Automatic Calibration in Crowd-sourced Network of Spectrum Sensors

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ABSTRACT

Spectrum monitoring is vital for optimizing wireless spectrum usage, minimizing interference, and ensuring efficient communication systems. In large-scale monitoring systems, the issue of trust in sensor data becomes critical. Separate from the issue of malicious actors, there must be an underlying level of trust in the basic quality of a sensor's data. A sensor can be compromised by physical obstructions, improper installation, or incorrect descriptions. This paper introduces an automated approach for evaluating RF sensor quality, leveraging airplane transponder signals to assess obstructions and other known man-made signals across frequency bands to quantify obstruction severity. Our experiments demonstrate the effectiveness of these techniques in automatically calibrating sensors without supervision.

CCS CONCEPTS

• **Hardware** → **Sensors and actuators**; **Signal processing systems**; **Hardware reliability screening**; • **Computer systems organization** → *Reliability*;

KEYWORDS

Automatic calibration, RF sensor Signal of opportunity, Spectrum monitoring

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1 INTRODUCTION

Spectrum monitoring will play a crucial role in tomorrow's wireless networking landscape. By continuously monitoring the spectrum, regulatory authorities, service providers, and businesses can ensure the quality and reliability of their wireless networks. Spectrum monitoring also facilitates the detection of unauthorized or illegal transmissions, aiding in the enforcement of regulations and the prevention of harmful interference. Some recent examples are the potential for interference from 5G cellular networks in airplanes' radio altimeters [29] and GPS systems [24]. Data on true interference levels provided by spectrum monitoring is crucial for understanding and resolving such situations. By providing valuable insights into spectrum usage patterns, spectrum monitoring supports the planning and deployment of future wireless networks, enabling the seamless operation of various applications and services that rely on wireless connectivity, such as telecommunications, IoT, and public safety.

Covering large geographical areas continuously presents significant challenges when performing spectrum monitoring [3], [37]. The sheer scale requires a substantial deployment of monitoring equipment and resources, which can be costly and time-consuming. As a result, distributed monitoring has been a long-standing problem in this area. Crowdsourcing holds significant potential in spectrum monitoring due to its ability to engage a large number of participants to cover large geographical areas [14]. In this approach, participants set up a spectrum sensor node such as a Software-Defined Radio (SDR) that captures and transmits spectrum related information to the cloud. *We envision a distributed system in which node operators offer spectrum sensing as a service and users pay to rent these services from operators.*

A key problem hindering the realization of this idea is how users can trust the quality of data offered by each operator. There are numerous problems that affect the quality of data such as the efficiency of the antenna and the sensitivity of the SDR in the desired spectrum bands, potential obstruction of the antenna in relation to the signal source, and installation issues such as damaged antenna cables. Consequently, if users require multiple sensors, manually testing each individual node becomes impractical, presenting a significant scaling issue. Note that these nodes are set up by random people around the world, and no assumptions can be made about the quality of the setup. Furthermore, since node operators are paid for these services, there is a potential incentive to provide fabricated or incorrect data in order to receive reimbursement.

Therefore, we propose an **automatic** calibration mechanism that evaluates the capability of a sensor node to accurately receive transmissions within specific frequency bands. We believe that this system will enable a trusted crowd-sourced network of spectrum sensors and will have a great

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impact by enabling spectrum resource virtualization. The idea behind our automatic calibration system is to compare the signals received by a sensing node with known signal sources in various frequency bands. At a high level, we draw inspiration from the ambitious concept of cognitive radios [32], which aims to achieve full-awareness sensing. However, the application of cognitive radio ideas has been mostly limited to dynamic spectrum sharing. We revisit this concept by considering many sources of RF transmissions, with the goal of providing accurate evaluations of sensor nodes.

