Implementation of Real-Time Spectrum Handoff with Blind Cooperative Spectrum Sensing for Cognitive Radio using Software-Defined Radios

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***Abstract*—As the demand for frequency resources increases due to the current trends in technology such as IoT and smart cities, efficient spectral usage becomes a prerequisite. To improve spectral efficiency, many studies have proposed cognitive radio (CR) as a solution. CR is mainly composed of two parts: spectrum sensing, which allows continuous identification of spectrum holes, and spectrum handoff, which ensures the cognitive user (CU) vacates the channel when a primary user (PU) becomes active. This study implemented a CR system with both spectrum sensing and handoff capabilities using the ADALM Pluto Software-Defined Radio (SDR) and GNU Radio. For spectrum sensing, we used cooperative blind spectrum sensing (BSS) techniques, specifically energy detector and the covariance-based detector. For spectrum handoff, a probabilistic scheme was used and compared with a traditional reactive scheme. The performance of the implemented system was evaluated in both an open area and a full anechoic chamber. It was observed that both energy and covariance-based detectors were able to detect PU activity accurately, but the latter was able to sustain its performance at a lower signal-to-noise ratio (SNR). For spectrum handoff, two setups were done: one in the open area utilizing Wi-Fi and LTE bands, and another in the anechoic chamber to enable CU transmission. Results also show that the probabilistic scheme had better performance in handoff latency and throughput than a reactive scheme.**

***Keywords*—Spectrum sensing, Spectrum handoff, Cognitive Radio, Cooperative sensing, SDR**

I. Introduction

With the growth of wireless communication technologies, the demand for frequency resources continues to increase. While most radio frequency (RF) bands in the spectrum are already allocated to primary users (PU), some are unoccupied most of the time, leading to resource under-utilization [1]. Because of this, cognitive radio (CR) became a promising solution towards efficient spectrum usage by allowing dynamic spectrum sharing between primary and cognitive users (CU/SU) without needing new allocations [2]. Recently, CRs are being applied in Radio Dynamic Innovation Zones, shielded areas where active spectrum sharing is experimented on [3], aiming to allow co-existence between different operators, wireless technologies, and legacy systems in the future.

The two main CR functionalities are spectrum sensing, which allows continuous identification of spectrum holes, and spectrum handoff, which ensures the CU vacates the channel at instances of PU activity to avoid collision [2]. However, spectrum sensing is limited by distance, noise, and obstructions that can cause missed detections, highlighting the importance of cooperative sensing of multiple nodes [4]. And given the limited implementation of Innovation Zones, small-scale testing and practical implementation of theoretical CR functionalities, especially sensing and handoff, are still needed.

Real-time and efficient spectrum sensing and handoff schemes are essential to support fast and dynamic spectrum sharing. However, most spectrum sensing techniques have high computational costs while most handoff techniques focus on theoretical optimization with complex methods over practical evaluation. With multiple theoretical schemes proposed in the previous years, this study assessed the performance of selected schemes in actual frequency transmissions where non-ideal conditions exist. Specifically, this project sought to:

- Accurately detect occupancy of desired frequency channels with a probability of detection (Pd) of at least 90% and a probability of false alarm (Pfa) of at most 10%, as prescribed in IEEE 802.22 WRAN.
- Implement practical single-user handoff with optimal channel selection when PU returns to the current channel.
- Evaluate the performance of the hardware-implemented system using key performance metrics.

II. Related Works

The algorithms presented offer a perspective on the advantages and disadvantages of different proposed algorithms for each functionality. Since the hardware implementation is limited by the devices used, it is crucial to choose to test it on algorithms that balances both computational complexity and efficiency. While some algorithms offer faster methods, it often requires more costly devices with faster processing.

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A. Spectrum Sensing and Cooperative Spectrum Sensing

Spectrum sensing algorithms can be broadly classified into two types: knowledge-aided spectrum sensing and blind spectrum sensing (BSS), which do not require knowledge of a PU, making it applicable to different PU signals.

