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A Dynamic Framework for Optimizing Spectrum Utilization and Interference Mitigation in White Space Networks

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Abstract

This study presents a framework for optimizing spectrum utilization and reducing interference in White Space (WS) networks using the Interference Mitigation Decision Framework (IMDF). The IMDF combines Geo-Location Spectrum Databases (GLSDs), reactive spectrum sensing, and Software Defined Radios (SDRs) to address the limitations of traditional spectrum allocation methods. The IMDF enhances allocation, reduces interference, and improves network performance by monitoring real-time spectrum usage. Simulations comparing IMDF with traditional GLSD-based methods show a 70% bandwidth saving, compared to 40% in traditional approaches. Additionally, IMDF reduces interference events by 30%, improving Quality of Service (QoS) and mitigating Cross Network Interference (CNI). With dynamic spectrum management, IMDF achieves 70% spectrum utilization, while traditional systems only reach 40%. These results demonstrate IMDF's effectiveness in dynamic environments, offering a robust solution for wireless service demand and interference mitigation in increasingly WS networks. The IMDF's adaptability, combined with its efficient resource management, makes it a promising framework for the future of spectrum allocation in increasingly congested network environments.

A. Introduction

Efficient spectrum management has become increasingly critical as the demand for wireless services surges and the availability of spectrum becomes scarcer. White Space (WS) networks, which utilize unused portions of the radio frequency spectrum, offer a promising solution to address this scarcity. However, WS networks face significant challenges, particularly Cross Network Interference (CNI), which occurs when multiple networks operate within the same frequency bands. This results in signal degradation and a decline in Quality of Service (QoS) for users. Effective CNI mitigation strategies are therefore essential to ensure the reliable and efficient operation of WS networks.

Existing WS prediction methods [1, 2, 3, 4], which primarily rely on Geo-Location Spectrum Databases (GLSDs), often suffer from inaccuracies due to outdated or incomplete data. These databases, which map available spectrum based on predefined usage patterns, may not account for real-time changes in network activity, leading to inefficient spectrum allocation and increased interference. To address these limitations, this paper introduces an innovative solution: the Interference Mitigation Decision Framework (IMDF).

The IMDF integrates machine learning algorithms, including Support Vector Machines (SVM) and reinforcement learning, for accurate WS channel prediction. SVM is employed to classify and predict the availability of WS channels by analyzing historical spectrum usage data, handling complex and non-linear relationships in the data for more accurate predictions [5]. Additionally, the IMDF utilizes cooperative spectrum sensing, combining data from multiple sensors to enhance primary user detection, and spatial and temporal sensing techniques to ensure context-aware management of spectrum resources.

The IMDF enhances WS prediction and discovery by combining GLSD data with reactive spectrum sensing techniques. This allows the system to monitor the spectrum in real time, identifying available channels more accurately and adapting to the dynamic nature of wireless networks. This hybrid approach improves the reliability of spectrum predictions, minimizes the risk of interference, and optimizes spectrum utilization. A key component of the IMDF is its use of Software Defined Radio (SDR) architectures, which enable the dynamic allocation of spectrum based on real-time conditions, significantly reducing CNI and improving network performance.

The IMDF demonstrates a remarkable 70% bandwidth savings in interference-free conditions, compared to only 14% savings using traditional methods. This significant improvement highlights the IMDF's potential to revolutionize spectrum management practices in WS networks. Beyond mitigating interference, the IMDF framework supports efficient spectrum sharing across multiple wireless systems, ensuring optimal use of spectrum resources and allowing networks to coexist with minimal interference.

In conclusion, the IMDF presents a highly efficient approach to dynamic spectrum management by integrating advanced algorithms, machine learning techniques, and SDR technologies. The IMDF not only addresses CNI but also optimizes bandwidth utilization, enhancing QoS for users in increasingly congested wireless environments. This comprehensive framework sets the foundation for the future of resilient and adaptive spectrum-sharing techniques, crucial for meeting the growing demand for wireless services.

Literature review and contextualization of the problem

Interference management in shared frequency bands is a critical challenge due to the growing number of wireless devices and services. Recent studies have explored various approaches to address this issue. [6] investigated the use of cognitive radio networks (CRNs) to manage interference through dynamic spectrum access, allowing secondary users to utilize underutilized spectrum bands without interfering with primary users . Similarly, the work by [7] focused on the application of machine learning techniques for interference detection and mitigation in heterogeneous wireless networks, highlighting the potential of artificial intelligence in improving spectrum efficiency and reducing interference. Another significant contribution came from [8], who proposed a cooperative spectrum sensing approach, where multiple cognitive radios collaborate to detect spectrum holes more accurately, thereby reducing false alarms and missed detections . This approach enhances the reliability of spectrum sensing, which is crucial for effective interference management in shared bands.

GLSDs have been widely used for WS prediction, providing information on available spectrum bands to avoid interference with primary users. GLSDs rely on databases containing information about the locations and operating frequencies of primary users, which helps secondary users identify vacant channels. However, the effectiveness of GLSDs is often compromised by outdated or inaccurate data. A study by Jiang et al. (2019) highlighted the limitations of GLSDs, noting that the accuracy of WS prediction is significantly affected by the timeliness and reliability of the data fed into these databases. Outdated information can lead to incorrect spectrum availability predictions, resulting in increased interference. Similarly, [5, 7] emphasized the need for real-time data updates and the integration of advanced sensing technologies to improve the accuracy of GLSDs.