We address two technical challenges in our work: 1) How can we automatically determine the presence of obstructions around a sensor node? For instance, the reception of a node can be affected by nearby buildings or mountains. 2) How can we automatically assess the reception capability of a node across frequency bands? For example, can a node truly receive the entire claimed range of 100 MHz to 6 GHz?

Our solution for the first challenge involves utilizing Automatic Dependent Surveillance – Broadcast (ADS-B) wireless messages transmitted by nearby airplanes. These messages inform air traffic controllers about location and speed of an aircraft. ADS-B operates at a frequency of 1090 MHz and relies on line-of-sight communication. Consequently, any obstruction significantly degrades the signal. Since airplanes fly in all directions, we can assess the reception capability of a stationary sensor node from various angles. For the second challenge, we measure the signal quality from known sources covering a wide frequency range. For example, cellular networks are an excellent candidate for this purpose, as they operate in different frequency bands ranging from a few hundred MHz to 6 GHz. With the advent of 5G, this range has extended to tens of GHz. Additionally, in dense urban environments cellular networks can provide some diversity in spatial measurements. Even if a signal is not present in the exact band of interest, there are often signals in neighboring bands sufficiently close to estimate receiver performance.

We have implemented this idea using software-defined radios and conducted evaluations by receiving and decoding ADS-B messages. Our measurements demonstrate the effective determination of obstructions around a sensor node using ADS-B messages. Additionally, we showcase the capability of utilizing diverse signals such as 4G/5G mobile networks and broadcast TV signals to assess the impact of obstructions across different frequency bands.

In this paper, we make the following contributions:

- We propose a methodology that utilizes existing wireless signals to automatically evaluate the quality of data provided by nodes in a network of spectrum sensors.
- We leverage ADS-B messages from nearby airplanes to determine the obstructions around a sensor node.
- We utilize signals across various frequency bands to assess the impact of obstructions on a sensor node's reception.

2 OVERVIEW

In this section, we briefly explain the architecture of spectrum monitoring networks. These networks consist of tens, hundreds, or even more sensor nodes that are deployed over large geographical areas. Each sensor node comprises a software-defined radio (SDR) capable of capturing wireless signals across a wide frequency range and a host processor that receives the raw I/Q data from the SDR. The host processor can be a low-power single-board computer such as a Raspberry Pi or a more powerful edge device. The host may perform various processing tasks on the I/Q data, such as signal detection or computing the Fast Fourier Transform, before transmitting the data to the cloud for storage and further processing.

Wireless signals exhibit variations across locations and over time, making spectrum monitoring challenging, particularly over large geographical areas. This underscores the importance of volunteers who contribute by installing sensor nodes. Their involvement is crucial for the success of large-scale spectrum monitoring systems. Encouragingly, networks of volunteer-run sensor nodes have been successfully employed for aircraft (FlightAware) and weather monitoring (Citizens Weather Observing Program). To achieve the widespread adoption of such systems, it is essential to incentivize volunteers. Installing and maintaining sensor nodes requires time, effort, and financial resources. Therefore, volunteers should be compensated for the services they provide. One approach to address this is virtualization. Sensor node operators can offer virtualized spectrum monitoring resources, which users then rent and pay for accordingly.

However, a significant concern arises regarding trust in the data generated by systems operated by other individuals. In particular, if those individuals are incentivized to offer low-quality or fabricated data, it becomes crucial to address this trust issue [7]. This paper focuses on tackling the question of data *quality* in spectrum monitoring systems operated by third parties. Our objective is to develop an automated evaluation process for sensor nodes without requiring human supervision. Through obtaining I/Q data from a node, we aim to calculate the quality of the data it generates. This technique is then applied to all sensor nodes within the network.