The energy detector approach is the most used BSS technique due to its simplicity and low computational costs. It provides sufficient performance despite not needing an *a priori* knowledge of the PU signal but suffers under low SNR conditions and noise uncertainty [2], [5]. The cyclostationary feature detection is more robust in low SNR conditions as it exploits the cyclostationarity of PU signal features (i.e., mean and autocorrelation) and the stationarity of noise. It requires knowledge of the cyclostationary period of these features, making it a semi-blind technique [6]. The covariance-based approach is a fully blind sensing approach where a covariance matrix is constructed from the signal samples, and then the ratio of the max and min eigenvalues is calculated [7]. This is more computationally expensive, but still less complex than machine learning-based techniques. This method is similar to the cyclostationary feature detector in that it assumes that the PU signals are correlated while noise is uncorrelated [2].

In some cases, spectrum sensing using a single node can already provide accurate detection; however, it is vulnerable to shadowing and fading. Cooperative spectrum sensing (CSS) is a solution that has been employed by many studies to mitigate this issue by introducing spatial diversity and redundancy [7], [9]. The gathered samples go through multiple stages during spectrum sensing. Each stage provides an opportunity for fusion, and generally, a fusion center closer to the SDR source provides a better performance improvement at a cost of higher computational complexity [8].

B. Spectrum Handoff

Traditionally, spectrum handoff schemes are categorized as either reactive or proactive. Reactive handoff does channel searching only when a PU is detected and without any prior information on occupancy of channels, while proactive handoff chooses another channel already before a trigger event [10] which can help decrease collision rate for large numbers of PUs [11]. Common proactive schemes rely on prediction of PU activity based on factors such as CU waiting period or handoff probability but most of them only estimate it through statistical models and assumptions [11].

Some studies explored the integration of proactive with reactive methods in order to account for the dynamic nature of users. PU traffic categorization is done by [12], [14], [15] based on factors such as PU intensity, periodicity and CU service time, and switches to the appropriate handoff scheme for each category. On the other hand, [13] uses the idea of idle probabilities to choose a channel and handing off only during a trigger event. And even with multiple schemes proposed, only a few have attempted to assess its hardware limitations such as [16] which explored the performance of using two processors to hold channel information for handoff.

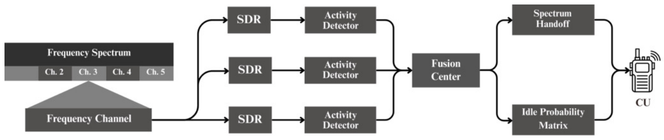

Fig. 1: System Overview

III. System Implementation

The overview of the implemented system is given by Fig. 1. The setup utilized multiple channels of chosen frequency bands. Each channel is monitored using multiple Software-Defined Radios (SDR), radios that can be programmed using a software such as the GNU Radio Companion, which allows for real-time processing of received signals. These SDRs were connected to separate GNU Radio workspaces, each with local sensing data that are sent to a fusion center. The fusion center combines the information gathered by each SDR on the same channel and outputs a global decision on channel occupancy. This combined information is then used to trigger handoff, if needed, and as a basis for calculating each channel's idle probability. The same fusion center is also used to control CU transmission parameters based on information it has received.

Moreover, the study was divided into three parts: (1) algorithm testing of chosen schemes, (2) hardware implementation, and (3) evaluation of performance indicators.

A. Algorithm Design and Implementation

1) Spectrum Sensing: In the covariance-based detector, the approximate sample covariance matrix R_y of the received signal $y(m)$ is estimated using the sample autocorrelation coefficients from zero to the smoothing factor L as shown by Eq. (1), where $\alpha(l)$ is the lth autocorrelation coefficient that is given by Eq. (2) and N_s is the number of samples from the signal.

$$\widehat{R}_y(N_s) = \begin{bmatrix} \alpha(0) & \alpha(1) & \dots & \alpha(L-1) \\ \alpha(1) & \alpha(0) & \dots & \alpha(L-2) \\ \vdots & \vdots & & \vdots \\ \alpha(L-1) & \alpha(L-2) & \dots & \alpha(0) \end{bmatrix} \quad (1)$$

$$\alpha(l) = \frac{1}{N_s} \sum_{m=0}^{N_s-1} y(m) y(m-l), \quad l = 1, 2, 3, ..., L-1 \quad (2)$$

