events in Polycentric governance in the Best Case Scenario	0.0047 ± 0.036	The number of Type B events is higher in the *BCS* for centralized governance
Number of Type B conflict events in Centralized governance in the Worst Case Scenario	Number of Type B conflict events in Polycentric governance in the Worst Case Scenario	0.4517 ± 0.052	The number of Type B events is higher in the *WCS* for centralized governance
Number of Type A conflict events in Centralized Governance and Local ML approach	Number of Type A conflict events in Polycentric governance and Local ML approach	12.0289 ± 0.2779	The number of Type A events is higher in the Local ML approach & centralized governance
Number of Type A conflict events in Centralized governance and Global ML approach	Number of Type A conflict events in Polycentric governance and Global ML approach	5.0175 ± 0.1601	The number of Type A events is higher in the Global ML approach & centralized governance

Table 26: T-test results and analysis for hypothesis H2.2

Hypothesis			**H3.1**
Relevant factors		**T-test result**	**Conclusion**
SU Transmission efficiency in self-governance in the Best Case Scenario	SU Transmission efficiency in centralized governance in the Best Case Scenario	0.0233 ± 0.0228	The SU Transmission efficiency is higher in the *BCS* and self-governance
SU Transmission efficiency in self-governance in the Worst Case Scenario	SU Transmission efficiency in centralized governance in the Worst Case Scenario	-0.1471 ± 0.0384	The SU Transmission efficiency is lower in the *WCS* and self-governance
SU Transmission efficiency in self-governance and local ML approach	SU Transmission efficiency in centralized governance and local ML approach	-0.2053 ± 0.0066	The SU Transmission efficiency is lower in the Local ML approach and self-governance

Table 27: T-test results and analysis for hypothesis H3.1

Hypothesis			**H3.2**
Relevant factors		**T-test result**	**Conclusion**
SU Transmission efficiency in polycentric governance in the Best Case Scenario	SU Transmission efficiency in centralized governance in the Best Case Scenario	0.0629 ± 0.0225	The SU Transmission efficiency is higher in the *BCS* and polycentric governance
SU Transmission efficiency in polycentric governance in the Worst Case Scenario	SU Transmission efficiency in centralized governance in the Worst Case Scenario	0.5243 ± 0.0364	The SU Transmission efficiency is higher in the *WCS* and polycentric governance
SU Transmission efficiency in polycentric governance and Local ML approach	SU Transmission efficiency in centralized governance and Local ML approach	0.0385 ± 0.0129	The SU Transmission efficiency is higher in the Local ML approach & polycentric governance
SU Transmission efficiency in polycentric governance and Global ML approach	SU Transmission efficiency in centralized governance and Global ML approach	0.0762 ± 0.0124	The SU Transmission efficiency is higher in the Global ML approach & polycentric governance

Table 28: T-test results and analysis for hypothesis H3.2

Hypothesis			H4
Relevant factors		**T-test result**	**Conclusion**
Number of conflict events in Centralized governance without (local) ML-inclusion	Number of conflict events in Centralized governance with (local) ML-inclusion	4.8312 ± 1.2457	The number of events is higher in Centralized governance without (local) ML-inclusion
Number of conflict events in Centralized governance without (global) ML-inclusion	Number of conflict events in Centralized governance with (global) ML-inclusion	8.4939 ± 1.1127	The number of events is higher in Centralized governance without (global) ML-inclusion

Table 29: T-test results and analysis for hypothesis H4

are applied is their performance assessment, particularly the accuracy of the classifications (predictions). In hypothesis **H5**, we evaluate the accuracy of the implemented ML models as a function of the governance approach. To better test, evaluate, and analyze hypothesis H5, we divide it into two hypotheses, namely H5.1, and H5.2.

In Table 30, we find the results of the t-test and analysis for hypothesis **H5.1**. We compare the average accuracy score of the five (5) machine learning classifiers available in our model as a function of the governance system. The results show that, within the predefined confidence interval (90%), in most scenarios, the average accuracy scores of ML models in centralized governance are higher than in self-governance. This does not allow us to reject the null hypothesis.

In Tables 31 and 32, we find the t-test results and analysis for hypothesis **H5.2**. We compare the average accuracy score of the machine learning classifiers available in our model as a function of the governance system and the type of ML application (i.e., local or global). The results show that, in most scenarios[4], the average accuracy scores of ML models built in polycentric governance are higher than those in centralized governance. This allows us to reject the null hypothesis.

[4] Note that, in the case of the local ML approach (see Table 31), in all but one scenario, the algorithms developed in centralized systems have higher accuracy scores than the models built in polycentric systems. This is not the case of the global ML approach (see Table 32), where in all scenarios the models built in polycentric governance have a higher accuracy than the algorithms used in centralized systems.

Hypothesis			H5.1
Relevant factors		T-test result	Conclusion
Logistic Regression average accuracy score in Self-governance and Local ML	Logistic Regression average accuracy score in Centralized governance and Local ML	-0.0224 ± 0.0026	The average Logistic Regression accuracy score is lower in Self-governance and Local ML
Support Vector Machine average accuracy score in Self-Governance and Local ML	Support Vector Machine average accuracy score in Centralized governance and Local ML	0.0016 ± 0.0003	The average Support Vector Machine accuracy score is higher in Self-governance and Local ML
Nearest Neighbor average accuracy score in Self-Governance and Local ML	Nearest Neighbor average accuracy score in Centralized governance and Local ML	-0.0534 ± 0.0026	The average Nearest Neighbor accuracy score is lower in Self-governance and Local ML
Random forest average accuracy score in Self-governance and Local ML	Random Forest average accuracy score in Centralized governance and Local ML	-0.0156 ± 0.0017	The average Random Forest accuracy score is lower in Self-governance and Local ML
xGBoost average accuracy score in Self-governance and Local ML	xGBoost average accuracy score in Centralized governance and Local ML	-0.0572 ± 0.0037	The average xGBoost accuracy score is lower in Self-governance and Local ML

Table 30: T-test results and analysis for hypothesis H5.1

Hypothesis			H5.2
Relevant factors		**T-test result**	**Conclusion**
Logistic Regression average accuracy score in Polycentric governance and Local ML	Logistic Regression average accuracy score in Centralized governance and Local ML	-0.1395 ± 0.0044	The average Logistic Regression accuracy score is lower in Polycentric governance and Local ML
Support Vector Machine average accuracy score in Polycentric governance and Local ML	Support Vector Machine average accuracy score in Centralized governance and Local ML	-0.2735 ± 0.0059	The average Support Vector Machine accuracy score is lower in Polycentric governance and Local ML
Nearest Neighbor average accuracy score in Polycenric Governance and Local ML	Nearest Neighbor average accuracy score in Centralized governance and Local ML	0.1613 ± 0.0103	The average Nearest Neighbor accuracy score is higher in Polycentric governance and Local ML
Random forest average accuracy score in Polycentric governance and Local ML	Random Forest average accuracy score in Centralized governance and Local ML	-0.4721 ± 0.0217	The average Random Forest accuracy score is lower in Polycentric governance and Local ML
XGBoost average accuracy score in Polycentric governance and Local ML	XGBoost average accuracy score in Centralized governance and Local ML	-0.4411 ± 0.0288	The average XGBoost accuracy score is lower in Polycentric governance and Local ML

Table 31: T-test results and analysis for hypothesis H5.2 (local ML approach)

Hypothesis			H5.2
Relevant factors		**T-test result**	**Conclusion**
Logistic Regression average accuracy score in Polycentric governance and Global ML	Logistic Regression average accuracy score in Centralized governance and Global ML	0.0531 ± 0.0089	The average Logistic Regression accuracy score is higher in Polycentric governance and Global ML
Support Vector Machine average accuracy score in Polycentric governance and Global ML	Support Vector Machine average accuracy score in Centralized governance and Global ML	0.1139 ± 0.0112	The average Support Vector Machine accuracy score is higher in Polycentric governance and Global ML
Nearest Neighbor average accuracy score in Polycentric Governance and Global ML	Nearest Neighbor average accuracy score in Centralized governance and Global ML	0.0844 ± 0.0242	The average Nearest Neighbor accuracy score is higher in Polycentric governance and Global ML
Random forest average accuracy score in Polycentric governance and Global ML	Random Forest average accuracy score in Centralized governance and Global ML	0.0701 ± 0.0074	The average Random Forest accuracy score is higher in Polycentric governance and Global ML
xGBoost average accuracy score in Polycentric governance and Global ML	xGBoost average accuracy score in Centralized governance and Global ML	0.1149 ± 0.0108	The average xGBoost accuracy score is higher in Polycentric governance and Global ML

Table 32: T-test results and analysis for hypothesis H5.2 (global ML approach)

In hypothesis **H6**, we aim to test if the simple coordination and communication implemented in distributed (i.e., "alternative") governance systems leads to fewer conflict events than the ML-enhanced scenarios.

Table 33 shows the results of the t-test and analysis for hypothesis **H6**. We compare the number of conflict events as a function of the distributed governance systems (i.e., polycentric and self-governance) and the application of (local or global) machine learning techniques. As we can observe, not in most scenarios, the number of conflict situations is higher when ML algorithms are part of the models than simple coordination (i.e., without ML). Thus, we cannot reject the null hypothesis.

The final component of Stage 4 is the implementation of two approaches for the addition of ML techniques: a local and a global ML approach. In **H7**, we compare and evaluate the performance of these approaches in terms of the number of conflict situations in each governance system

In Tables 34 and 35, we find the t-test results and analysis of hypothesis **H7**. We evaluate the average number of conflict events per interaction as a function of the type (local or global) of the machine learning approach in each governance system. The results show that, in most scenarios, the number of conflict events when a local ML approach is used is lower than those when a global ML approach is applied. Thus, it is possible to reject the null hypothesis.

8.3 Sensitivity analysis

The models, parameters, and scenarios defined for the different stages in this dissertation account for vast possibilities in terms of parameter combinations. The combinations that we have deemed essential result from varying the main parameters impacting sharing conditions (e.g., number of participants). These parameter combinations permitted us to explore how the sharing agreement behaves under different governance mechanisms, resource access strategies, and types of participants (e.g., ML-enhanced agents). The results from this analysis have already been explored through our hypotheses and presented in the results section (see Section 7).

Hypothesis			**H6**
Relevant factors		**T-test result**	**Conclusion**
Number of conflict events in Self-governance and with (local) ML	Number of conflict events in Self-governance and without (local) ML	-0.6763 ± 0.5387	The average number of conflicts per interaction is lower in Self-governance with (local) ML
Number of conflict events in Polycentric governance and with (local) ML	Number of conflict events in Polycentric governance and without (local) ML	0.0296 ± 0.2826	The result of the test is not conclusive in the confidence interval
Number of conflict events in Polycentric governance and with (global) ML	Number of conflict events in Polycentric governance and without (global) ML	1.9408 ± 0.3244	The average number of conflicts per interaction is higher in Polycentric governance and with (global) ML

Table 33: T-test results and analysis for hypothesis H6

Hypothesis			H7
Relevant factors		T-test result	Conclusion
Number of conflict events in Centralized governance, Logistic Regression, and Global ML	Number of conflict events in Centralized governance, Logistic Regression and Local ML	-3.3101 ± 0.5903	The average number of conflicts per interaction is lower in Centralized governance, Logistic Regression, and Global ML
Number of conflict events in Centralized governance, Support Vector Machine, and Global ML	Number of conflict events in Centralized governance, Support Vector Machine, and Local ML	-4.5328 ± 0.6973	The average number of conflicts per interaction is lower in Centralized governance, Support Vector Machine, and Global ML
Number of conflict events in Centralized governance, Nearest Neighbor, and Global ML	Number of conflict events in Centralized governance, Nearest Neighbor, and Local ML	2.775 ± 0.5425	The average number of conflicts per interaction is higher in Centralized governance, Nearest Neighbor, and Global ML
Number of conflict events in Centralized governance, Random Forest, and Global ML	Number of conflict events in Centralized governance, Random Forest, and Local ML	-3.4072 ± 0.5434	The average number of conflicts per interaction is lower in Centralized governance, Random Forest, and Global ML
Number of conflict events in Centralized governance, xGBoost, and Global ML	Number of conflict events in Centralized governance, xGBoost, and Local ML	-4.2894 ± 0.5697	The average number of conflicts per interaction is lower in Centralized governance, xGBoost, and Global ML

Table 34: T-test results and analysis for hypothesis H7 (centralized governance)

Hypothesis			**H7**
Relevant factors		**T-test result**	**Conclusion**
Number of conflict events in Polycentric governance, Logistic Regression, and Global ML	Number of conflict events in Polycentric governance, Logistic Regression and Local ML	2.7761 ± 0.2509	The average number of conflicts per interaction is higher in Polycentric governance, Logistic Regression, and Global ML
Number of conflict events in Polycentric governance, Support Vector Machine, and Global ML	Number of conflict events in Polycentric governance, Support Vector Machine, and Local ML	0.1005 ± 0.1343	The result of the test is not conclusive in the confidence interval
Number of conflict events in Polycentric governance, Nearest Neighbor, and Global ML	Number of conflict events in Polycentric governance, Nearest Neighbor, and Local ML	5.0445 ± 0.3208	The average number of conflicts per interaction is higher in Polycentric governance, Nearest Neighbor, and Global ML
Number of conflict events in Polycentric governance, Random Forest, and Global ML	Number of conflict events in Polycentric governance, Random Forest, and Local ML	2.1489 ± 0.2442	The average number of conflicts per interaction is lower in Polycentric governance, Random Forest, and Global ML
Number of conflict events in Polycentric governance, xGBoost, and Global ML	Number of conflict events in Polycentric governance, xGBoost, and Local ML	0.0227 ± 0.1626	The result of the test is not conclusive in the confidence interval

Table 35: T-test results and analysis for hypothesis H7 (polycentric governance)

To gain additional insights into how patterns and emergent properties are generated in the models, to examine the robustness of these emergent properties, and to quantify the variability in the outcomes resulting from the model parameters, we performed additional sensitivity analyses. Many methodologies have been developed to perform sensitivity analysis within the ABM framework (a complete summary is presented in [217, 218]). For this dissertation, we select two well-known and widely used techniques: One-Factor-At-A-Time (OFAT) and a Sobol global sensitivity analysis.

8.3.1 One-Factor-At-A-Time (OFAT) sensitivity analysis

In OFAT, we vary one parameter[5] at a time while keeping all other parameters fixed at a base setting (i.e., a nominal value). An important objective of OFAT is to reveal the form of the relationship between the varied input parameter and the model output (e.g., linear or non-linear relationship). OFAT can yield a better understanding of the model mechanisms by showing the relationship between a single parameter and the model outcomes. The OFAT sensitivity analysis provides insights into qualitative aspects of model behavior and the patterns that emerge from the model. These qualitative aspects can lead us to a better understanding of the connection between the macro-phenomena and the individual parameters [219].

For our work, we perform the OFAT sensitivity analysis using the main factors influencing the conditions of a spectrum sharing scheme. In addition, we use ten (10) replications per parameter setting to estimate the spread of the outputs. Table 36 lists the nominal values (i.e., default settings) and ranges of variation of all the parameters used in our sensitivity analysis. We run our analysis for the extreme values of this range and ten (10) equidistant points in between for each governance system in the model.

8.3.1.1 Number of primary users The first input parameter to be tested in our sensitivity analysis is the number of Primary Users (PUs) in the system. These agents correspond to higher-tier participants (e.g., Federal and PAL) that receive interference protection.

[5] We vary each parameter over several points within a wide range.

Parameter	Nominal value	Range
Number of primary users	10	2 - 20
Number of secondary users	50	10 - 100
REM sensor density	0.5	0.1 - 1.0
REM fading deviation (error)	2.5	0.5 - 5.0
SU (transmission) load	0.5	0.1 - 1.0

Table 36: Model parameters and range for the sensitivity analyses

In Figure 112, we observe the number of conflict situations (left graph) and the SU transmission efficiency (right graph) as a function of the number of primary users in each governance system.

When either centralized or self-governance approaches are a part of the system, the average number of events per interaction increases as the number of PUs goes from minimum (2) to maximum (20). In the case of polycentric governance, as previously demonstrated, the agents in conjunction with their local *coordinators* can adapt to the conditions of the band. Therefore, the number of conflict events in polycentric governance remains constant regardless of the number of high-tier agents. For the efficiency in the use of resources by the new entrants (right graph), we observe a similar outcome. The SU transmission efficiency in centralized and self-governance is reduced when the number of PUs increases. Contrary, the efficiency remains constant in polycentric governance regardless of the change in the number of PUs.