Two key aspects need to be assessed for each sensor node. Firstly, we evaluate the node's ability to receive signals from different directions. The antenna connected to the SDR may have directional gains, and certain directions might be obstructed by physical structures such as buildings or mountains. Consequently, the sensor might not be able to receive wireless signals from some directions properly. Our intention is not to disentangle antenna pattern from physical occlusions, but rather to determine where the combination of the two allows reception from different directions. The second aspect involves assessing the reception capability of the sensor node across various frequency bands. Different frequencies have widely varying propagation characteristics. Therefore, we need to evaluate the impact of obstructions detected in the first step on the reception capability of the sensor across different frequency bands. Our aim is to quantify this aspect through passive testing, as active signal generation from other nodes may not be feasible due to distance, lack of transmission capability, and legal restrictions on transmission in most frequency bands.

3 AUTOMATIC CALIBRATION

In this section, we delve into the details of the techniques we have devised to assess the capabilities of sensor nodes in terms of receiving signals from various directions and across diverse frequency bands. Furthermore, we present preliminary experimental results that validate these techniques.

3.1 Evaluating directional reception

In order to evaluate the efficacy of a node in receiving wireless signals from different directions, we measure how well it can receive ADS-B signals transmitted from nearby airplanes (within a 100 km range) . ADS-B (Automatic Dependent Surveillance-Broadcast) is a wireless network that allows aircraft to broadcast their position, altitude, and velocity information to other aircraft and ground stations. This information is transmitted over two frequencies: 1090 MHz and 978 MHz. ADS-B Ground stations are typically located at airports and other strategic locations, and they receive ADS-B transmissions from aircraft. Airplanes broadcast their position and velocity at least two times per second when they are airborne [34]. These messages are not encrypted. Therefore, they can be received and decoded by any receiver within range. We exploit this open architecture and receive ADS-B messages on the sensor we want to evaluate. These messages reveal which directions have an unobstructed view and which directions are occluded.

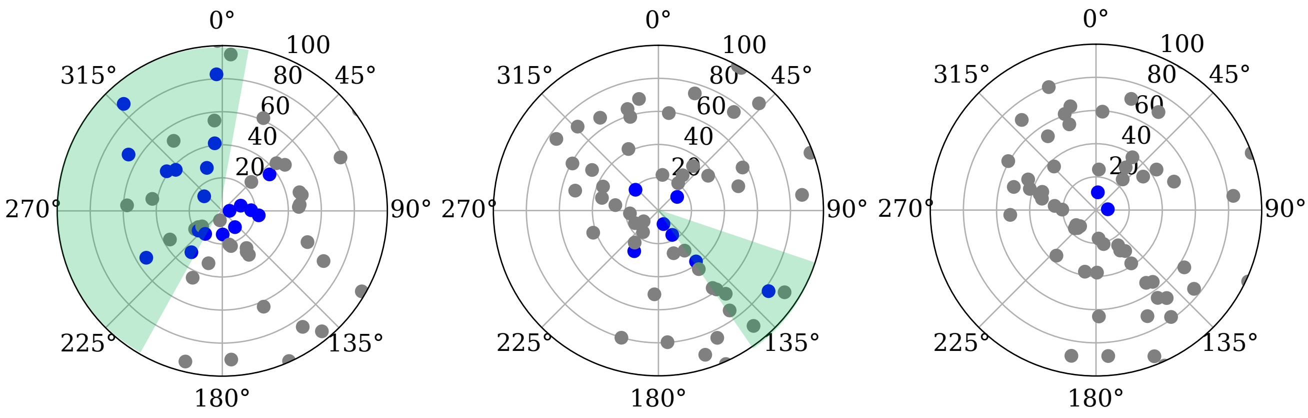
We use the dump1090 program [10] to decode the signal we receive on the SDR. dump1090 provides RSSI information, but transmit power can be between 75 and 500 W [28], limiting the utility of this information from one measurement on one receiver. We use the ICAO aircraft address to identify the airplane that transmitted a given ADS-B message. Receiving ADS-B messages from a distant airplane is a strong indicator that the field of view is open in that direction. However, not receiving any messages from a direction does not necessarily indicate blockage. It could be the case that there were no aircraft in that direction at the time of measurement. Therefore, we combine the data we receive on a node with the data we retrieve from another source to see if there is any airplane in the direction from which we received no messages. We query the FlightRadar24 website[1] through an API to acquire the ground truth when we evaluate a node.