The eigenvalues of the covariance matrix is then calculated, and the ratio of its maximum and minimum is compared against the threshold γ_c to determine the spectrum activity [7]. This can be expressed as:

$$\text{PU} = \begin{cases} \text{present}, & T_{MME} = \frac{\lambda_{max}}{\lambda_{min}} \geq \gamma_c \\ \text{absent}, & T_{MME} = \frac{\lambda_{max}}{\lambda_{min}} < \gamma_c \end{cases} \quad (3)$$

The energy detector measures the power level within the target frequency band and subsequently compares it against a predefined threshold. Its main idea is that in the presence of a PU, the signal power is considerably higher than when the PUs are absent.

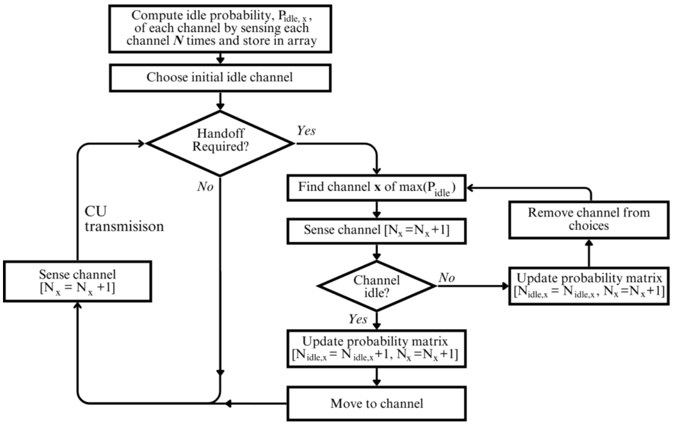

Fig. 2: Dynamic Spectrum Access

$$T_{ED} = \frac{1}{N_s} \sum_{m=0}^{N_s-1} |y(m)|^2 \tag{4}$$

$$\text{PU} = \begin{cases} \text{present}, & T_{ED} \geq \gamma_{ED} \\ \text{absent}, & T_{ED} < \gamma_{ED} \end{cases} \tag{5}$$

Test statistic fusion was used for CSS as it serves as the middle ground between performance and simplicity. In the case of covariance-based detection, this was done by simply taking the average of the different calculated test statistics from each node. In doing so, the global test statistic was more robust to shadowing and fading present in the minority of the sensing nodes.

2) Spectrum Handoff: The probabilistic handoff scheme derived from the work of [13] was implemented as it offers less complexity and computational costs compared to the others. It chooses a channel based on its probability to be idle and only administers handoff when activity is detected. A channel's idle probability is calculated using Eq. (6):

$$P_{idle,x} = \frac{N_{idle,x}}{N_x} \tag{6}$$

where N_x is the number of times the channel has been sensed and $N_{idle,x}$ is the number of unoccupied detections.

At initialization, each channel is sensed N times to create an initial probability matrix where an initial channel will be chosen after. If deemed unoccupied, the CU will begin its transmission at that channel and continuously monitor it. Once another activity is detected, it selects from the matrix for the next channel with the highest probability and transmits on it if unoccupied and so on. Every time a channel is sensed, the matrix is updated. The detailed flowgraph of the handoff scheme for dynamic spectrum access is shown by Fig. 2.