In centralized and self-governance, we observe a logarithmic relationship between the number of events and SU transmission efficiency when there is a change in the number of PU participants. Thus, in self-governance there is a strong positive correlation for the number of events ($R = 0.966$ and $R^2 = 0.9332$) and a strong negative correlation for the SU transmission efficiency ($R = -0.7962$ and $R^2 = 0.6339$). In centralized systems, we also detect a strong positive correlation ($R = 0.7898$ and $R^2 = 0.6238$) with the number of conflicts, and a strong negative correlation with the transmission efficiency of secondary

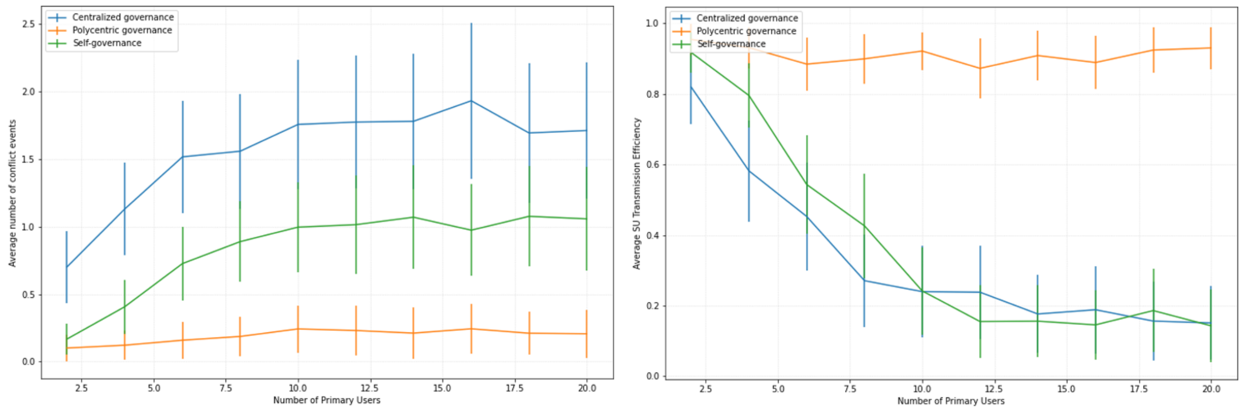


Figure 112: OFAT sensitivity analysis - Effect of the number of primary users in the model outcomes number of conflict events (left) and SU transmission efficiency (right)

users ($R = -0.8776$ and $R^2 = 0.7702$)[6].

8.3.1.2 Number of secondary users The second parameter that is varied in our sensitivity analysis is the number of secondary users. These are agents located in lower tiers of the scheme and that, typically, receive little protection against the presence of conflict situations.

In Figure 113, we observe the number of conflict events (left graph) and the SU transmission efficiency (right graph) as a function of the number of secondary users in each of the governance mechanisms implemented in our models. Regarding the average number of conflict situations per interaction, we observe a similar outcome to the number of primary users. As the number of secondary users increases, the number of conflict events increases for the centralized and self-governance approaches. In the case of polycentric governance, the number of conflict situations remains constant when the number of secondary participants goes from minimum (10) to maximum (100). When analyzing the SU transmission efficiency, we observe how as the number of secondary users goes up, there is a decrease in efficiency

[6] In polycentric governance, even though there is a correlation between the number of events ($R = 0.4939$ and $R^2 = 0.2439$) and the SU transmission efficiency ($R = 0.2803$ and $R^2 = 0.0786$), the relationship with the number of PUs is weak.

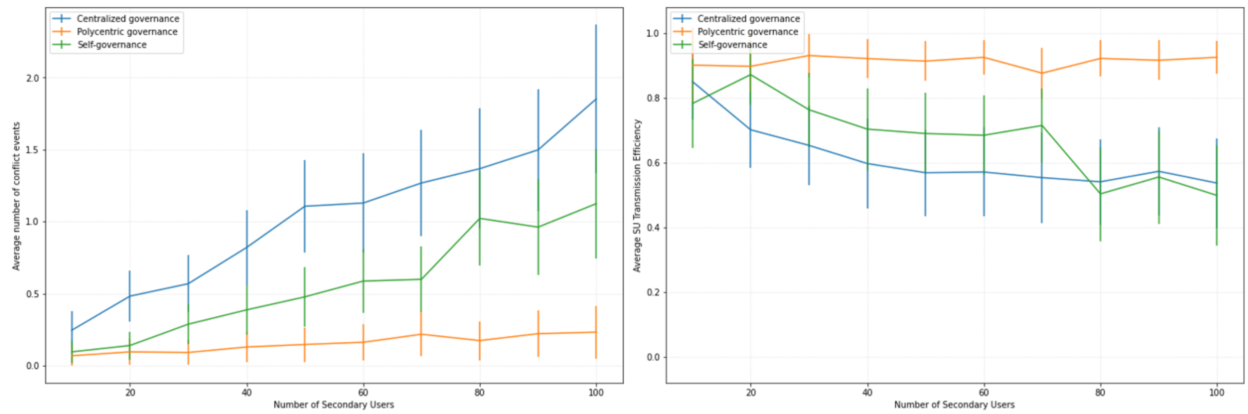


Figure 113: OFAT sensitivity analysis - Effect of the number of secondary users in the model outcomes number of conflict events (left) and SU transmission efficiency (right)

in centralized and self-governance.

There is a linear relationship between the number of secondary users and the number of conflict situations in centralized and self-governance. For centralized systems this positive correlation is given by $R = 0.9871$ and $R^2 = 0.9744$ and for self-governance it is given by $R = 0.9709$ and $R^2 = 0.9426$. In the case of the SU transmission efficiency, we can observe a decreasing algorithmic relationship with both centralized ($R = -0.7992$ and $R^2 = 0.6387$) and self-governance ($R = -0.906$ and $R^2 = 0.8208$)[7].

8.3.1.3 Secondary users load In the previous section, we analyze the impact of a change in the number of secondary users. Another critical parameter regarding the new entrants is their activity level. In other words, the amount of resources that the SUs require to meet their transmission needs. We refer to this secondary user feature as the *SU load*.

The number of events (left graph) and SU transmission efficiency (right graph) as a function of the transmission load of the secondary users for each governance system is depicted in Figure 114. In centralized and self-governance, there is an increasing trend in the number of

[7] In polycentric governance, the number of SUs does not show a strong correlation with the total number of events ($R = 0.4744$ and $R^2 = 0.2251$) and the SU transmission efficiency ($R = 0.5239$ and $R^2 = 0.2745$).

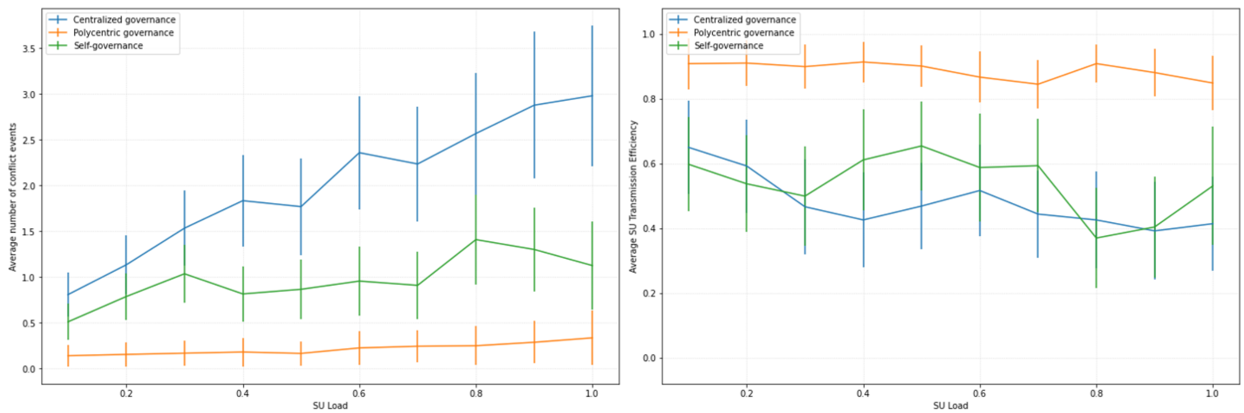


Figure 114: OFAT sensitivity analysis - Effect of the *SU load* in the model outcomes number of conflict events (left) and SU transmission efficiency (right)

conflict events, when the congestion of the system (i.e., average *SU load*) goes from minimum (0.1) to maximum (1.0). This is not the case in polycentric approaches, where the number of conflict situations remains constant regardless of the *SU load*. For the SU transmission efficiency, we observe that as the load of the new entrants increases, the efficiency in the use of resources decreases when centralized or self-governance systems are implemented.

For centralized and self-governance, there is a linear correlation between the number of events and the increase in the *SU load*. Thus, for centralized governance, we observe a strong positive correlation of $R = 0.979$ and $R^2 = 0.9584$. In the same light, when self-enforcement is the chosen governing system, there is a strong positive linear correlation ($R = 0.8084$ and $R^2 = 0.6535$)[8]. When analyzing the relation between the SU transmission efficiency and the congestion in the system (i.e., *SU load*), we observe a negative linear relationship in both centralized ($R = -0.8161$ and $R^2 = 0.6667$) and self-governance ($R = -0.9099$ and $R^2 = 0.8279$) approaches[9].

[8] In the case of polycentric governance, the number of events remains constant as the congestion in the system increases ($R = 0.4327$ and $R^2 = 0.1872$).

[9] For polycentric governance, there is a weak correlation between the SU load and the SU transmission efficiency ($R = 0.1071$ and $R^2 = 0.0115$).

8.3.1.4 REM sensor density To construct the REM's spectrum map, we take a group of (simulated) measurements within a region of interest. These measures are gathered by MCDs or sensors. In this section, we study the relationship between the proportion of sensors[10] in the IC map and the model outcomes.

Figure 115 shows the number of events (left graph) and the SU transmission efficiency (right graph) as a function of the *sensor density* in each governance system. As analyzed in Section 7.2, the impact of the *sensor density* in the number of errors is significant only when a small number of sensors is used in the construction of the IC map. These results are also shown in the OFAT sensitivity analysis. For values below 30%, we see an increment in the number of events and a reduction in the SU transmission efficiency. For the remaining *sensor density* settings, we do not observe a significant change in the number of events or the resource usage efficiency.

The number of conflict events has a strong negative correlation with the *sensor density* when centralized governance is implemented ($R = -0.8328$ and $R^2 = 0.6936$). In self-governance scenarios, there is a moderate negative correlation ($R = -0.6555$ and $R^2 = 0.4797$) between the number of conflicts and the *sensor density*. In polycentric governance approaches, even though there is a negative correlation, the relationship between sensor density and the number of events is very weak ($R = -0.268$ and $R^2 = 0.0718$).

When analyzing the relationship between the SU transmission efficiency and the *sensor density*, we observe a negative relationship in centralized and self-governance structures. Thus, as the *sensor density* increases, the SU transmission efficiency decreases. However, this relationship is very week as shown by the different correlation coefficients in centralized ($R = -0.2799$ and $R^2 = 0.0783$) and self-governance ($R = -0.4352$ and $R^2 = 0.2864$) arrangements. When a polycentric approach is utilized, although technically there is a positive correlation, the relationship between efficiency and *sensor density* is weak ($R = 0.3875$ and $R^2 = 0.1502$).

[10] In our models, the variable *sensor density* determines this proportion.

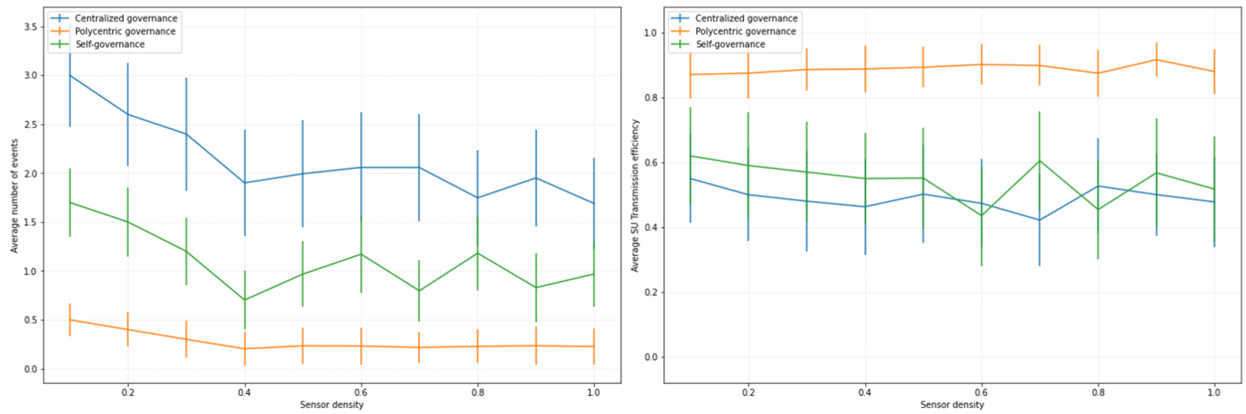


Figure 115: OFAT sensitivity analysis - Effect of the *sensor density* in the model outcomes number of conflict events (left) and SU transmission efficiency (right)

8.3.1.5 Average fading deviation of the measurements in the REMs The other parameter that influences the number of errors in the IC map is the accuracy of the measurements taken by the different MCDs. To capture this, our model includes a *fading deviation* parameter. This specification simulates the presence of wireless phenomena (e.g., slow fading) that impacts the quality of the received measurements.

In Figure 116, we observe the results of the number of conflict events (left graph) and SU transmission efficiency (right graph) as a function of the average *fading deviation* for each governance mechanism. Regarding the number of events, we observe a similar outcome as the other model parameters. When the *fading deviation* value, and consequently the IC errors, increases, the number of conflict situations also surges in centralized and self-governance approaches. In the case of polycentric governance, once again, the number of conflict situations remains constant regardless of the changes in the *fading deviation*. When evaluating the SU transmission efficiency, we observe that for centralized and polycentric governance systems the efficiency is reduced when the *fading deviation* increases. For self-governance, the SU transmission efficiency remains relatively constant when the *fading deviation* changes.

There is a positive linear relationship between the number of conflict situations and the *fading deviation* in the system for both the centralized ($R = 0.97$ and $R^2 = 0.9409$) and

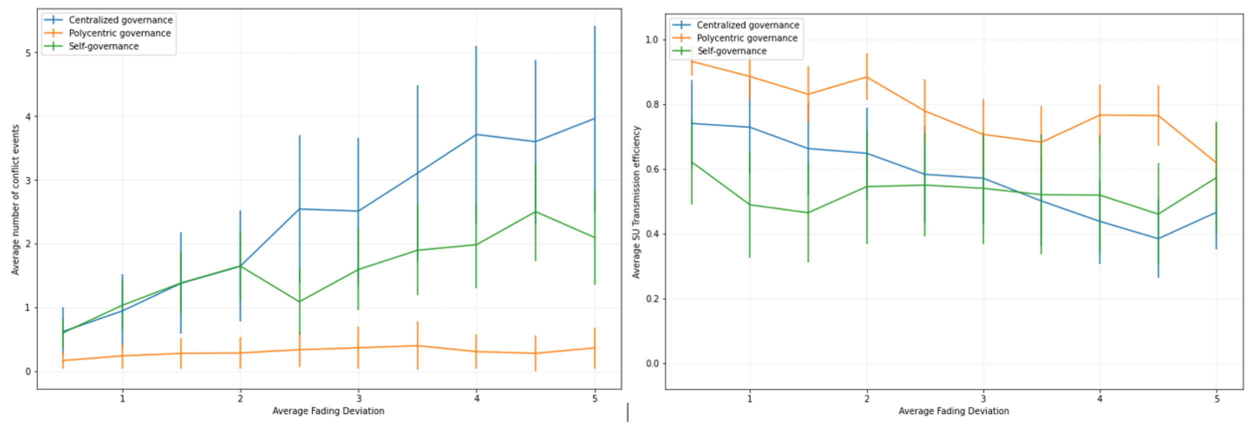


Figure 116: OFAT sensitivity analysis - Effect of the *fading deviation* in the model outcomes number of conflict events (left) and SU transmission efficiency (right)

self-governance ($R = 0.9349$ and $R^2 = 0.874$) organizations[11]. In the case of the efficiency in the resource utilization, there is negative correlation between it and the *fading deviation* for the centralized ($R = -0.965$ and $R^2 = 0.9312$) and polycentric methodologies ($R = -0.8489$ and $R^2 = 0.7206$)[12].