Procedure: We run the dump1090 program on the sensor node for 30 seconds to give the node enough time to receive messages from all airplanes in the vicinity. We dump all the decoded messages into a file. 15 seconds into the measurement, we retrieve all flight data from FlightRadar24 in a radius of 100 km from the location of the sensor. At the end of the measurement, we go through all flights reported by FlightRadar24 and compare their unique ICAO aircraft address with the messages we decoded using dump1090. If the flight is found, we mark it as an observed airplane. FlightRadar24 reports a latency of 10 s, meaning reported aircraft are within 2.5 km of reported location, sufficient for our purpose. Next, we evaluate this methodology to see if it can tell if the field of view is obstructed or not for different directions.

Experiment setup: We connect a BladeRF xA9 SDR to a Microsoft Surface Pro acting as the host machine. We attach a wide-band antenna with a frequency range of 700 MHz to 2700 MHz to the SDR. The tablet runs Ubuntu 22.04. We use a Python script that runs dump1090 and queries FlightRadar24 using the Python FlightRadarAPI library [16]. We place the node in three locations. Location ① is located on the rooftop of an apartment building on the 6th floor. It has an open field of view to the west as indicated by the yellow shaded area in the figure. Some building structures on the rooftop obscure its view in other directions. Location ② is behind a window that faces southeast on the 5th floor. Because of the buildings to the left and right, this location has a narrow field of view. Finally, Location ③ is inside the building on the 5th floor at least 8 meters away from windows, with no field of view to the outside.

Results: Figure 1 shows the results of this experiment in the three locations described above. The shaded area shows the unobstructed field of view. Each point on these plots represents an airplane within 100 km of the sensor. Blue points represent airplanes that the sensor successfully received at least one ADS-B message from during the 30 second measurement period. Gray points are airplanes that no message was received from. Recall that we know there was an airplane at the location indicated by gray points based on ground truth data from FlightRadar24. All three plots in Figure 1 show a clear correlation with their respective fields of view. Figure 1(a) indicates the sensor could receive ADS-B messages from many airplanes up to 95 km from the sensor in the west sector of the plot, which matches the field of view at Location ①. The building structure prevented reception of messages from distant airplanes in the other sectors of the plot. Figure 1(b) shows that the narrow field of view at location ② allowed the sensor to receive ADS-B messages from a few airplanes in the slim unobscured direction up to 80 km away. Finally, Figure 1(c) shows that the sensor inside the building could only receive some messages from airplanes very close to the sensor. For each location, ADS-B transmissions within 20 km of the receiver have a chance of being received regardless of direction, likely due to a combination of multipath reflections and penetrating walls. This only limits accuracy in a small portion of the effective reception area. We repeated these experiments over 10 times at these locations, obtaining similar results. These experiments show that binary presence

[1] FlightRadar24.com is a popular flight tracking website that provides real-time information on aircraft positions, flight routes, and other flight-related data. It utilizes a dense crowd-sourced network of ground and satellite ADS-B receivers to gather comprehensive data from airplanes.



(a) Rooftop at ① (b) Behind window at ② (c) Inside building at ③

Figure 1: ADS-B performance for measuring directionality. ● message received for airplane, ● message was not received

or absence of ADS-B messages, along with their content for location and ID, is a useful indicator for field of view even when lacking additional transmitter information.

3.2 Evaluating reception across frequencies

SDRs offer the advantage of supporting a wide frequency range, making them versatile enough for many applications. In the context of renting a sensor node, it becomes crucial for users to assess the node's performance within frequency bands relevant to their needs given differing propagation and reception characteristics. Therefore, our automatic evaluation technique aims to effectively characterize the node's performance at all frequency bands supported by the node. Note that ADS-B messages characterize a node at the 1090 MHz frequency band only. In other words, if our first technique determines a node is fully or partially obstructed, we would like to know how the obstruction impacts its capability in other bands.