B. Hardware Setup

The sensing nodes, transmitters, and receivers all used ADALM-Pluto SDRs developed by Analog Devices Inc., capable of both transmitting and receiving frequencies ranging from 325 MHz to 3.8 GHz. All data and signal processing is done through the GNU Radio Software. A central machine

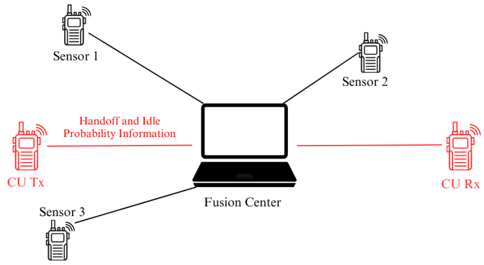

Fig. 3: Hardware Overview

served as the fusion center of the system which, not only was used to combine data from each node but also to dynamically adjust CU transmission frequency. Information on spectrum activity was monitored in this central machine and then used by the handoff mechanism to make its decisions. Fig. 3 shows an overview of the hardware setup.

For the first part of the hardware implementation, two frequency bands transmitting orthogonal frequency-division multiplexed (OFDM) signals were utilized: the 2.4GHz Wi-Fi band and the 700MHz LTE band. For this setup, only an emulated CU is done, where CU transmission was only virtual, since interference with actual licensed transmissions by unlicensed ones must be avoided. This setup was done to assess the performance of the system on existing on-air transmissions with known rampant activity where handoffs are most likely to happen.

For the second half of the implementation, the system was implemented in a full anechoic chamber as shown by Fig. 4, which protects outside RF signals from interference and vice versa. This allowed for over-the-air transmission of the CU and assessment of transmission quality where the effect of sensing delays and real-time collisions on the CU can be examined. SDRs are connected via a USB hub to the central machine. Each is randomly placed but sufficiently spaced across the room with non-uniform distances from the transmitter to simulate a dynamic CU environment where some CU are obstructed while some are not. Since no other signals can be detected inside, controlled PUs were also simulated using SDRs, each with varying patterns of idleness, to simulate dynamic PU activity on different channels. This was done to force the system to initiate handoff at certain points in time and imitate a real-world RF environment.

Only singular CU activity is simulated for the study as multiple CU would require additional complexity in terms of priority for CUs sharing a channel as well as a separate processing machine for each CU. The number of sensing nodes was also limited to three to avoid overloading and further degrading the processing time of the central machine.

C. Evaluation of Key Metrics

1) Receiver Operating Characteristics (ROC) curves: The performance of the spectrum sensing was assessed using ROC curves with OFDM signals which shows the probability of detection (Pd) against the probability of false alarm (Pfa). A bigger area under the curve means better performance as it is desirable to have higher Pd at smaller Pfa. This was used to