8.3.1.6 Summary of the OFAT sensitivity analysis The One-Factor-At-A-Time sensitivity analysis allows us to explore the relationship between the individual input parameters and the corresponding outcomes of the model. In particular, we study the link between each model parameter and both, the number of conflict events and SU transmission efficiency, as summarized in Table 37[13].

Figures 117 and 118 present a "heatmap" representation of the number of conflict events and SU transmission efficiency as a function of the different model parameters tested in the

11 In polycentric governance, there is a positive correlation; however, the relationship between the *fading deviation* and the number of conflicts is weak ($R = 0.122$ and $R^2 = 0.0149$).

12 For self-governance, even though there is a positive correlation, the relationship between the variables is very weak ($R = 0.0323$ and $R^2 = 0.001$).

13 Since Polycentric governance approaches show a weak correlation between the model parameters and outcomes, Table 37 shows the average scores for the centralized and self-governance systems.

One-Factor-At-A-Time (OFAT) sensitivity analysis				
Parameter	**Number of conflict events**		**SU transmission efficiency**	
	R	R^2	R	R^2
Number of primary users	0.8821	0.7785	-0.8369	0.7504
Number of secondary users	0.9785	0.9585	-0.8526	0.7297
SU load	0.8937	0.8059	-0.863	0.7473
Sensor density	-0.7439	0.5867	-0.3575	0.1835
Fading deviation	0.9524	0.9074	-0.9069	0.8259

Table 37: Summary of the OFAT sensitivity analysis

OFAT sensitivity analysis. These graphs not only show the individual relationship between the model parameters and outcomes, but also the relationship that exists among the different model parameters. Note that the values presented in Figures 117 and 118 are normalized between zero (0) and one (1)[14].

In Figure 117, we observe that low values (e.g., 10%) in the number of secondary users and their corresponding load (i.e., *SU load*) lead to the fewest conflict events in the system. On the other hand, when there are multiple SUs with high transmission load, the sharing agreement presents the maximum number of conflict events.

In Figure 118, we study the relationship between the models' input parameters and the average SU transmission efficiency. The number of primary users is inversely related to the SU transmission efficiency. Thus, the presence of multiple PUs reduces the available opportunities for new entrants. Contrary, in the case of the highest efficiency, this is achieved when the number of primary users is at its minimum possible. Note that when the number of secondary users is at its minimum value, the system also reaches a very high SU transmission efficiency.

[14] A value of zero (0) implies the minimum outcome, while a value of one (1) suggests the maximum outcome in the system.

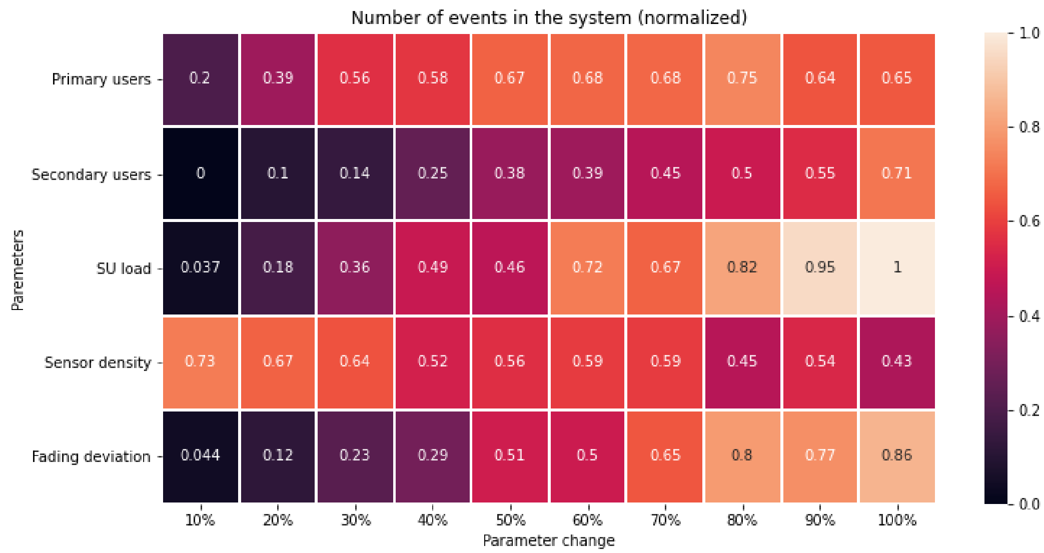


Figure 117: OFAT sensitivity analysis - *Heatmap* of the relationship between the variation in the model (input) parameters and the total number of conflict situations (normalized)

8.3.2 Global sensitivity analysis

The results of the OFAT sensitivity analysis show the robustness of the model behavior concerning changes in a single (one-at-a-time) input parameter. This analysis allows us to reveal whether emergent patterns depend on strong assumptions. However, OFAT does not consider the effects of the model parameters interactions. To unveil such interactions, we supplement OFAT with a global sensitivity analysis. Such global analysis allows us not only to examine the interaction effects of the input parameters but also to quantify model variability [220]. The main goal of the global sensitivity analysis is to assess the interaction effects by sampling the model output (Y) over a wide range of input parameter values ($[x_1, x_2, x_3, ...x_n]$) [218]. In this light, we draw multiple samples (i.,e., specific random parameter settings) from the parameter space and combine the corresponding model outcomes in a statistical measure, namely the variance of the model's output. The model's sensitivity to an input parameter is measured as the proportion of the model variance that can be

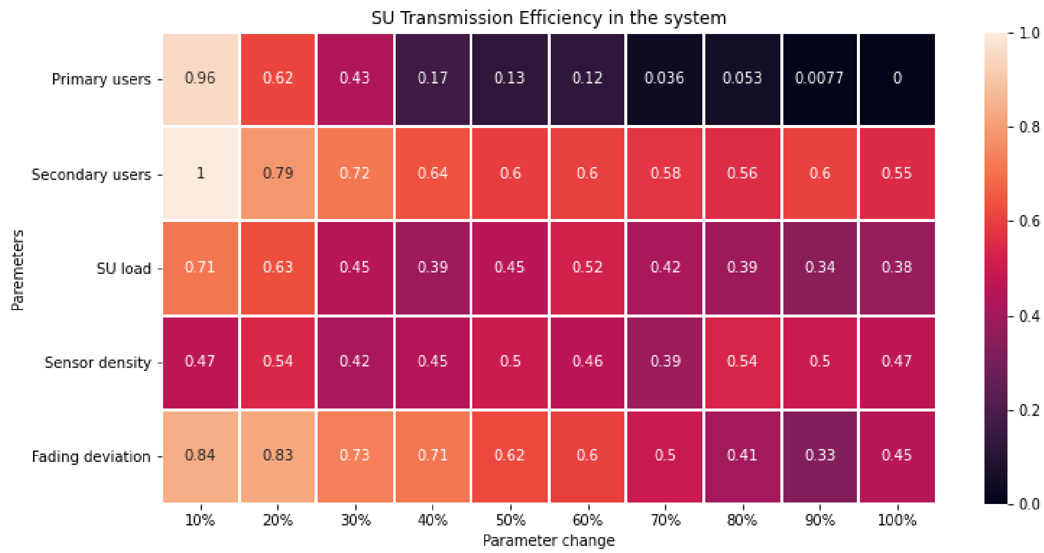


Figure 118: OFAT sensitivity analysis - *Heatmap* of the relationship between the variation in the model (input) parameters and the average SU transmission efficiency (normalized)

explained by changes in that model parameter. Since the analysis calculates the total model variance to normalize the sensitivity of each parameter, the individual sensitivities of different parameters can be directly compared. There are several methods used to decompose the model output variance and to calculate the sensitivities of different model parameters. In this work, we use the decomposition methodology proposed by Sobol [221]. This method does not involve the use of regression models or other fitted functions. Instead, it estimates the contributions of different combinations of parameters to the models' output variance.

The primary outcomes of the global sensitivity analysis based on Sobol's definitions are the first-order (*S1*), second-order (*S2*), and total-order (*ST*) indices [217]. The *first-order* index of a parameter represents the reduction of the variance of the model output that would occur, on average, if the parameter became exactly known. Second, the *total-order* index illustrates the proportion of the variance that would remain, on average, when all other parameters are exactly known. Finally, the *second-order* index explains the variance of the model due to the interaction of two or more model parameters.

The Sobol global sensitivity analysis is based on the decomposition of the variance of the model output $V(y)$ that holds if the input parameters, m, are independent of each other (see Equation 8.3). Using this decomposition it is possible to calculate the partial variance as defined in Expression 8.4, where $x_{\sim i}$ denotes all other parameters except for x_i

$$V(y) = \sum_i V_i + \sum_{ij} V_{ij} + ... + V_{ij,...,m} \tag{8.3}$$

$$V_i = V_{x_i}(E_{x_{\sim i}}(y|x)) \tag{8.4}$$

We compute the expectation value $(E_{x_{\sim i}}(y|x))$ of the model output while keeping the parameter, x_i, fixed and varying all other parameters. Then the system computes the variance of this expectation value over the possible values of x_i. In this light, if V_i is large, the expected model outcome steadily varies depending on x_i, indicating the parameter to be sensitive. The system defines the sensitivity indices by considering the partial variance relative to the total variance, as shown in Equation 8.5. Then, the system calculates higher-order sensitivity indices by computing the partial variance over two or more parameters instead of a single parameter.

$$S_{s,i} = \frac{V_i}{V(y)} \tag{8.5}$$

In our global sensitivity analysis, we use the Saltelli sampling method to compute Sobol' *first-order* and *total-order* sensitivity indices [218]. The total number of samples (i.e., model runs) is equal to 1,800[15]. Table 36 summarizes the input parameters used in our global sensitivity analysis. We use uniform distributions in each parameter range as the parameter space[16].

In Figure 119, we find the first-order (*S1*) and total-order (*ST*) indices for the (outcome) average number of conflict events. The results indicate that the number of secondary users is

15

The total Number of samples, S, is given by $S = N(2D + 1)$, where $D = 5$ is the number of input parameters and $N = 150$ is the sample multiplier.

16

In Appendix J, we find the tables that summarize the results of the Sobol global sensitivity analysis.

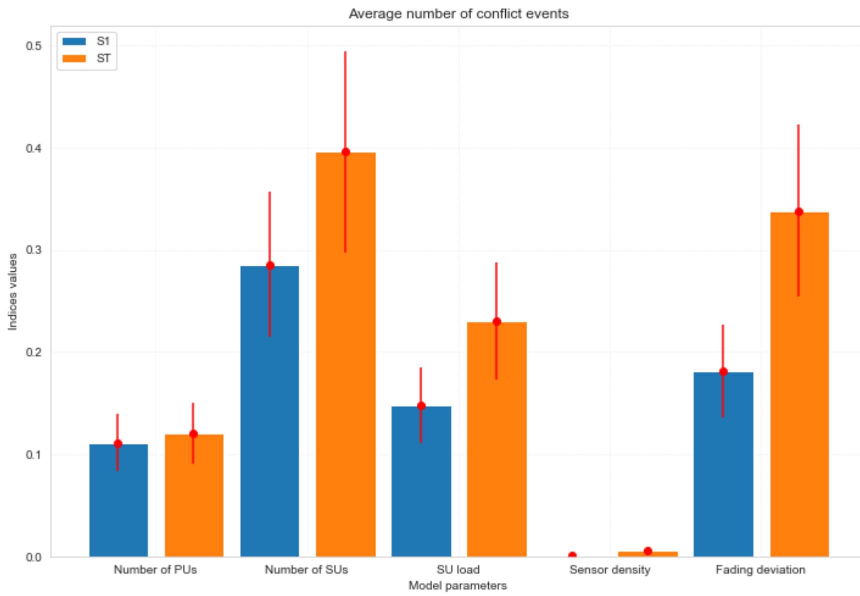


Figure 119: Global sensitivity analysis - First-order (*S1*) and total-order (*ST*) indices for the model outcome average number of conflict events

the most important parameter contributing to $\sim 29\%$ (i.e., $S1 \approx 0.29$) of the model output (average number of conflict events). The other parameters with a substantial contribution to the model output are *fading deviation* ($S1 \approx 0.18$) and *SU load* ($S1 \approx 0.15$). The results also indicate that the number of secondary users, *fading deviation*, and *SU load* are the three most important input parameters, in which the number of SUs is the most dominant parameter with a total-order (*ST*) sensitivity index of ~ 0.4.

In Figure 119, we observe that both, total-order (*ST*) and first-order (*S1*) indices, have similar values. This result shows that there are no significant second-order (*S2*) interactions between parameters. We observe the mentioned above outcome in Figure 120, where the nodes in the network represent the *S1* (black) and *ST* (magenta) indices and the edges depict the *S2* index magnitude between the different model parameters (nodes). We note that the most strong interaction happens between the number of PUs and the *SU load*. We also find strong interactions among the number of PUs, number of SUs, and *SU load*. However, as previously explained, these second-order interactions are not quite significant ($S2 \approx 0.07$) in terms of the variance of the model output (number of conflict events).

In Figure 121, we show the first-order (*S1*) and total-order (*ST*) indices for the model output SU transmission efficiency as a function of the input parameters. We observe that the number of primary users and the average *fading deviation* of sensor measurements are the most significant parameters contributing to $\sim$ 30% and $\sim$ 28% (i.e., $S1 \approx 0.3$ and $S1 \approx 0.28$), respectively of the model outcome (SU transmission efficiency). The results of the global sensitivity analysis also indicate that the number of PUs and the *fading deviation* variable are the two most important input parameters, with total order (ST) indices of ~ 0.55 and ~ 0.51, respectively.

Figure 121 shows that the total-order (ST) and first-order (*S1*) indices do not have similar values. This result suggests that there are significant second-order (*S2*) interactions between the model parameters. We observe this outcome in Figure 122, where the nodes in the network represent the *S1* (black) and *ST* (magenta) indices and the edges depict the *S2* index magnitude between the different model parameters (nodes). The results show that the relation (i.e., *S2* index) between the number of PUs and the *fading deviation* is the most significant interaction, contributing $\sim$ 15% (i.e., $S2 \approx 0.15$) of the variance of the model outcome (SU transmission efficiency). The interactions between the number of PUs and the *SU load* ($S2 \approx 0.13$) and between the *fading deviation* and *SU load* ($S2 \approx 0.12$) also have a significant impact in the variance of the model output.