To accomplish this, we utilize known signals in a variety of frequency bands. One excellent candidate source of such signals is 4G/5G cellular networks because they operate in a wide range of spectrum. Moreover, the locations of their towers and the frequency bands they use are known. Mobile networks in North America can operate from as low as 617 MHz all the way to 4499 MHz in 4G networks. In addition, 5G also supports millimeter-wave bands from 24 to 48 GHz. Broadcast TV is another good source of known signals that covers the sub-600 MHz range down to 85 MHz in most parts of the world. In this section, we perform some measurements using these two systems to demonstrate their potentials in evaluating sensors.

Cellular Networks

Experiment setup: We use a BladeRF xA9 with the same setup as before in the three locations indicated in Figure **??**. We utilized srsUE [31] as software client user equipment. This tool is an integral component of the open-source srsRAN project, which provides a complete software stack for both 4G and 5G networks. srsUE is able to scan for nearby cellular networks and measure their Reference Signal Received Power (RSRP). RSRP quantifies the strength of the received signal from the base station, serving as a crucial indicator of the signal quality experienced by mobile devices. There are databases such as cellmapper.net that show cellular towers in a region with their exact channel (i.e., ARFCN). This information can be used to configure srsUE to scan the frequency bands of interest. Figure 2 illustrates the location of cellular towers used in this experiment with respect to the experiment site.

Figure 2: Mobile network experiment testbed

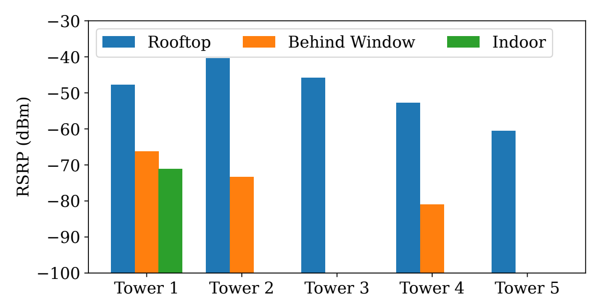


Figure 3: Cellular networks: different frequency bands

Results: Figure 3 shows the performance of a node when placed on a rooftop, behind a window, and inside the building far from windows (i.e., locations ①, ②, and ③ as described

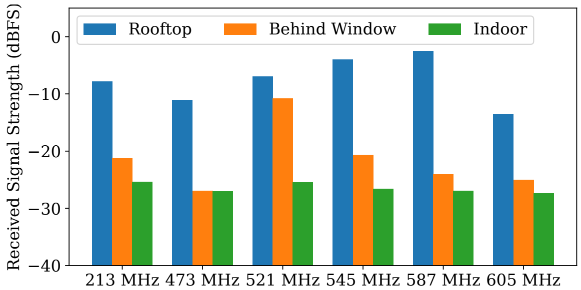


Figure 4: Broadcast TV: different frequency bands

above). In this experiment, we measure the RSRP from five nearby 4G/5G cellular base stations as illustrated in Figure 2. The downlink frequencies of the base stations at towers 1 to 5 are 731, 1970, 2145, 2660, and 2680 MHz, respectively. The coverage range in the low-band (i.e., tower 1) is up to 40 km, while the range is 1.6 to 19 km for the mid-band (i.e., towers 2-5). All of these towers are 500 to 1000 meters from the experiment site, therefore, we expect excellent reception for these towers in the absence of obstructions.