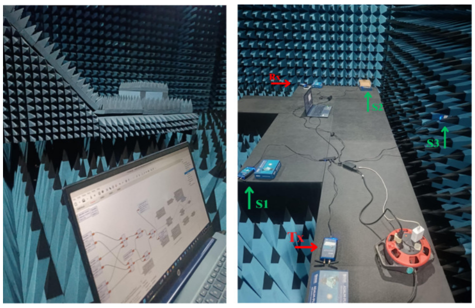

Fig. 4: Anechoic Chamber Setup

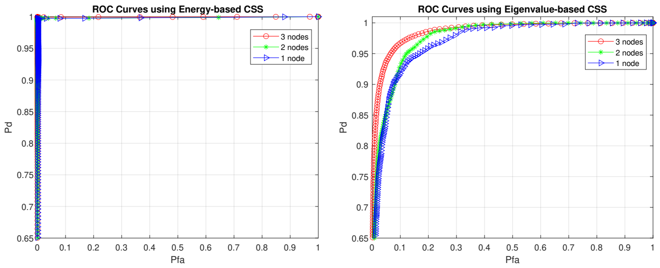

Fig. 5: ROC curves for varying CSS nodes count @ 17.2dB

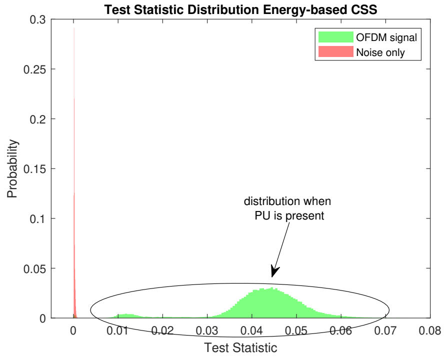

Fig. 6: Test Statistic Distribution for Energy-based CSS

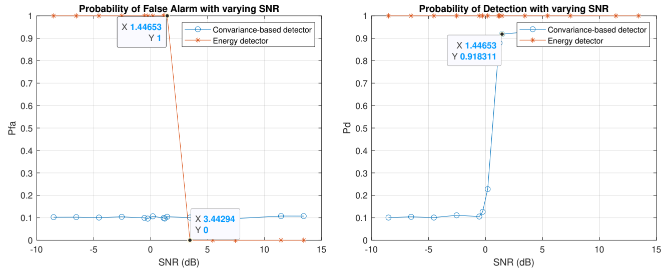

Fig. 7: Probability of detection and false alarm at varying SNR

asses the performance of the detection algorithms as well as the effect of increasing sensing nodes. In order to construct an ROC curve, we must have full control over the PU activities. To do so, our system was implemented in a full anechoic chamber to avoid colliding with telecom companies.

2) Average Handoff Latency: The performance of the handoff algorithm was evaluated through its average handoff latency, the total time it takes to administer handoff successfully once interference is detected.

3) Throughput: To assess the overall system, sample files were transmitted through OFDM by the CU and its throughput or the rate of data transferred were measured, which was mainly affected by both handoff delays and collisions with other users from missed detections.

As a benchmark for comparison, a purely reactive scheme was also implemented where channels are searched on-demand since it usually performs well in ideal scenarios as it has the least computational cost.

IV. Results and Discussion

A. Receiver Operating Characteristics (ROC) curves

Fig. 5 shows that the performance of both the energy detector and the covariance-based detector for all numbers of nodes meet our specifications for accuracy – if the Pfa is set to 10%, the corresponding Pd exceeds 90%. The set of curves on the left uses energy detection and as we can see, it is a step function, which signifies perfect accuracy. The addition of CSS cannot improve the already perfect accuracy. The set of curves in the right uses the covariance-based detector. Its ROC curves, even though not perfect, still satisfy our specification. It is visually evident that its performance increases as the number of nodes also increases; the exact values for areas are 0.9865 (3 nodes), 0.9761 (2 nodes), and 0.9698 (1 node).

In the anechoic chamber, there is minimal noise and leakages from any nearby PU activity. As a result, the sampled signal has a high SNR, which explains the perfect performance of the energy detector. Fig. 6 shows the probability distribution of the energy, which is the test statistic, of the received signal in the presence and absence of a PU at 17.2 dB. We can see that the two distributions have no intersection due to the large energy gap between the signals. Decreasing the SNR will bring these two distributions closer and intersect with each other, which results in the uncertainty of the presence of a PU. In the case of Fig. 6, if the threshold γ_{ED} is set to be between 0W and 10mW, using Eq. (5) we can see that the performance will be perfect.

Since we had no control over the SNR in the implementation of the system in the anechoic chamber, we used GNU Radio to simulate various SNR conditions and evaluate our spectrum sensing scheme's performance. Fig. 7 shows the probability of false alarm and detection at various SNRs. Both techniques suffer from low SNR conditions. The energy detector always detects that a PU signal is present regardless of the actual presence of the PU. On the contrary, the covariance-based detector detects that a PU signal is absent most of the time, regardless of the actual presence of the PU. The energy detector had a good performance until 3.44dB, while the covariance-based detector was until 1.44dB. By this comparison, the covariance-based detector can operate at a lower SNR than the energy detector while still meeting our accuracy specification. The weaker performance of the covariance-based detector might be due to the insufficient observation time. The short sampling window must have made the PU signal appear uncorrelated, making the max eigenvalue λ_{max} smaller, similar to when a PU is absent.

B. Wi-Fi and LTE Band with Emulated CU

Two handoff mechanisms were implemented for each band: probabilistic and purely reactive. Each was run for 30 minutes. Since no prior information about channel activities is used, there is no way of knowing if detected are actual licensed users. It is assumed that channel activities, licensed or unlicensed, sensed by the CU are considered as PU activity.