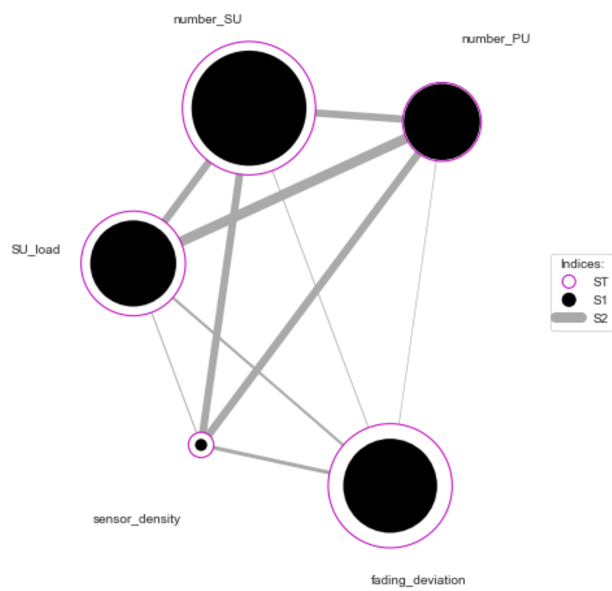


Figure 120: Global sensitivity analysis - (Network representation) interactions of the first-order (*S1*), second-order (*S2*), and total-order indices (*ST*) for the model outcome average number of conflict events

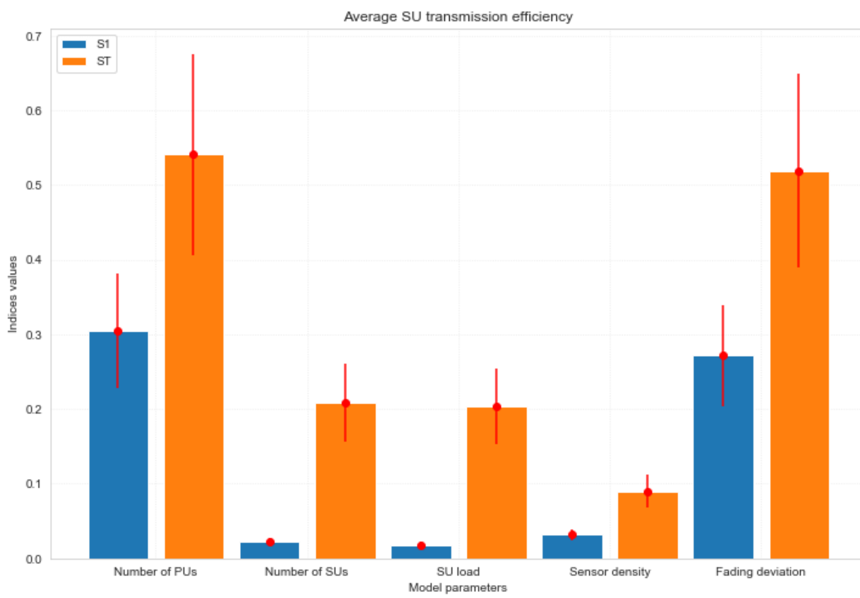


Figure 121: Global sensitivity analysis - First-order (*S1*) and total-order (*ST*) indices for the model outcome average SU transmission efficiency

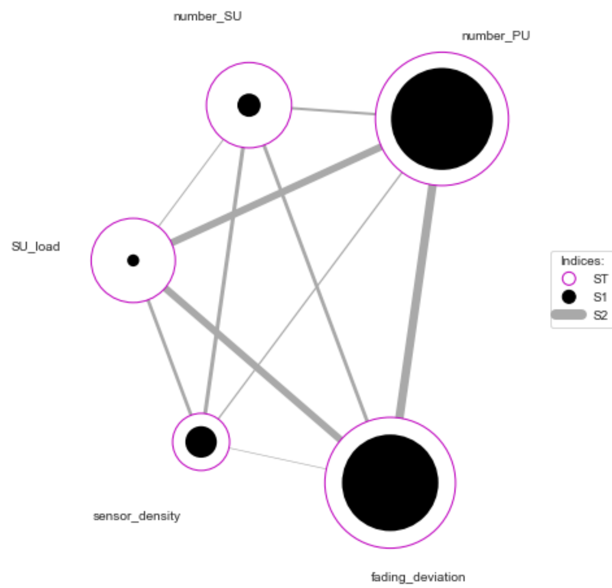


Figure 122: Global sensitivity analysis - (Network representation) interactions of the first-order (*S1*), second-order (*S2*), and total-order indices (*ST*) for the model outcome average SU transmission efficiency

9.0 Conclusions

The work presented in this dissertation provides a comprehensive analysis of the different aspects of capturing local patterns in spectrum sharing scenarios. The goal is to capture patterns that allow us to provide local solutions to local problems. In this light, we studied two main concerns in spectrum sharing settings: 1) from the perspective of higher tier users (e.g., Federal transmitters), the number of conflict situations (e.g., "harmful" interference) that might impact the sound operations of the system, 2) from the point of view of new entrants, the availability of shared resources in the agreement. To achieve these goals, we selected two spectrum and network-specific characteristics that helped us to capture local sharing agreements, assess the emergence of conflict situations, and examine the resource availability: resources access strategy and governance framework. By focusing on these specific characteristics, we provided a richer perspective of what spectrum usage entails and how conflicts arise at a local level.

One path to apply local solutions in spectrum sharing scenarios is to change the traditional governance and enforcement approach of command-and-control. A key challenge with this centralized governance method is the fact that it applies global solutions to localized problems, including those of local relevance. In this light, we successfully introduced two well-known distributed governance systems from the CPR literature as alternatives for sharing settings, namely polycentric and self-governance.

The original approach for spectrum sharing considers two tiers or levels of agents, specifically incumbents and new entrants. Even though this two-tiered definition proved to be successful in simple scenarios, it does not provide enough flexibility for its application in more dynamic sharing environments. Thus, regulators, including the FCC in the U.S., have proposed more flexible sharing settings (e.g., the CBRS scheme). Our models also include these more flexible definitions by expanding the available resource access strategies. Thus, we develop, test, and analyze both, two-tier and multi-tier, spectrum sharing settings throughout this dissertation.

To complete the different research stages presented in this work, we rely on three fundamental components: First, the definition of spectrum for wireless communications as a Common Pool Resource (CPR). Second, the development of Agent-Based Models to capture the main components of spectrum sharing settings. Third, the endogenous addition of ML models within the ABM framework. Placing spectrum as a CPR allowed us to utilize multiple definitions, frameworks, and theories widely used in the CPR literature. This process was fundamental to define the agents, environment, and interactions of the different models we developed. The use of ABM permitted us to capture the emergence of macro-phenomena by defining rules at the agent and the environment level. In addition, ABM is a key component to examine alternative governance structures and more flexible resource access strategies. Finally, the endogenous connection between ML and ABM was fundamental to achieve greater flexibility in our models. We successfully developed agents that learn from past executions and make informed decisions to try and avoid conflict situations.

In Stage 1, we showed that a key aspect of self-governing is the successful interaction of primary and secondary users. We showed that the size of the boundaries around the incumbent users, and hence the ability to detect "bad guys" within the system, stems only from the negotiation process of independent agents. Further, the system successfully allocates the shared resources according to the band's predefined set of rules irrespective of the initial conditions, such as initial signaling. Thus, spectrum sharing under a self-governing arrangement is possible under a wide variety of realistic circumstances. Regarding the actual process of self-governance, we showed that once the initial boundaries are assigned into the categories of limited and unlimited use, the trust signal of reducing the size for the starting point has the biggest impact on the governance of the spectrum. When starting with the smallest size, we can expect little or no interference with the system, which is consistent with the continuous dealing principle: good gestures by primary users are "paid" by the secondary users, and vice versa.

The results from Stage 1 showed that one of the main benefits of adopting self-governance frameworks is that sharing schemes can switch from static and centralized definitions to local and dynamic agreements. Such agreements would reflect the local conditions of the sharing process, provide enough protection to the incumbent, and add significant value and incentives to the new entrants. In addition, these results show that a self-governance structure is possible in spectrum sharing scenarios under the right circumstances. For the two-tier sharing scenario, these circumstances include a set of well-defined participants, communication channels, sharing conditions, and, most importantly, a common goal of defining optimal protection zones (i.e., avoid conflict situations for the PU while providing incentives and value for the SU). Additionally, the band provides a clear definition for the different interactions between agents and the associated rewards for a “good” behavior.

An essential factor for CPR-based decentralized governance mechanisms to be sustainable is continuous access to local information. In the case of spectrum sharing settings, this information includes information about the spectrum situation, current rules, governance characteristics, among others. Radio Environment Maps (REMs) have proven to be a viable tool to provide agents, especially for users in lower tiers, with valuable information about their local environment.

In Stage 2, we successfully designed, developed, and implemented an REM simulator. The main goal is to provide agents with the available information about their local spectrum situation. The main outcome of this REM simulator is the Interference Cartography (IC) or spectrum map of the sharing scheme. This IC map allows different agents to access local information about their spectrum situation and make informed decisions regarding the available shared resources.

The typical process to construct an IC map within a region of interest is to gather a (limited) set of wireless measurements (e.g., RSS) and interpolate the remaining values to obtain a complete representation of the current spectrum situation. The results of Stage 2 showed that our REM simulator successfully fulfills these tasks. First, it is able to simulate different sets of measurements from a very flexible number of input parameters (e.g., number of transmitters and sensors). Then, we showed that the error introduced in the interpolation process is in line with other REM implementations in the literature. Thus, our REM simulator is an effective tool not only for the creation of IC maps but as a source of REM-related information. In Stage 2, besides developing an REM simulator, we successfully transformed its static definitions into dynamic ABM models. This REM-ABM connection permitted us to provide the agents in our simulations with more dynamic representations of their environment. For this purpose, the REM simulator provides ABM with non-static IC maps and additional information related to the REM (e.g., PU's locations).

For Stage 3, we successfully developed and created a new version of the spectrum sharing ABM using the outcomes from stages 1[1] and 2[2]. In *Model 2.0*, we expand the resource access strategy from a two-tier to a multi-tier model. The inclusion of more flexible access strategies allows us to evaluate the different interactions of agents in different tiers in a better way. Additionally, we include Polycentric governance as a valid approach for governing spectrum sharing settings. Polycentric governance arrangements are capable of striking a balance between centralized and fully decentralized governance systems.

Results from Stage 3 show, once again, that distributed governance models are viable in specific spectrum sharing settings. In the case of self-governance, the agents are able to interact with each other without the participation (at least as a principal actor) of a central entity or a third-party institution. Further, agents in different tiers can reach stable agreements regarding the sharing conditions of the band (e.g., Interference Threshold (IT)). These results show the ability of agents to maintain continuous dealing relationships for sustainable self-governance settings.

For the application of polycentric governance, we designed a multi-level nested governance arrangement. In this way, we divide the environment into smaller local coordination areas. In each of these jurisdiction zones, a local coordinator allows us to capture the local conditions of the system and take actions exclusively for that coordination area in a better way. The results of Stage 3 show that this governance arrangement proved to be successful. There is a considerable reduction in the number of conflict situations when compared to centralized governance and, in many cases, self-governance. In addition, the results showed that the local coordinator and the agents in the coordinator's jurisdiction better adapt to changes in the conditions of the system (e.g., Interference Threshold).

Besides the number of conflict events in the system, the ability of new entrants to utilize the available resources is an essential aspect in the success of sharing situations. It is true that in *Model 2.0* all governance mechanisms reduce the number of conflict situa-

[1] The successful inclusion of distributed methods of governance in spectrum sharing scenarios.

[2] The advantageous inclusion of dynamic environments through the introduction of an REM's Interference Cartography (IC) map.

tions. However, as we observed in the results of Stage 3, in the case of centralized and self-governance this reduction comes at a “price”, where the SUs cannot use the available resources. In other words, the SU transmission efficiency is very low for both centralized and self-governing approaches. In the case of polycentric governance, the SU transmission efficiency is considerably higher in all scenarios we tested. Thus, in polycentric governance systems, we see a reduction in the number of conflict events and high efficiency in resource use by the new entrants.

In the final stage of this dissertation, we successfully integrate Machine Learning and Agent-Based Modeling. The result of this integration is an improved spectrum sharing model (*Model 3.0*), where agents utilize ML techniques to predict the potential emergence of conflict situations in their interactions.

To accomplish the goal of reducing the number of conflict situations, in our ML-enhanced model, we utilize supervised learning techniques. In particular, we build ML classification algorithms (e.g., SVM). As shown in the results for Stage 4, the constructed ML classifiers overall produce good performance metrics (e.g., accuracy) that allow us to use them as conflict predictors in the agents’ interactions. In addition, we find out that linear methods such as Logistic Regression show high performance scores in all scenarios and governance systems. In this light, we observe linear interactions between the target variable (i.e., conflict) and the spectrum characteristics of the system.

In the case of centralized governance, adding ML techniques in the system led to a significant reduction in the number of conflict situations. However, this decrease in the number of conflicts resulted also in a reduction in the SU transmission efficiency. One explanation for this result is that agents in *Model 3.0* study past executions for their decisions while always trying to guarantee the sound operation of the system. Thus, we observe a “trade-off” between the number of events and the given opportunities for secondary users.

The results from Stage 4 also showed that the addition of ML does not lead to a significant reduction of the number of events or an increase in the SU transmission efficiency for distributed governance systems. Note that the ML-enhanced model requires additional computational resources to execute the data gathering, model building, and model evaluation phases. Thus, in distributed governance systems, in many scenarios, simple coordination among local agents leads to better results than adding smarter agents in the sharing agreement.

In Stage 4, we successfully developed two approaches for including ML in the agents' internal engines. In the first approach, the agents are fully responsible for the computational costs. In this light, the agents are exclusively responsible for all the ML-related stages. We also implemented a global approach, where the computational cost of storing the data and constructing ML models is transferred to the (local or central) coordinator(s).

When comparing the local vs. the global ML approach, we observe that results vary according to the governance system in place. Thus, the local method leads to a higher number of conflicts and higher efficiency than the global approach for centralized governance. On the other hand, in polycentric governance approaches, the local approach leads to higher efficiency and a lower number of conflict situations in the system. This result shows, once again, that capturing the local patterns in the system and applying local solutions lead to better spectrum sharing environments for all agents in the system.

10.0 Future Work

There are several avenues to continue the research presented in this dissertation. In Stages 1 and 3, we could explore additional rules of association and negotiation in the self-enforcement approach, including the initial assignment of property rights, as well as study additional strategies and rules in the agents' behavioral space that may influence the stability of the system. Along these lines, we also seek to explore the efficiency of the "stable" state of the system by incorporating a marginal analysis, on behalf of the PU, of costs of detection and benefits of less "harmful interference". More research is also necessary regarding the top-down aspects of self-governance. Ostrom [222] emphasized that the success of self-governance depends in part on the extent that higher-level authorities recognize the rights to self-governance. Pennington [223] extends Ostrom's perspective by showing that to understand why top-down government works better than bottom-up governance, it is necessary to explicitly consider the information and incentives problems confronting government. Additionally, we could study the impact of information in the governance systems. In particular, we aim to study the impact of information sharing in the number of conflict situations and the mitigation strategies implemented in the governance systems.

In Stage 2, we utilized different interpolation techniques to obtain a complete representation of the IC map in the region of interest. For this purpose, we relied on traditional interpolation techniques such as Nearest Neighbor, Natural Neighbor, etc. To assess more appropriately various sharing and governance strategies, we need to improve the accuracy of the available spectrum maps. One alternative is to improve upon or boost the REM simulator through Machine Learning techniques. The goal is that ML builds upon the context of the simulated values by modeling the errors of the simulation with respect to the available observations (similar examples are presented in [224, 225]).

A major challenge with the construction of the Interference Cartography (IC) map in REMs is the limited availability of up-to-date and widespread spectrum measurements. One part of this problem is the cost and complexity of sensor design and deployment. Machine Learning techniques can also be included in our REM simulator to minimize the number of

Measurement Capable Devices or sensors required to build an accurate spectrum map (see for example [226, 227]).

For the development of *Model 2.0*, we included additional resource access strategies (e.g., multi-tier users) and governance frameworks (e.g., polycentric) to improve our ABM. We could expand the model by including resource definitions in the model. Thus, we could include "naked" spectrum negotiations[1] and virtualized resources. For the latter, there exists a mapping of physical resources to performance metrics (e.g., coverage, throughput, etc.) to be shared in the system (see for example [17]). In addition, the system could benefit from the inclusion of market-based resource access strategies. For instance, the development of secondary spectrum markets in the system or the inclusion of private negotiations for the access of unused private resources (see the work of Gomez et al. [11]).

In our *Model 2.0*, we assumed that secondary users are cooperative (i.e., there are no "rogue" actors in the system). Thus, the only type of conflict situation in the system is *Type I*. We could expand the model by including the other types of conflict situations in the model. In particular, we could include non-cooperative agents as part of the system. This would allow us to study the impact of "rogue" users in distributed governance mechanisms such as polycentric and self-governance.

In our models, we define the agent's behaviors as simple interactions among the agents in the different tiers. To refine such behaviors, we could rely on game theory analysis. Thus, we could create a two-player (PU and SU) game to define the possible outcome of the system, the different payoffs, the equilibrium (if available), and the specific characteristics of such interaction.

In this work, conflict situations are defined as the activities of lower-tier participants (e.g., GAA) impacting the normal operations of higher-tier users (e.g., IA). To expand the analysis of conflict situations, we could analyze conflict situations within the different levels in the sharing structure. For instance, we can study conflict situations among opportunistic-access agents.