Figure 3 shows that RSRP is very high indicating excellent reception for all 5 towers when the sensor is placed on the rooftop. The sensor either has a line of sight to the tower or is partially obstructed. However, Figure 3 reveals significant signal attenuation when the sensor is not installed outside. A missing bar indicates that the signal was too weak for srsUE to decode successfully. When the sensor is placed inside a building at location ③ it can only decode wireless packets from tower 1. This is because tower 1 operates in the 700 MHz band. 700 MHz signals can penetrate buildings much better than mid-band signals from towers 2 through 5, although the difference varies based on building materials. When the sensor is placed behind a window at location ② the signal is attenuated significantly but it can still see the signals coming from Towers 1, 2, and 3. However, the obstructions around location 3 kill the signal completely at higher frequencies. These findings are inline with cellphone reception at these locations. A phone shows only one or two bars when placed at these locations and its connection is very weak.

Broadcast TV

Experiment setup: We employ broadcast TV signals to extend the previous cellular network frequency response experiment down to 200 MHz. The physical setup is identical to the previous experiment. However, to measure signal quality, we developed our own program using the GNU Radio software environment [11]. The SDR was configured with a fixed gain to prevent measurement differences from automatic gain control. The received power was measured by bandpass filtering a desired ATSC channel, then applying Parseval's identity to measure the band's power by running the magnitude-squared time-domain samples through a very long moving average filter for a live measurement.

Results: We measure the received signal strength from multiple TV broadcast towers up to 50 km away from the experiment site. Figure 4 shows the results for the 3 experiment locations. The experiment shows that at locations ② and ③ the building structure degrades reception, but we are still able to receive a relatively strong signal. The exception to this behavior is the very strong signal at 512 MHz when the sensor is placed behind a window. This is because the tower broadcasting at this frequency is in the field of view of the sensor and the building structure minimally impacts the signal. This experiment shows that despite some attenuation at locations ② and ③ they can be used for sub-600 MHz spectrum measurements.

Furthermore, combining the results from multiple experiments, including ADS-B, cellular networks, and broadcast TV, can provide additional insights such as determining whether an installation is indoor or outdoor. For instance, if the sensor consistently receives all signals with high quality when placed on a rooftop, it can be inferred that the sensor is installed outdoors. Conversely, if there is significant signal degradation observed at specific locations, such as ② and ③, at higher frequencies, it suggests that the sensor is located inside a building. By analyzing the combined experimental data, valuable information about the installation environment and the placement of the sensor can be deduced. These deductions can be used to independently verify claims about a node installation.

3.3 Applications in other domains

We have focused on automatic evaluation in the context of crowd-sourced networks of spectrum sensors. However this technique applies to many other systems. For instance, wireless networking in the Citizens Broadband Radio Service (CBRS) [20] is becoming a hot research topic due to its unique multi-tier access system. Since the maximum transmission power in CBRS systems depends on the installation specifics, every CBRS modem is required to **self-report** its location, indoor/outdoor status, installation situation, and other relevant information. The methodologies proposed in this paper provide valuable insights that can aid in the development of an automatic verification system to validate the reported information from CBRS modems. This can contribute to ensuring the integrity and reliability of CBRS networks and their compliance with regulatory requirements.

4 RELATED WORK

The area of cooperative and distributed spectrum sensing is particularly important in light of tiered access systems like CBRS [20] and TV whitespace[9]. However, much existing work such as [14] and [7] focuses on detecting or preventing malicious actors, but does not address the limitations of poor siting or equipment setup.

There has always been a desire to automatically calibrate any sensor or communications system to reduce the cost and risk of deployment, and prevent human errors. Solutions vary from dedicated hardware used to send or receive calibration signals, such as in [15], to lower-cost "blind" calibration schemes such as [19] which use *a-priori* unknown signals during operation. Blind calibration has the additional advantage that it can often be conducted during operation and used to adapt to performance variations as conditions change. Hall [12] coined the term "signals of opportunity" (SoO) for useful pre-existing signals in the radio environment. SoOs can be used for sensor localization [12],[17], passive radar [6], and hardware calibration [21],[1],[33],[4]. Wi-Fly [2] uses ADS-B SoOs as an indicator for presence of an opportunistic relay node, a sort of control calibration signal.