1) 2.4GHz Band: Five non-overlapping channels, each with 25MHz bandwidth, were utilized for the Wi-Fi band with center frequencies from 2.412GHz to 2.512GHz. Since the Wi-Fi band has intentional overlapping channels, spectral leakages are considered as PU activity. The average normalized power recorded for channels is shown in Table I, which provides insight into the idle probabilities of the channels. The resulting channel distribution is given by Fig. 8, while the handoff key metrics are given by Table II.

The channel distribution clearly shows that for the probabilistic handoff, the CU only switches between two channels, 2.462 GHz and 2.487 GHz, and this is apparent in the average powers recorded, with the fourth channel having the lowest. For the reactive handoff, the distribution is spread out in different channels. Since the 2.484GHz channel is restricted in the country and is located at the edge of the Wi-Fi band, the fourth channel is expected to have the least activity or leakages detected. In terms of the handoff key metrics, the results show that the latency for a reactive scheme is worse than the probabilistic one with a greater number of handoffs. Since the reactive scheme chooses a random channel, it is likely that it will take time to find an unoccupied channel and it increases handoffs when it selects channels that are not fully occupied. This means that for the probabilistic handoff, the CU is likely to stay in a channel for a longer period.

2) 700MHz Band: Eight channels each with 10MHz bandwidth was utilized for the LTE band with center frequencies ranging from 713MHz to 783MHz. Similarly, the average energies recorded for each channel is shown at Table III while the channel distribution and handoff metrics is given by Fig. 9 and Table IV respectively.

Similar to the Wi-Fi band, the channel distribution also only switches between a few channels and the handoff latency is also less when using a probabilistic handoff in the LTE band. Although the number of handoffs for the reactive scheme is less, opposite to the Wi-Fi band, the delay difference is much larger in it since there are more channels to search, which also affects the time of actual transmission within the given period. For a frequency band with more channels, the reactive scheme performs much worse due to increased delays in channel searching, especially if most channels are occupied.

TABLE I: Average Normalized Power for Wi-Fi Channels

Freq. (GHz)	**2.412**	**2.437**	**2.462**	**2.487**	**2.512**
Power (e-6 mW/mW)	9.2784	217.93	10.618	0.0728	242.91

TABLE II: Spectrum Handoff Key Metrics for Wi-Fi Band

Handoff Scheme	**Ave. Handoff Latency**	**Total No. of Handoffs**
Reactive	1.87835 s	266
Probabilistic	1.09436 s	180

While both schemes have a high number of handoffs for the time of measurement, it is worth noting that both bands have bursty transmissions, as observed during simulation. That is, the activity in the channel occurs in very short intervals and it is possible that the sensing intervals were able to sense parts in-between bursts.

C. Over-the-air CU Transmission

For the setup in the anechoic chamber, four channels were used, each with a simulated PU with different periodicity. Sample files were transferred by the CU in order to assess the effect of handoff delays and missed detection in actual data throughput. Two transmission setups were done each with different file sizes and runtime: (1) a five-minute transmission of 9-byte files and (2) a 10-minute transmission of 68-byte files. The handoff key metrics for both transmission is shown at Table V and Table VI respectively while the data throughput is illustrated by Fig. 10.

The handoff metric remains consistent with the observed performance from the Wi-Fi and LTE bands, wherein the probabilistic schemes have less latencies. By using controlled PUs, the number of handoffs is smaller for the given time since transmission is not in bursts but the results show both schemes having a close number of handoffs, mainly because of fewer channels used. However, the contrast is much more apparent with the data throughput as the probabilistic scheme has a visibly larger throughput, more than twice the reactive scheme for both setups, which is a large improvement. While both schemes were not able to fully avoid collisions, as seen from the packet losses due to the receiver unable to decode the data, the reactive scheme still perform much worse. Although the throughput seemed to decrease for larger packet sizes, this is likely caused by the small transmission intervals of the CU for the setup, since sensing and transmission work alternately. To achieve higher throughput for larger packets, transmission intervals can be increased but at the cost of interference detection delays, which can cause more collisions.