In Stage 4, we utilized five (5) well-known ML classification methods as the basis to

[1] Individual frequency bands/swatches.

predict the emergence of conflict situations. To improve the ML-enhanced model (i.e., *Model 3.0*), we could include additional ML classification models to test the overall performance of the system. A problem with supervised learning techniques is the fact that these methods require the generation and gathering of historical data. Thus, we could also implement Reinforcement learning as a valid ML training method. An agent can perceive and interpret its environment, take actions and learn through trial and error (see [228]). Besides the application of these "trainless" ML techniques, we could expand the behavior of the agents by devising different methods for rewarding desired behaviors and punishing negative behaviors (see for example [229]).

In *Model 3.0*, we use ML models exclusively to predict the emergence of conflict events. We could also develop an adaptive approach to choose appropriate conflict mitigation approaches. Thus, in each governance system, we can examine how ML techniques can help select and trigger the most appropriate conflict mitigation approach, according to the conditions of the band. In addition, we could use ML techniques to optimize transmission power and rates for the secondary users as an additional effort to reduce conflict situations.

The addition of machine learning algorithms implies the presence of out-of-band communications and infrastructure costs (e.g., computational and storage requirements). In this light, we can perform a cost-benefit analysis between the added costs of ML and the benefits of reducing the conflict situations in the system.

The analysis of interactions and conflict situations presented in this dissertation relates to the coexistence among active users. We could include other types of spectrum usage in our models. In particular, the analysis of active-passive use. The goal is to study the specific constraints related to passive spectrum use (e.g., scientific spectrum) and spectrum sharing schemes.

Appendix A

Baseline parameters

In this appendix, we detail the baseline parameters used throughout this dissertation. In Table 38, we find the base parameters use in the propagation models for the construction of the Interference Cartography maps presented in Section 7.2.

In Tables 39 and 40, we find the baseline parameters for the machine learning models used in Section 7.4.

Propagation models characteristics	
Free Space Path Loss (FSPL)	
Path Loss Constant (lo)	43.31 dB
Path Loss Exponent (α)	2
Longley Rice	
Antenna polarization	Horizontal
Ground conductivity (S/m)	0.005
Ground permittivity (scalar)	15
Atmospheric reactivate (scalar)	301
Climate zone	Continental temperature
Time variability tolerance (scalar)	0.5
Situation variability	0.5
Rain	
Line-of-sight (LOS)	True
Terrain and earth curvature	False
Rain rate (non-negative scalar)	16
Tilt angle of signal	0

Table 38: Propagation model baseline parameters

Logistic Regression		Support Vector Machine		Nearest Neighbor	
Parameter	**Value**	**Parameter**	**Value**	**Parameter**	**Value**
Penalty	12	Probability	True	N_neighbors	3
Dual	False	Random_state	0	Radius	1.0
Tol	0.0001	Degree	3	Algorithm	Auto
C	1.0	Tol	0.0001	Leaf_size	30
Fit_intercept	True	Max_iter	-1	Metric	Minkowski
Intercept_scaling	1	Decision_function	oui	P	2
Random_state	0	class_weight	None	Metric_params	None
Solver	lbfgs	Shrinking	True	n_jobs	None
Max_iter	100	Kernel	rbf	Random_state	0

Table 39: Machine learning algorithms baseline parameters (Table 1)

Random Forest		xGBoost	
Parameter	**Value**	**Parameter**	**Value**
N_estimators	100	objective	reg:linear
random_state	0	collapse_bytree	0.3
Criterion	gini	Max_depth	5
Max_depth	None	N_estimators	10
Min_samples_split	2	Booster	gbtree
Min_samples_leaf	1	Learning_rate	0.3
Bootstrap	True	Min_split_loss	0
Max_features	None	Sampling_method	Uniform
Max_leaf_nodes	None	Reg_lambda	1

Table 40: Machine learning algorithms baseline parameters (Table 2)

Appendix B

Spatial representation of the Interference Cartography Maps

In section 7.2, we analyze the map representation outcome of the REM simulator developed in Stage 2 of this dissertation. This representation is composed of three individual maps: *real-values*, *simulated-measurements*, and *error*. In Figure 123, we present the semivariogram of the different maps as a function of the SNR. We observe a measure of how much two samples taken from the IC map will vary in SNR depending on the distance between those samples. As we can observe, samples taken far apart will vary more than samples taken close to each other. In Figure 124, we observe the semivariogram of the different map representations and the corresponding RSS measured in the maps. As we can observe, there is a change in RSS as samples are further apart. These results help us confirm that the generated maps in the REM simulator are correctly capturing the "spatial autocorrelation" principal for its future interpolation.

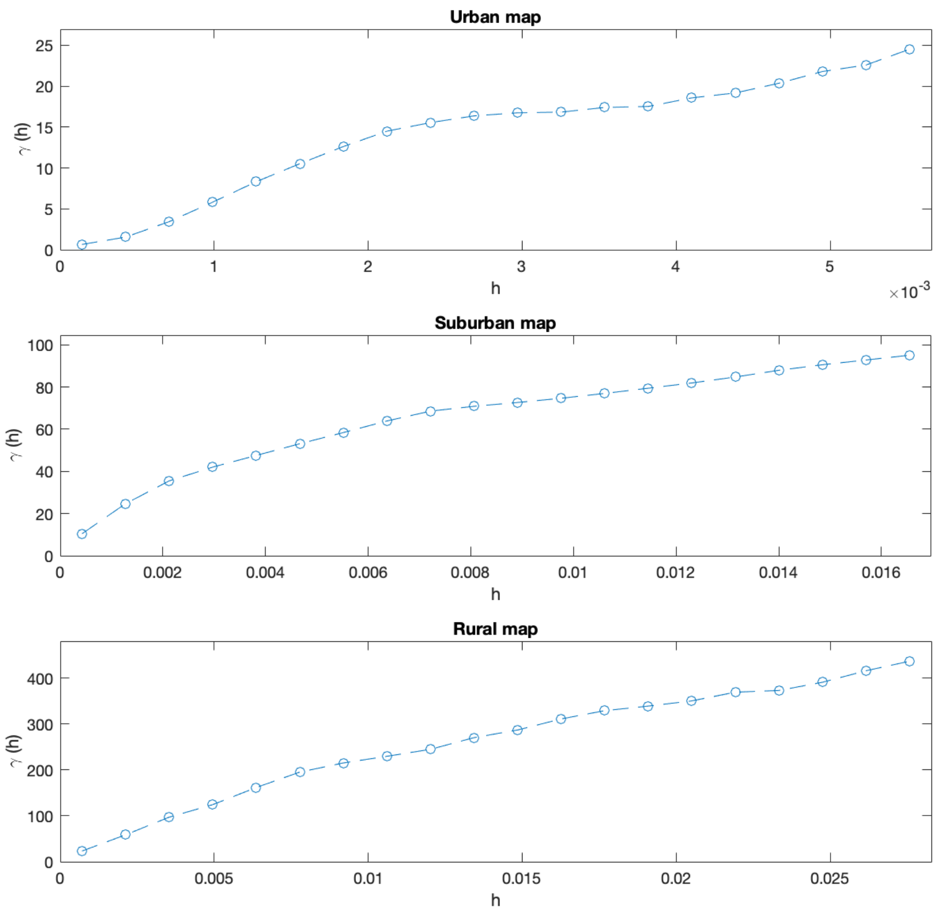


Figure 123: Stage 2 - Semivariogram of the constructed urban, suburban, and rural maps as a function of the SNR values in the representations

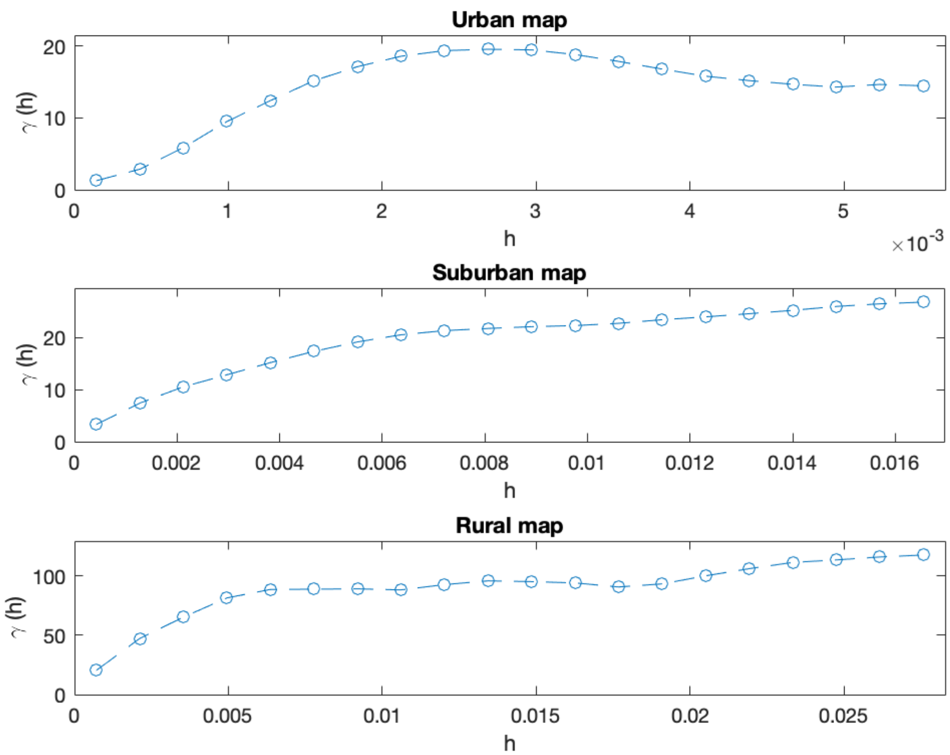


Figure 124: Stage 2 - Semivariogram of the constructed urban, suburban, and rural maps as a function of the RSS values in the representations

Appendix C

Definitions of the agents' interactions in the action situation of the IAD framework

In figures 125, 126, and 127 we see the interactions for the IAD framework action situation defined for each of the governance systems in the sharing agreement model (i.e., *Model 2.0*).

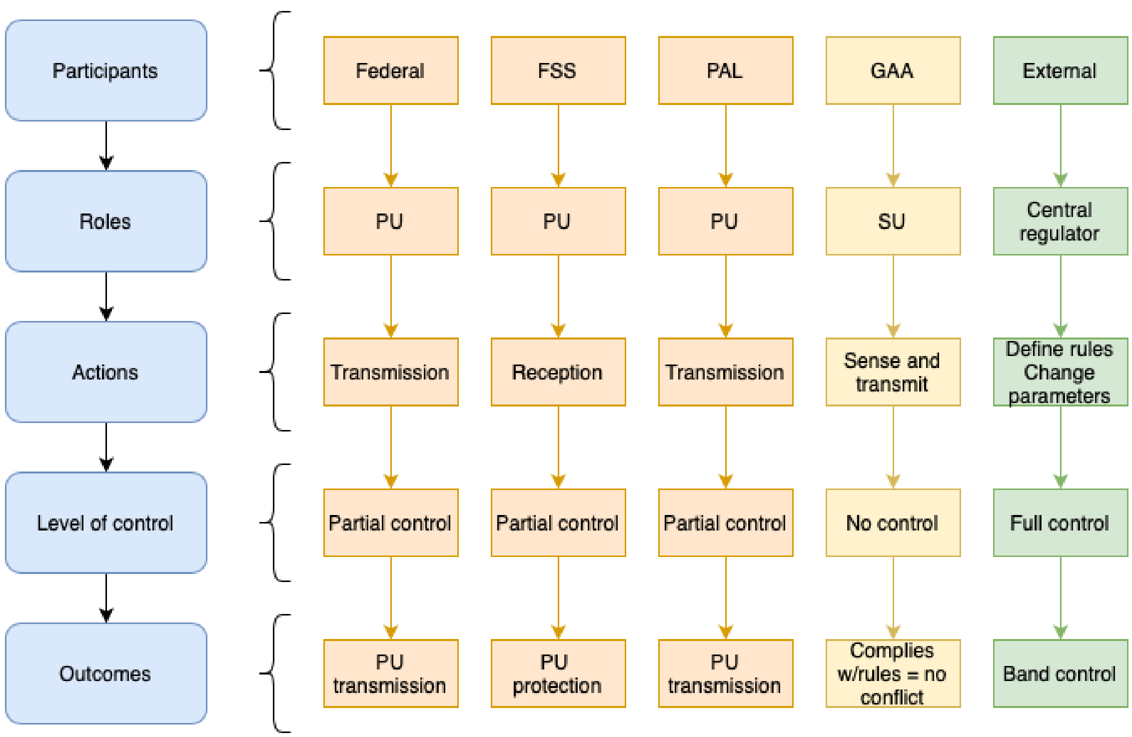


Figure 125: Stage 3 - IAD framework *interaction* definitions for centralized governance

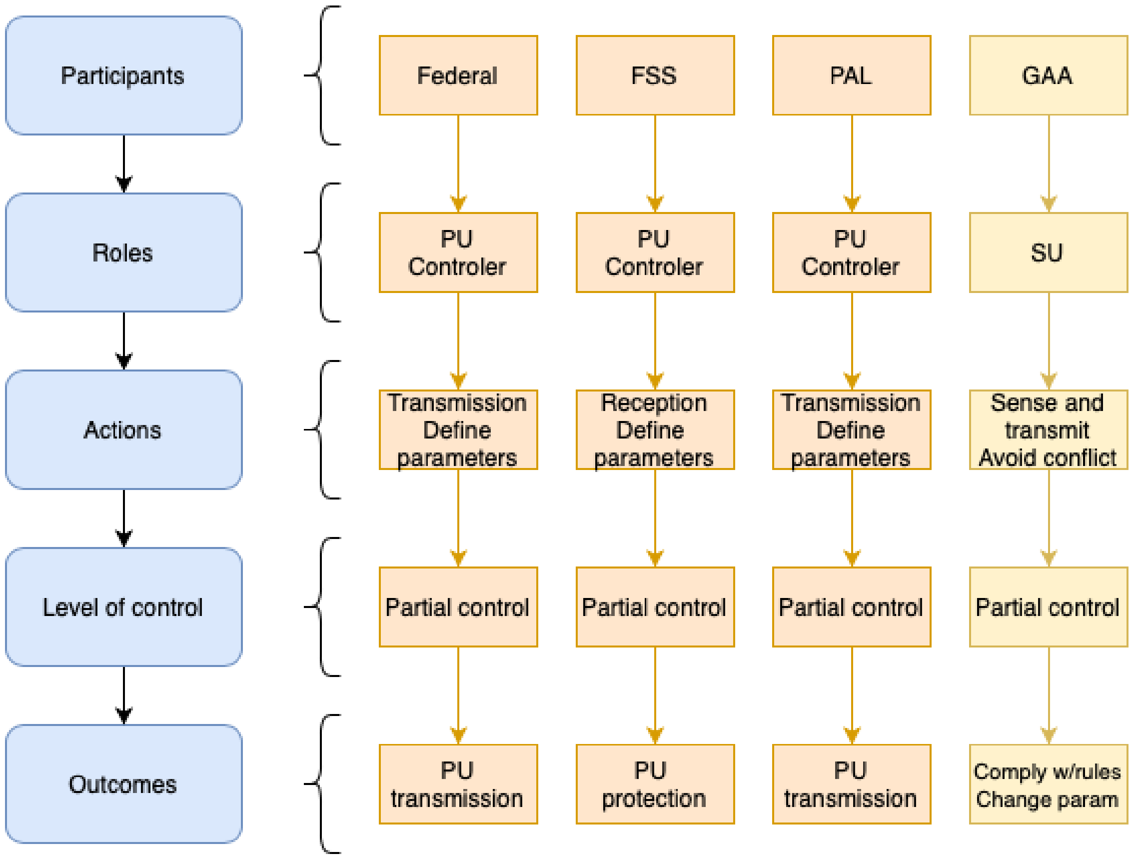


Figure 126: Stage 3 - IAD framework *interaction* definitions for self-governance