A related problem to calibrating frequency and angle response for spectrum monitoring exists in the space of wireless sensor network localization [22], where the potentially unknown positions of each sensor must be identified. Depending on the localization algorithm, parameters such as gain [5] and phase [30] may also be required. Calibration becomes particularly important in environments with heterogeneous sensors and sensing modalities [36]. Many of these techniques, however, are enabled by having simultaneous access to multiple sensor nodes observing the same signals whereas our proposal is intended to be self-sufficient on a single node. Vision systems such as LiDAR and cameras can take advantage of environmental features such as light sources [23] and geometry [13] along with other constraints to automatically calibrate. The analogs in our system would be fixed transmitters and mobile transmitters, such as aircraft.

Distributed spectrum sensing networks such as SpecNet and Spectrum Observatory have gained in popularity and complexity over the past decade [8],[35],[27],[38]. These networks have relied on relatively expensive SDR hardware without radio calibration. The Electrosense and RadioHound projects are closest to our vision of crowd-sourced networks with inexpensive hardware. Electrosense [25] is a crowd-sourced network of spectrum sensors that collect and analyze data from the electromagnetic spectrum. Electrosense sensors are designed using inexpensive and easily accessible software-defined radio (SDR) front-ends and embedded platforms like Raspberry Pi, enabling worldwide deployment at a relatively low cost. Unfortunately, Electrosense does not have an automatic calibration system. The quality of data provided by each node is unknown unless individually and manually tested, preventing large-scale operation. The RadioHound [18] project aims to achieve better control over signal quality while maintaining low-enough cost for distributed deployment through a custom analog frontend which enables low-cost commercial SDRs to tune to frequencies and achieve dynamic ranges beyond their designed capabilities. However, the RadioHound nodes still require manual calibration upon deployment.

5 DISCUSSION AND CONCLUSION

In this paper, we propose two methodologies for automatically evaluating sensor nodes in distributed spectrum monitoring systems. Firstly, we utilize ADS-B messages from nearby airplanes to assess the field of view of a sensor node. Secondly, we leverage known signals across different frequency bands to quantify the impact of obstructions on sensor performance. These methodologies contribute to enhancing the accuracy and reliability of sensor node evaluation in spectrum monitoring networks. However, in order to enable an end-to-end automatic verification system the following topics require future study:

- **End-to-end system**: An end-to-end system must decide when to perform ADS-B measurements to gain as much information as possible, as flight schedules vary over time. Then, use model-based or ML-based techniques to calibrate a sensor given the observed and ground-truth airplane locations. An example of such techniques is using algorithms, such as k-nearest neighbors (KNN) or a support vector machine (SVM), to estimate the true sensor field of view. Some recent studies have started looking at ML-based techniques to obtain different types of information from signals of opportunity, such as using Wi-Fi and cellular signals to determine if a device is indoor or outdoor [26].
- **Establishing trust**: Incorporating trust into the system is essential to ensure the reliability and integrity of the collected data. This becomes particularly important for policy makers and regulatory enforcement purposes. However, it is crucial to address the challenge of preventing sensor nodes from fabricating data, as incentivizing volunteers through monetary compensation might inadvertently lead to poor installation practices or even the submission of false information.
- **RF sources**: Although we have utilized ADS-B, broadcast TV, and cellular network signals for calibration in this study, there exists a wide range of other RF sources that can contribute to the evaluation process. Future work will focus on identifying and incorporating additional RF sources to enhance the comprehensiveness and accuracy of the calibration techniques employed.
- **Other types of calibration**: While our current work primarily focuses on evaluating the impact of environmental factors on the reception capabilities of spectrum sensors, it is important to acknowledge that different applications may require additional types of calibration. For instance, if precise measurements of absolute received signal power are needed, further techniques would be necessary as SDRs are not inherently calibrated for this purpose.

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