V. Conclusion

The implementation of the system both in an open area and in the anechoic chamber was able to detect PU activity accurately and relocate its transmission during interference. The two employed blind spectrum sensing schemes met our specifications for accuracy, with the covariance-based detector able to operate at a lower SNR. Although not fully avoided, the system was also able to minimize collision with the PU

TABLE III: Average Normalized Power for each LTE Channel

Freq. (MHz)	**713**	**723**	**733**	**743**
Power (e-3 mW/mW)	9.937082	0.032758	0.007120	0.007929
Freq. (MHz)	**753**	**763**	**773**	**783**
Power (e-3 mW/mW)	0.022569	0.282115	0.316478	0.109068

TABLE IV: Spectrum Handoff Key Metrics for LTE Band

Handoff Scheme	**Ave. Handoff Latency**	**Total No. of Handoffs**
Purely Reactive	4.039737 s	219
Probabilistic	1.42462 s	336

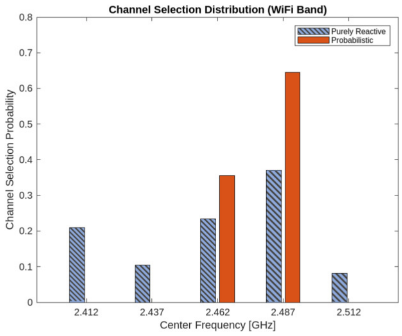

Fig. 8: Channel Distribution in Wi-Fi Band

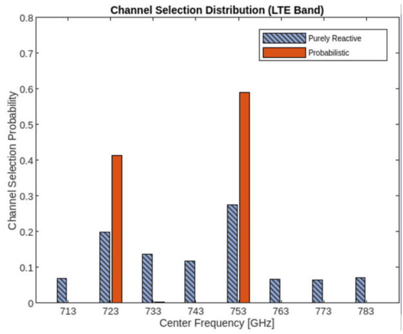

Fig. 9: Channel Distribution in LTE Band

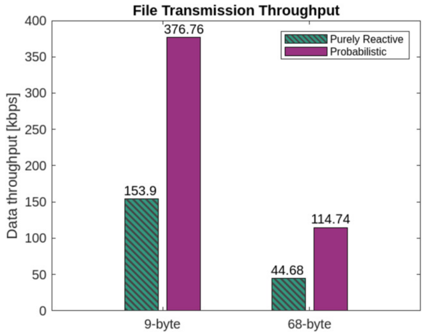

Fig. 10: Data Throughput of CU Transmission

by successfully switching to a vacant channel. Despite the varying results on the number of handoffs, we saw a decrease in the average handoff latency in both cases when using the probabilistic handoff scheme. We also saw a higher throughput in using a probabilistic handoff scheme, with the overall throughput of the transmission of a larger packet size being lower due to insufficient transmission intervals.

Future works may consider utilizing a spectrum sensing scheme that has a good performance at low SNR conditions. More computationally expensive algorithms such as cyclostationary detection or even machine learning based detection can be adopted to provide performance improvements, albeit requiring better hardware. Knowledge-aided sensing, such as matched filter detection, could also provide performance improvements, especially at low SNR. The transmission interval could also be adjusted to accommodate transmission of bigger packet sizes in exchange for a delay in the detection of interferences. For future implementations, other schemes can be explored, as well as higher-end SDRs, which can offer better performance in hardware implementations. And since CR systems are meant for a larger scope, multiple CU can be assessed in future iterations, and how the addition of more CU could impact system performance.

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TABLE V: Handoff Key Metrics for 9-byte transmission

Handoff Scheme	Ave. Handoff Latency	Total No. of Handoffs
Purely Reactive	8.451708 s	12
Probabilistic	1.294035 s	13

TABLE VI: Handoff Key Metrics for 68-byte transmission

Handoff Scheme	Ave. Handoff Latency	Total No. of Handoffs
Purely Reactive	3.58236 s	47
Probabilistic	1.410709 s	42

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