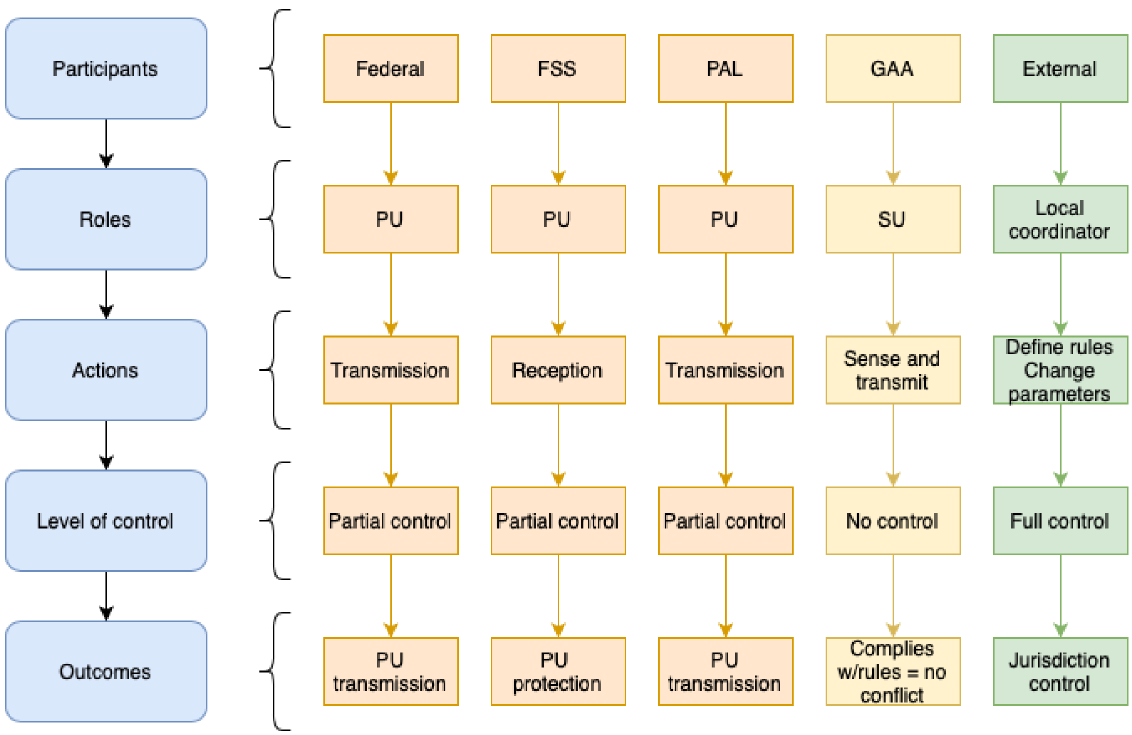


Figure 127: Stage 3 - IAD framework *interaction* definitions for polycentric governance

Appendix D

Rules-in-use of the IAD framework for the multi-tier spectrum sharing agreement

Tables 41, 42, and 43 show the *Rules-in-use* defined for the IAD framework and to be utilized in the multi-tier spectrum sharing ABM for centralized, polycentric, and self-governance, respectively.

Governance system:			**Centralized**		
Rules	**A**	**D**	**I**	**C**	**O**
Position	Federal	Assigned	PU	All the time	None
	FSS	Assigned	PU	All the time	None
	PAL	Assigned	PU	All the time	None
	GAA	Assigned	SU	All the time	None
	External	Assigned	Central authority	All the time	None
Authority	External	Obligated	Define conditions	All the time	None
Aggregation	Federal	Permitted	Operate	All the time	None
	FSS	Permitted	Operate	Passive	None
	PAL	Permitted	Operate	In channel	None
	GAA	Permitted	Operate	RSS <IT	Change parameters
	External	Obligated	Control operations	All the time	Change parameters
Information	GAA	Permitted	Get IC value (REM)	Active	None
	External	Permitted	Conflicts	All the time	None

Table 41: Stage 3 - *Rules-in-use* for the IAD framework in centralized governance systems

Governance system:			**Polycentric**		
Rules	**A**	**D**	**I**	**C**	**O**
Position	Federal	Assigned	PU	All the time	None
	FSS	Assigned	PU	All the time	None
	PAL	Assigned	PU	All the time	None
	GAA	Assigned	SU	All the time	None
	External (4)	Assigned	Local authority	All the time	None
Authority	External	Obligated	Define local conditions	All the time in jurisdiction	None
Aggregation	Federal	Permitted	Operate	All the time	None
	FSS	Permitted	Operate	Passive	None
	PAL	Permitted	Operate	In channel	None
	GAA	Permitted	Operate	RSS <IT	Change parameters
	External	Obligated	Control local operations	All the time in jurisdiction	Set avoidance strategy
Information	GAA	Permitted	Get IC value (REM)	Active	None
	External	Permitted	Conflicts	All the time in jurisdiction	Set avoidance strategy

Table 42: Stage 3 - *Rules-in-use* for the IAD framework in polycentric governance systems

Governance system:			Self-governance		
Rules	**A**	**D**	**I**	**C**	**O**
Position	Federal	Assigned	PU	All the time	None
	FSS	Assigned	PU	All the time	None
	PAL	Assigned	PU	All the time	None
	GAA	Assigned	SU	All the time	None
Authority	PU	Obligated	Define protection parameters	All the time	None
	PU	Permitted	Change parameters	If conflict	None
	SU	Permitted	Change parameters	If conflict	None
Aggregation	Federal	Permitted	Operate	All the time	None
	FSS	Permitted	Operate	Passive	None
	PAL	Permitted	Operate	In channel	None
	GAA	Permitted	Operate	RSS <IT	Set avoidance strategy
Information	GAA	Permitted	Get IC value (REM)	Active	None
	GAA	Permitted	Conflicts	If conflict	Set avoidance strategy
	PU	Permitted	Conflicts	If conflict	Change parameters

Table 43: Stage 3 - *Rules-in-use* for the IAD framework in self-governance systems

Appendix E

Multi-game settings in governance mechanisms for spectrum sharing agreements

In figures 128, 129, and 130, we find the multi-game settings defined for the different governance systems in the multi-tier spectrum sharing agreement model. These diagrams show the policy games taking place under the different characteristics described in Section 6.3.1.4 for centralized (see Figure 128), polycentric (see Figure 129), and self-governance (see Figure 130).

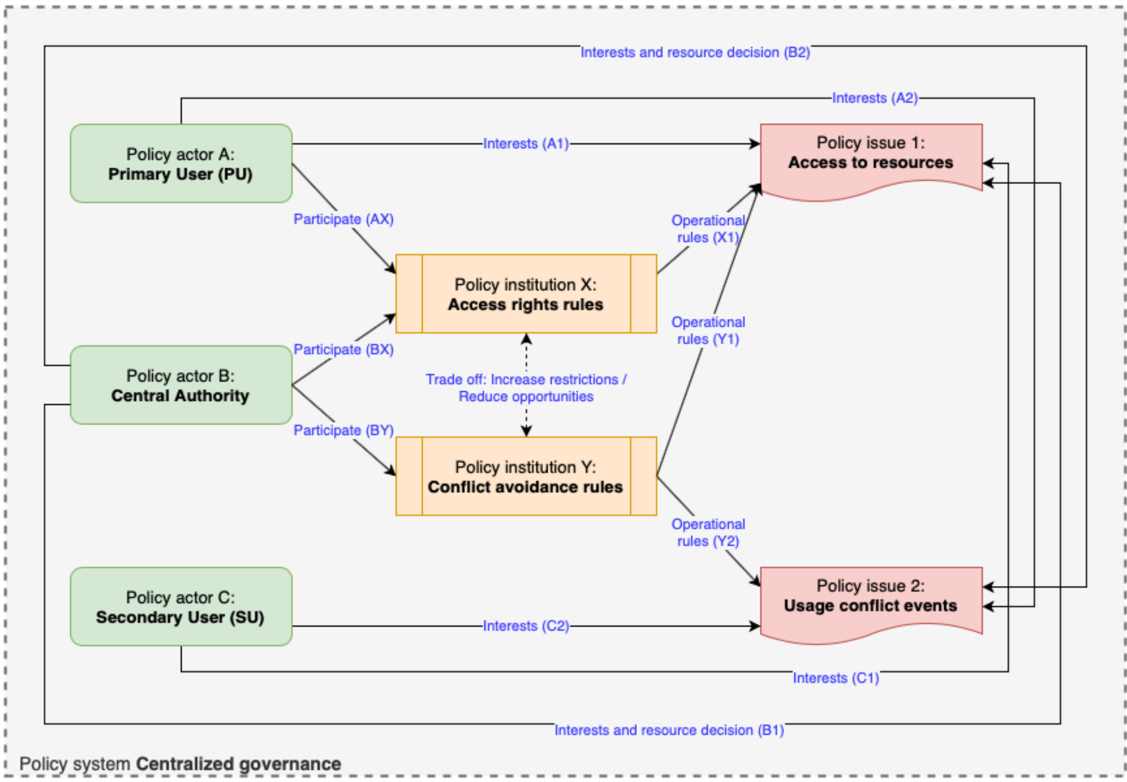


Figure 128: Stage 3 - EG framework - Centralized governance multi-game setting

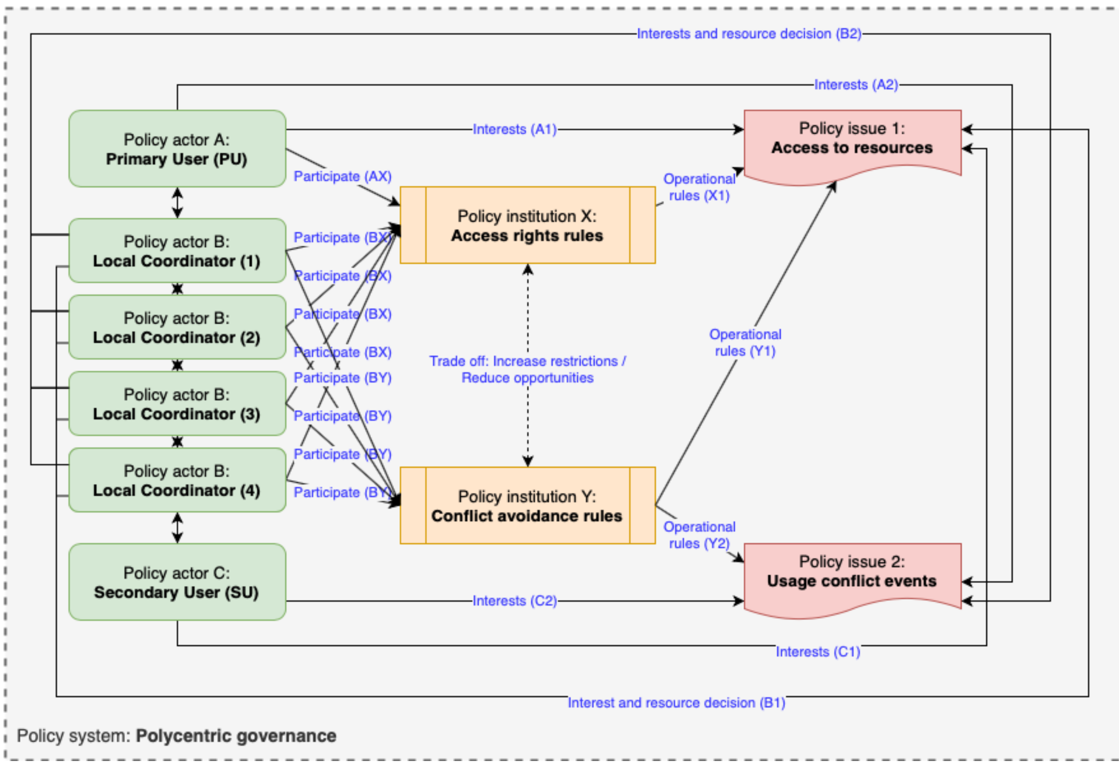


Figure 129: Stage 3 - EG framework - Polycentric governance multi-game setting

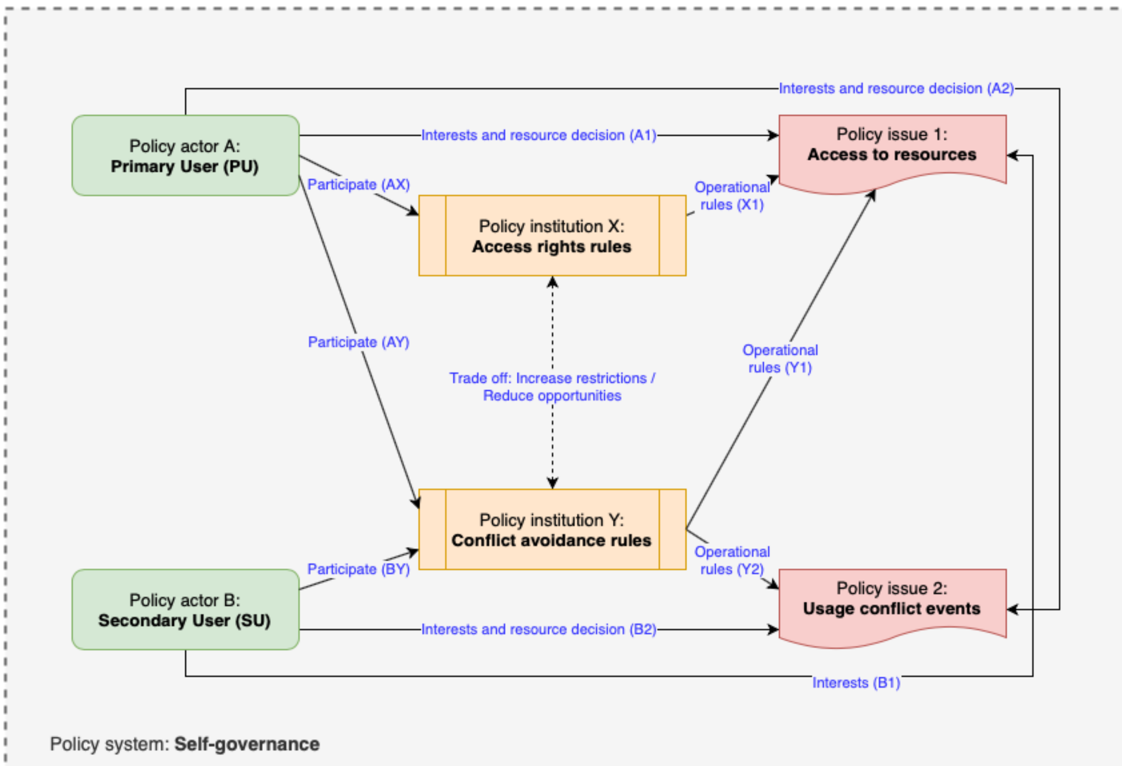


Figure 130: Stage 3 - EG framework - Self-governance multi-game setting

Appendix F

Implementation details of *Model 1.0*

We design *Model 1.0* to test the viability of "alternative" governance mechanisms in spectrum sharing settings. In particular, the implementation of a self-governing system in the two-tier model of the 1695-1710MHz band. In this light, we implement our ABM model in the ®NetLogo platform. This platform allows the addition of multi-agent programming and a modeling environment for simulating natural, artificial, and social phenomena. One of the main characteristics of NetLogo is that it is particularly well suited for modeling complex systems evolving. This tool also facilitates the exploration of connections between micro-level behaviors of independent individuals (i.e., agents) and macro-level patterns that emerge from their interactions [159]. The resulting model is the product of the agents and their corresponding rules, norms, strategies, and interactions, as shown through the model screenshot included in Figure 131.

We design *Model 1.0* on a modular scheme. Thus, the model is composed of three main modules (see Figure 132). First, the *Code* module is the core of *Model 1.0*, where we delineate all the definitions of the agents, environment, and interactions. Then, the *Experiment* module. In this part of the model, we detail all the experimental components. In other words, it contains the variables, levels, and experiment setup to test the different definitions presented in the *Code* element. Finally, the model also contains a *Graphical User Interface* module. In this part, the user can test different combinations of parameters and observe in real-time the model outcomes in the different plots and displays created for the GUI.

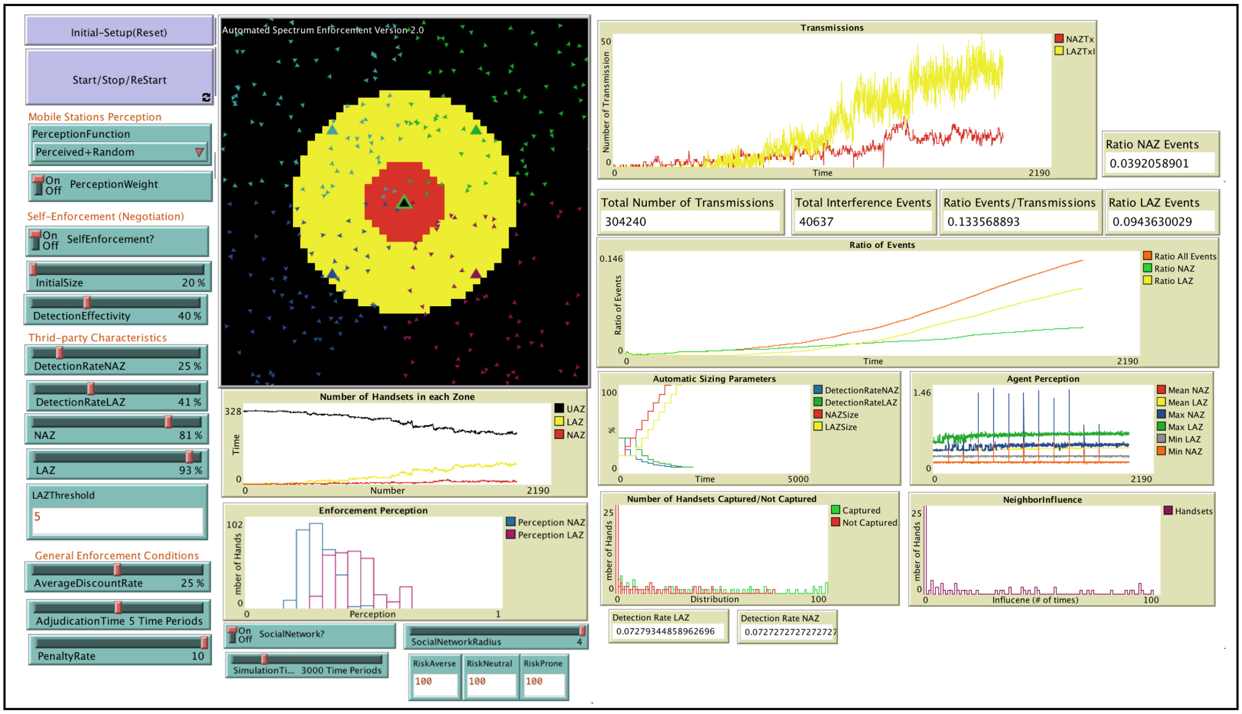


Figure 131: Screenshot of the graphical user interface (GUI) of *Model 1.0* implemented in Netlogo

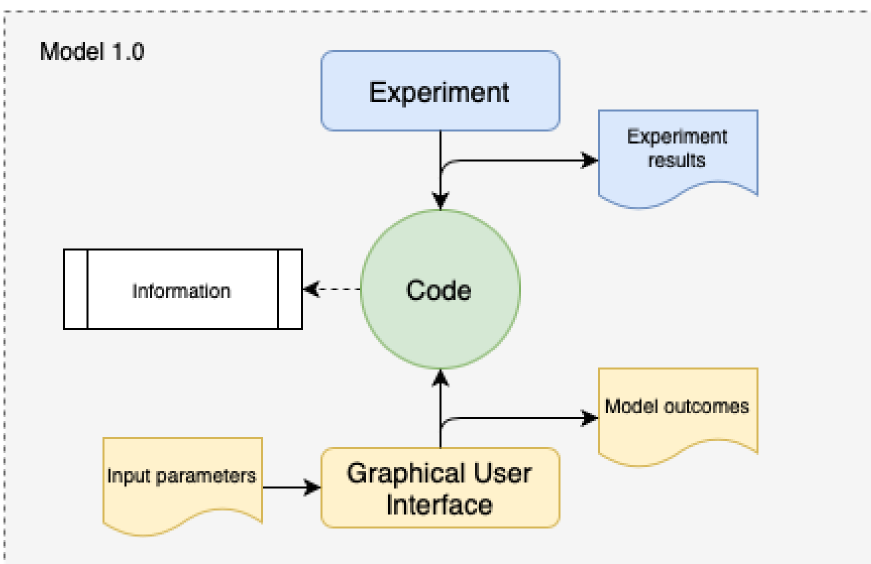


Figure 132: *Model 1.0* modeling structure

Appendix G

Implementation details of *Model 2.0*

As previously mentioned, we use ®Netlogo to develop the first version of our two-tier spectrum sharing ABM. We utilize Netlogo for our *Model 1.0* due to its simplicity to generate agent-based models and how popular it is among social scientists and in other disciplines. However, similar to any other tool, there are some trade-offs when working with Netlogo. The two main limitations of Netlogo are i) the lack of some of the standard software development tools, and ii) the limited performance with more complex models [230]. Netlogo lacks some of the standard software development tools, for example, a testing and debugging module. Currently, the modeler is in charge of running tests to minimize the risk of code errors. Finally, Netlogo is not a tool for highly optimized simulations. It has no code parallelization capacity or any other support for High-Performance Computing) (HCP). Consequently, for the following stages of this dissertation, we use a tool that addresses these particular challenges.

For *Model 2.0* and *Model 3.0* we use Python as our main modeling tool. For the Agent-Based Modeling part of our models, we use ®*Mesa* for Python. The advantage of using *Mesa* is that it is a modular framework for building, analyzing, and visualizing ABMs [231]. In this light, *Mesa* implements modeling, analysis, and visualization components that are kept separate but intended to work together. These modules are grouped into three categories, as follows:

- **Modeling:** This includes the models to build the Agent-Based Models. Thus, it includes components for the development of models, agents, a scheduler to determine the sequence in which the agents act, and space for them to move around.
- **Analysis:** Tools to collect data generated from your model or to run it multiple times with different parameter values.
- **Visualization:** Classes to create and launch an interactive model visualization using a

server with a JavaScript interface.

Similarly to *Model 1.0*, to construct *Model 2.0* and *Model 3.0*, we develop them in a modular architecture (see Figure 133). Three main modules are part of our ABM. First, *Model*, this is the engine of the simulation. It serves as the interface for the definitions of the agents, environment, and schedule (i.e., interactions). Further, it allows for the integration of external modules such as *Scikit-learn* for the integration of Machine Learning techniques in the model[1]. The second module is the *Analysis* component. This module allows us to implement the different experimental setups and sensitivity analyzes of the ABM. Finally, we implemented a Graphical User Interface (GUI) using the *Visualization* module of Mesa (see Figure 134). This interface allows the modelers to vary the different input model parameters of the simulation and observe in real-time both the agents' interactions and the outcomes of the agents' interactions (e.g., number of conflict events).

[1] This is the main component for the improvement of *Model 2.0* and creation of *Model 3.0*.

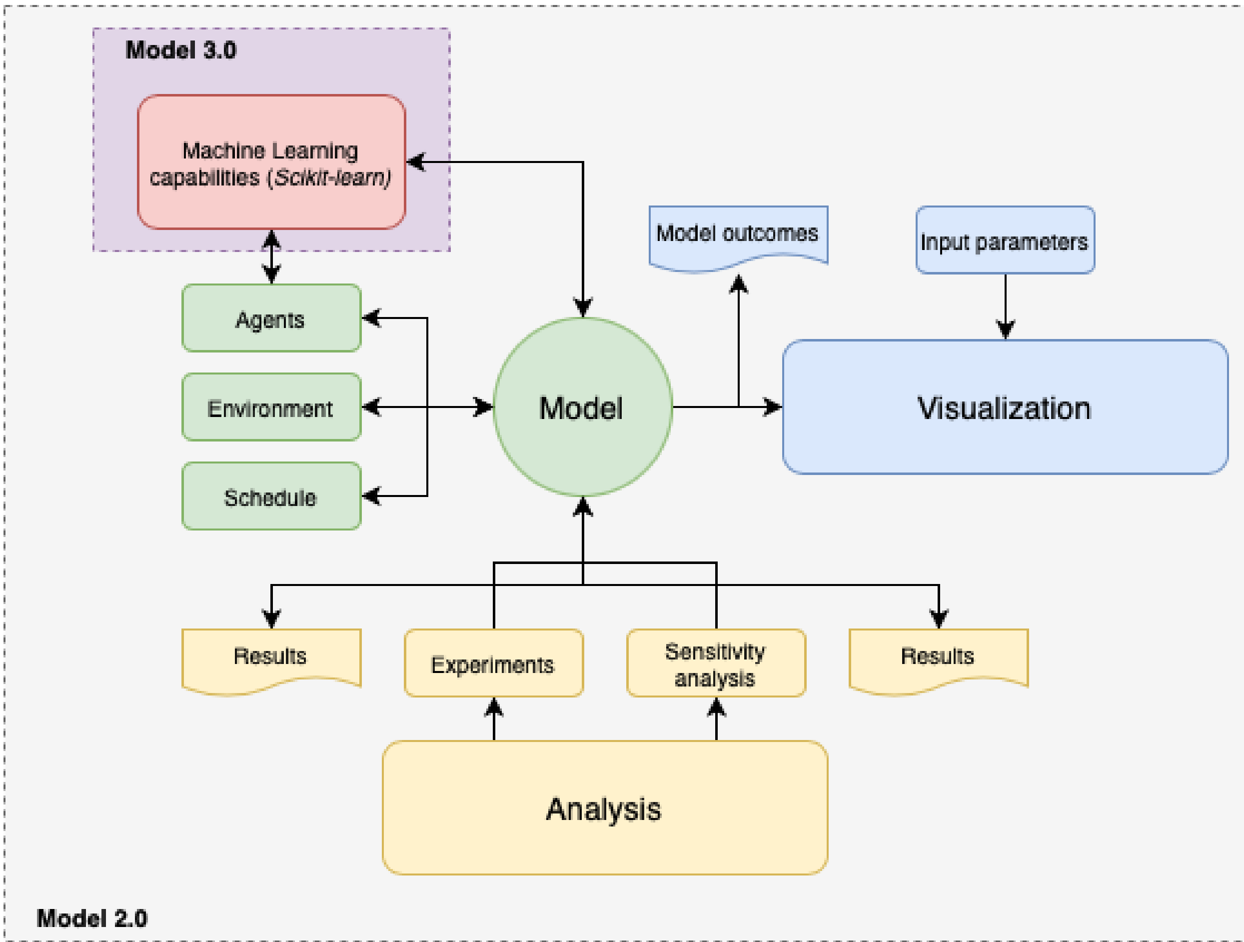


Figure 133: *Model 2.0* and *Model 3.0* modeling structure

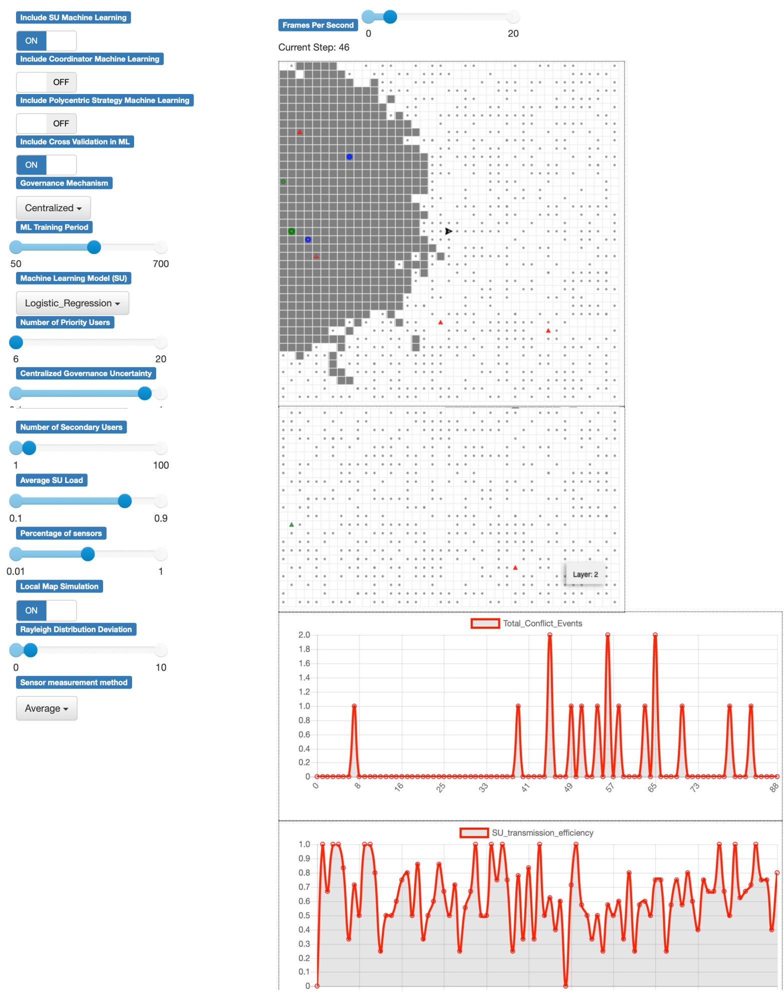


Figure 134: Screenshot of the graphical user interface (GUI) of *Model 2.0* and *Model 3.0* implemented in Python using the *Mesa* framework

Appendix H

Example of the preliminary data exploration process discussed in Stage 4

In Figures, 135, 136, and 137, we find an example of the preliminary data exploration process followed in Stage 4. These figures show the process followed in a centralized governance scheme, for a global machine learning approach, and a data-gathering phase of four hundred (400) agents' interactions. The goal of this exploration is to learn additional details of the data being used to build and fit the ML models we implement in Stage 4. In Figure 135, we show the general descriptors of the data, including the type of variables for each parameter, the number of unique values, and the distribution in the target variable (i.e., conflict), etc. Figures 136, and 137 depict a graphical presentation of the data, where we graphically explore the relationship between different feature variables. This exploration includes the distribution of SU's TxPower and *margin of error*, the number of active users per interaction, the relationship between the RSS, interference threshold, and conflict, among others.

```python
# Summary of the data
print(centralized_data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6741 entries, 0 to 6740
Data columns (total 8 columns):
Iteration                 6741 non-null int64
Agent_id                  6741 non-null int64
Conflict                  6741 non-null int64
RSS                       6741 non-null float64
TxPower                   6741 non-null float64
Channel                   6741 non-null object
ErrorMargin               6741 non-null int64
Interference_Threshold    6741 non-null float64
dtypes: float64(3), int64(4), object(1)
memory usage: 421.4+ KB
None
```

```python
# Number of unique values in each column
centralized_data.nunique()
```

```
Iteration                  400
Agent_id                   100
Conflict                     2
RSS                       6610
TxPower                    143
Channel                      2
ErrorMargin                  1
Interference_Threshold      87
dtype: int64
```

```python
# Number of NaN values in the data
centralized_data.isna().sum()
```

```
Iteration                 0
Agent_id                  0
Conflict                  0
RSS                       0
TxPower                   0
Channel                   0
ErrorMargin               0
Interference_Threshold    0
dtype: int64
```

```python
# General data description
centralized_data.describe().round(decimals = 3)
```

	Iteration	Agent_id	Conflict	RSS	TxPower	ErrorMargin	Interference_Threshold
count	6741.000	6741.000	6741.000	6741.000	6741.000	6741.0	6741.000
mean	197.537	2545.535	0.269	-84.320	0.474	0.0	-81.551
std	114.681	31.164	0.444	3.075	0.266	0.0	0.982
min	0.000	2496.000	0.000	-130.000	0.050	0.0	-83.597
25%	101.000	2516.000	0.000	-85.438	0.280	0.0	-82.353
50%	197.000	2544.000	0.000	-84.116	0.485	0.0	-81.534
75%	298.000	2575.000	1.000	-82.882	0.664	0.0	-80.723
max	399.000	2595.000	1.000	-80.040	1.100	0.0	-80.000

```python
# Number of data instances for the "target" variable
# 0 = No conflict; 1 = conflict
centralized_data.Conflict.value_counts()
```

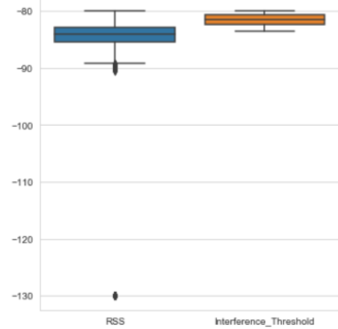
```
0    4927
1    1814
Name: Conflict, dtype: int64
```

```python
# Average of the target value (Conflict)
centralized_data.Conflict.mean()
```

```
0.26909954012757753
```

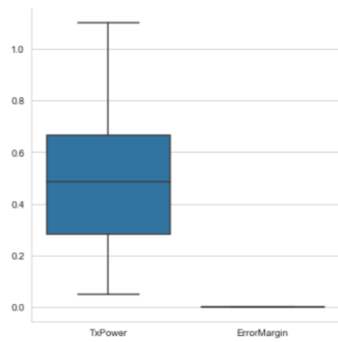
Figure 135: Stage 4 - Example of a preliminary data exploration process - General data descriptors

```python
# Distribution of the RSS from the IC map and the Interference Threshold (IT) of the system
sns.catplot(data = centralized_data[['RSS','Interference_Threshold']], kind='box')
plt.show()
```



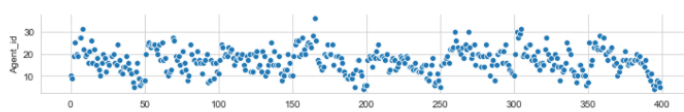

```python
# Distribution of the SU transmission power and margin of error
sns.catplot(data=centralized_data[['TxPower','ErrorMargin']],kind='box')
```

```
<seaborn.axisgrid.FacetGrid at 0x7fdac534e7d0>
```




```python
# Number of active agents (SUs) per interaction
active_agents = centralized_data[['Iteration','Agent_id']].groupby(by=['Iteration']).count()
sns.set_style('whitegrid')
sns.relplot(data=active_agents,x=active_agents.index.values,y='Agent_id',aspect=2)
plt.xlabel('Iteration')
```

```
Text(0.5, 6.799999999999994, 'Iteration')
```




```python
# Number of conflict situations (Conflict = 1) per interaction
conflicts_per_interaction = centralized_data[['Iteration','Conflict']].groupby(by=['Iteration']).sum()
p=sns.relplot(data=conflicts_per_interaction,x=conflicts_per_interaction.index.values,y='Conflict',aspect=1.75)
plt.xlabel('Iteration')
```

```
Text(0.5, 6.799999999999994, 'Iteration')
```

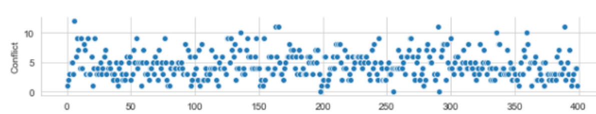
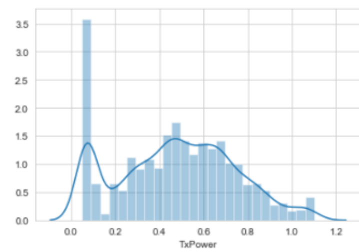


Figure 136: Stage 4 - Example of a preliminary data exploration process - Graphical exploration (1)

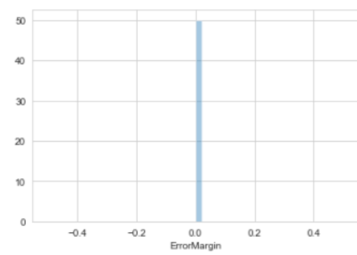
```python
# Histogram of transmission power
sns.distplot(centralized_data.TxPower)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fdac9f9d310>



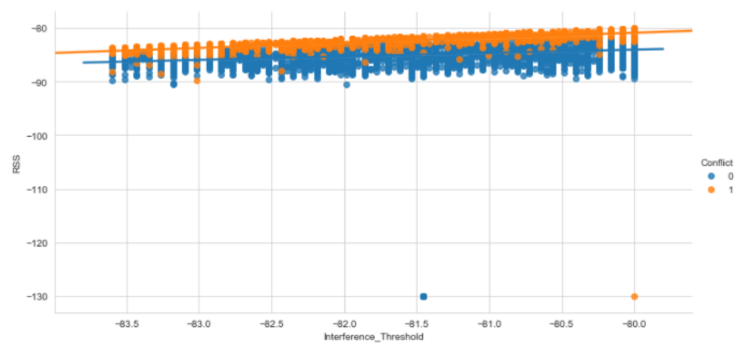

```python
# Histogram of margin of error
sns.distplot(centralized_data.ErrorMargin)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fdaca129950>




```python
# Relation betwen RSS, interference threshold, and conflicts
sns.lmplot(data = centralized_data, y = 'RSS', x = 'Interference_Threshold',hue='Conflict',aspect=2)
```

<seaborn.axisgrid.FacetGrid at 0x7fdac9e6ed10>




```python
# Relationship between RSS, margin of error, and conflict
sns.lmplot(data=centralized_data,y='RSS',x='ErrorMargin',hue='Conflict',aspect=2)
```

<seaborn.axisgrid.FacetGrid at 0x7fdaca249450>

Figure 137: Stage 4 - Example of a preliminary data exploration process - Graphical exploration (2)

Appendix I

Hypothesis testing and statistical validation

In this chapter we present additional details regarding the hypothesis testing and statistical validation presented in Section 8.2. The following tables summarize the results of the T-test valuations implemented in each Hypothesis.

Hypothesis					H1	
Scenario	**T statistic**	**P-value**	**Difference in mean**	**Confidence Interval**	**Lower bound**	**Upper bound**
1	15.2515	7.6541E-41	9.1927	90%	8.4189	9.9665
				95%	8.1987	10.1867
2	4.0528	6.2E-5	0.4656	90%	0.31807	0.6130
				95%	0.2761	0.6549
3	10.5634	6.7904E-23	2.55	90%	2.2400	2.8599
				95%	2.1519	2.9480

Table 44: Hypothesis testing details - H1

Hypothesis					H2.1	
Scenario	**T statistic**	**P-value**	**Difference in mean**	**Confidence Interval**	**Lower bound**	**Upper bound**
1	3.3951	7.3E-4	0.0167	90%	0.0103	0.0229
				95%	0.0085	0.0247
2	10.2054	3.1535E-22	6.6261	90%	5.7928	7.4593
				95%	5.5560	7.6961
3	1.3637	0.01728	0.0031	90%	0.0001	0.0059
				95%	0.0006	0.0063
4	18.3595	9.2377E-63	0.3728	90%	0.3467	0.3988
				95%	0.3393	0.4062
5	46.1437	1.45E-65	7.4300	90%	7.2236	7.6364
				95%	7.1651	7.6949

Table 45: Hypothesis testing details - H2.1

Hypothesis					H2.2	
Scenario	**T statistic**	**P-value**	**Difference in mean**	**Confidence Interval**	**Lower bound**	**Upper bound**
1	0.5288	0.5970	0.0022	90%	-0.0031	0.0076
				95%	0.0046	0.0091
2	14.2270	3.2944E-37	8.7294	90%	7.9417	9.5171
				95%	7.7177	9.7411
3	3.4416	6.02E-4	0.0047	90%	0.0029	0.0064
				95%	0.0024	0.0069
4	19.9153	5.5768E-71	0.3997	90%	0.3797	0.4254
				95%	0.3667	0.4327
5	79.3435	1.45E-65	12.0288	90%	11.8345	12.2231
				95%	11.7794	12.2782
6	80.4231	1.75E-67	5.0175	90%	4.8575	5.1775
				95%	4.7665	5.0245

Table 46: Hypothesis testing details - H2.2

Hypothesis					H3.1	
Scenario	**T statistic**	**P-value**	**Difference in mean**	**Confidence Interval**	**Lower bound**	**Upper bound**
1	1.8677	0.0062	0.0232	90%	0.0005	0.0461
				95%	0.0027	0.0437
2	-7.0198	5.8407E-12	-0.1470	90%	-0.1739	-0.1202
				95%	-0.1815	-0.1125
3	-28.1549	1.211E-166	-0.2053	90%	-0.2146	-0.1959
				95%	-0.2173	-0.1933

Table 47: Hypothesis testing details - H3.1

Hypothesis					H3.2	
Scenario	**T statistic**	**P-value**	**Difference in mean**	**Confidence Interval**	**Lower bound**	**Upper bound**
1	5.1271	3.8018E-7	0.0629	90%	0.0471	0.07865
				95%	0.0427	0.0831
2	26.4186	7.3084E-100	0.5243	90%	0.4988	0.5498
				95%	-0.4916	0.5570
3	5.4713	4.6005E-8	0.0385	90%	0.0295	0.0475
				95%	0.0269	0.0501
4	11.2488	3.9152E-29	0.0761	90%	0.0674	0.0848
				95%	0.0650	0.0873

Table 48: Hypothesis testing details - H3.2

Hypothesis					H4	
Scenario	**T statistic**	**P-value**	**Difference in mean**	**Confidence Interval**	**Lower bound**	**Upper bound**
1	7.8061	5.2446E-14	4.831	90%	4.0365	5.6254
				95%	3.8106	5.8513
2	14.0720	3.665E-36	8.4938	90%	7.7189	9.2688
				95%	-7.4985	9.4889

Table 49: Hypothesis testing details - H4

Hypothesis					H5.1	
Scenario	**T statistic**	**P-value**	**Difference in mean**	**Confidence Interval**	**Lower bound**	**Upper bound**
1	-1.2194	0.00167	-0.0224	90%	-0.0250	-0.0198
				95%	-0.0255	-0.0193
2	3.6813	4.55E-4	0.0016	90%	0.0010	0.0022
				95%	0.0005	0.0027
3	-6.9707	3.6178E-7	-0.0534	90%	-0.0567	-0.0501
				95%	-0.0582	-0.0048
4	-3.7354	4.1435E-5	-0.0156	90%	-0.0163	-0.0149
				95%	-0.0171	-0.0142
5	-1.7519	0.0006	-0.0572	90%	-0.0609	-0.0535
				95%	-0.0635	-0.0509

Table 50: Hypothesis testing details - H5.1

Hypothesis					H5.2	
Scenario	**T statistic**	**P-value**	**Difference in mean**	**Confidence Interval**	**Lower bound**	**Upper bound**
1	-9.9611	7.7891E-10	-0.1395	90%	-0.1439	-0.1351
				95%	-0.1471	-0.1319
2	-9.2718	6.6789E-10	-0.2735	90%	-0.2794	-0.2676
				95%	-0.2832	-0.2638
3	18.2591	5.3476E-21	0.01613	90%	0.0112	0.0210
				95%	0.0064	0.0258
4	-29.0445	6.1298E-26	-0.4720	90%	-0.4920	-0.4519
				95%	-0.5390	-0.4050
5	-13.8071	3.7614E-15	-0.4411	90%	-0.4699	-0.4123
				95%	-0.5175	-0.3647

Table 51: Hypothesis testing details - H5.2 (local ML approach)

Hypothesis					H5.2	
Scenario	**T statistic**	**P-value**	**Difference in mean**	**Confidence Interval**	**Lower bound**	**Upper bound**
1	2.0911	4.6732E-5	0.0531	90%	0.0422	0.0620
				95%	0.0430	0.0632
2	2.8031	5.1531E-5	0.0478	90%	0.0404	0.0552
				95%	0.0372	0.0584
3	3.8116	3.8621E-7	0.0844	90%	0.0732	0.0956
				95%	0.0688	0.1001
4	7.5331	7.4398E-11	0.0700	90%	0.0629	0.0771
				95%	0.0568	0.0832
5	5.5528	8.9734E-9	0.1041	90%	0.0933	0.1149
				95%	0.0855	0.1227

Table 52: Hypothesis testing details - H5.2 (global ML approach)

Hypothesis					H6	
Scenario	**T statistic**	**P-value**	**Difference in mean**	**Confidence Interval**	**Lower bound**	**Upper bound**
1	-2.6759	0.0077	-0.6763	90%	-1.0007	-0.3519
				95%	-1.0929	-0.2597
2	-0.2389	0.8112	-0.0295	90%	-0.1883	0.1291
				95%	-0.2334	0.1743
3	14.9684	5.1366E-43	1.9407	90%	1.7744	2.1071
				95%	1.7271	2.1543

Table 53: Hypothesis testing details - H6

Hypothesis					H7	
Scenario	**T statistic**	**P-value**	**Difference in mean**	**Confidence Interval**	**Lower bound**	**Upper bound**
1	-10.6014	2.6953E-23	-3.3100	90%	-3.7107	-2.9092
				95%	-3.8247	-2.7952
2	-11.9123	4.6190E-28	-4.5327	90%	-5.0212	-4.0442
				95%	-5.1601	-3.9053
3	9.3754	4.8830E-19	2.7750	90%	2.3950	3.1549
				95%	2.2870	3.2629
4	-11.4941	1.2163E-26	-3.4072	90%	-3.7877	-3.0267
				95%	-3.8959	-2.9185
5	-13.8013	1.8665E-35	-4.2894	90%	-4.6884	-3.8904
				95%	-4.8019	-3.7769

Table 54: Hypothesis testing details - H7 (Centralized governance)

Hypothesis					H7	
Scenario	**T statistic**	**P-value**	**Difference in mean**	**Confidence Interval**	**Lower bound**	**Upper bound**
1	20.2784	8.6705E-72	2.7761	90%	2.6004	2.9517
				95%	2.7761	3.0016
2	-0.9611	0.3370	-0.1005	90%	-0.2348	0.0337
				95%	-0.2730	0.071
3	28.5943	5.7668E-116	5.0044	90%	4.7799	5.2289
				95%	4.7161	5.2927
4	16.1278	3.7760E-50	2.1489	90%	1.9779	2.3198
				95%	1.9294	2.3683
5	0.1795	0.8575	0.0227	90%	-0.1399	0.1855
				95%	-0.1862	0.2317

Table 55: Hypothesis testing details - H7 (Polycentric governance)

Appendix J

Results of the (Sobol) global sensitivity analysis

In Tables 56 and 57, we find the summary of the global sensitivity analysis presented in Section 8.3.2. Table 56 depicts the first-order (*S1*), second-order (*S2*), and total-order (ST) indices for the model outcome average number of conflict events. In Table 57, we observe the first-order (*S1*), second-order (*S2*), and total-order (ST) indices for the model outcome average SU transmission efficiency.

(Sobol) global sensitivity analysis				
Outcome:	**Average number of conflict situations**			
Parameter	**S1**	**S1_conf**	**ST**	**ST_conf**
Number_PU	0.111304	0.025179	0.120311	0.014738
Number_SU	0.285583	0.039033	0.395771	0.027254
SU_load	0.148057	0.024676	0.230436	0.026582
Sensor_density	0.000671	0.004610	0.005379	0.000867
Fading_deviation	0.181231	0.024270	0.338132	0.030291
Second-order interactions				
Parameter			**S2**	**S2_conf**
Number_PU, number_SU			0.060236	0.029900
Number_PU, SU_load			0.082246	0.030549
Number_PU, sensor_density			0.063428	0.026696
Number_PU, fading_deviation			0.008078	0.032988
Number_SU, SU_load			0.060761	0.053771
Number_SU, sensor_density			0.062231	0.053090
Number_SU, fading_deviation			0.009588	0.053330
SU_load, sensor_density			0.011494	0.031063
SU_load, fading_deviation			0.022650	0.037584
Sensor_density, fading_deviation			0.032303	0.005828

Table 56: (Sobol) global sensitivity analysis - Variance indices for (output) average number of conflict situations

(Sobol) global sensitivity analysis				
Outcome:	**SU transmission efficiency**			
Parameter	**S1**	**S1_conf**	**ST**	**ST_conf**
Number_PU	0.305037	0.098881	0.540494	0.064322
Number_SU	0.022510	0.054446	0.208744	0.040063
SU_load	0.018087	0.049972	0.203050	0.040670
Sensor_density	0.031486	0.038476	0.090126	0.014825
Fading_deviation	0.271389	0.091642	0.518900	0.073107
Second-order interactions				
Parameter			**S2**	**S2_conf**
Number_PU, number_SU			0.037898	0.054815
Number_PU, SU_load			0.120278	0.058647
Number_PU, sensor_density			0.020294	0.052241
Number_PU, fading_deviation			0.143357	0.047735
Number_SU, SU_load			0.013851	0.028634
Number_SU, sensor_density			0.061220	0.027843
Number_SU, fading_deviation			0.054825	0.032915
SU_load, sensor_density			0.052045	0.027497
SU_load, fading_deviation			0.119452	0.048005
Sensor_density, fading_deviation			0.006260	0.025685

Table 57: (Sobol) global sensitivity analysis - Variance indices for (output) SU transmission efficiency

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