To address these limitations, [2, 8] proposed a hybrid approach that combines GLSDs with real-time spectrum sensing, allowing for dynamic verification of database information and reducing the probability of errors in WS prediction. This integration enhances the overall performance of spectrum management systems by ensuring that spectrum availability information is both accurate and current. Several techniques have been proposed in recent years to mitigate CNI, with a significant focus on algorithms and SDR architectures. SDRs provide a flexible platform for implementing various interference mitigation strategies due to their ability to adapt to different frequency bands and modulation schemes.

[1] Introduced an adaptive interference mitigation algorithm that dynamically adjusts transmission parameters based on real-time spectrum conditions. This algorithm leverages the reconfigurability of SDRs to optimize spectrum usage and minimize interference. Following this, [4] developed a machine learning-based interference classification system that enables SDRs to identify and mitigate different types of interference in real-time, further enhancing the robustness of wireless communication systems. Moreover, recent advancements in SDR architectures have facilitated more effective CNI mitigation. The work by [10] demonstrated the use of SDRs for implementing cooperative interference

cancellation techniques, where multiple radios collaborate to suppress interference signals, improving overall network performance. Additionally, [11] explored the integration of SDRs with advanced signal processing algorithms, such as beamforming and MIMO (Multiple Input Multiple Output), to further enhance interference mitigation capabilities.

[11-13] These studies underscore the potential of combining advanced algorithms with the flexibility of SDRs to develop robust solutions for CNI mitigation, paving the way for more efficient and reliable wireless networks.

Objectives and definitions

The primary objective of this study is to develop an innovative framework for mitigating CNI and enhancing QoS in WS networks. With increasing wireless service demand and growing spectrum scarcity, efficient spectrum management is critical. The framework aims to provide a dynamic solution that addresses the shortcomings of current WS prediction methods, which rely heavily on historic data from GLSDs. To acquire the necessary data for simulating the graphs related to optimizing spectrum utilization and interference mitigation in WS networks using the IMDF, we've reach out to the relevant department or researchers at Council for Scientific and Industrial Research (CSIR)who are involved in spectrum management or wireless communication studies. You can find their contact details on the CSIR website. Specified Data Requirements clearly outline the specific data needed for our study, and obtain the data from the CSIR. The data acquired from CSIR includes the following:

1. Spectrum utilization data (traditional GLSD vs. IMDF)
2. Interference event occurrences
3. Bandwidth allocation data (traditional GLSD vs. IMDF)
4. Quality of Service (QoS) metrics:
   - Latency
   - Packet loss
   - Throughput
5. Prediction accuracy of WS channel availability (SVM model)
6. Number of interference events over time
7. Spectrum availability over time
8. Dynamic spectrum access decisions
9. Signal strength measurements
10. Channel occupancy rates
11. Spectrum sensing data from SDRs
12. SVM training and testing datasets (for channel prediction)
13. Frequency of CNI occurrences
14. Power consumption data for different spectrum management techniques.

By integrating reactive spectrum sensing with GLSDs, the proposed IMDF seeks to improve the accuracy of WS discovery and enhance overall network performance. Additionally, the study strives to maximize bandwidth utilization by employing algorithms and SDR architectures, supporting more efficient spectrum sharing. Ultimately, the research contributes to the advancement of adaptive spectrum management techniques to improve the coexistence of multiple wireless systems with minimal interference.

Definitions of WS refers to unused portions of the radio frequency spectrum that can be repurposed for wireless communications without interfering with primary licensed users. The ability to use WS effectively depends on mitigating CNI, which occurs when multiple networks share the same frequency bands, leading to signal degradation and reduced network performance. QoS is the measurement of how well a network meets user expectations in terms of speed, reliability, and overall performance. In WS networks, QoS can be affected by inaccuracies in predicting available spectrum, which are often due to outdated information in GLSDs. Reactive spectrum sensing is a method that involves real-time monitoring of the radio spectrum to detect available channels, providing a dynamic solution to spectrum allocation. To facilitate this, SDR is employed, offering flexibility through software control over communication hardware. The IMDF is a system that integrates GLSDs with reactive spectrum sensing and SDR technologies to dynamically manage spectrum use, reducing interference and optimizing bandwidth utilization.

This study begins with a comprehensive literature review to examine the current challenges in managing CNI and improving QoS in WS networks. Existing methods, particularly those based on GLSDs, are scrutinized for their reliance on outdated and historic data, which hinders effective spectrum management. The review highlights the need for a more dynamic and real-time approach to spectrum prediction, forming the foundation for the development of the IMDF. The IMDF is designed to combine the predictive capabilities of GLSDs with reactive spectrum sensing, allowing the framework to verify the availability of WS in real time and dynamically adjust spectrum allocations to reduce interference.

Finally, the study considers the potential for interference with coexisting systems, acknowledging that as wireless networks become more crowded, the risk of unintended interference increases. Further research is proposed to refine the IMDF and enhance its adaptability in congested wireless environments. By addressing these challenges, the study aims to validate the IMDF as a practical and efficient solution for future wireless networks, ensuring both improved spectrum efficiency and reduced interference.

B. Research Method

Proposed Framework

The IMDF is designed to enhance the accuracy of WS prediction and improve QoS by effectively mitigating CNI. The IMDF integrates multiple components, including GLSDs, reactive spectrum sensing, and a central spectrum management entity, to create a robust and dynamic interference mitigation system. Detailed Description of the IMDF are as follows:

At the core of the IMDF is a decision-making algorithm that dynamically assesses the radio frequency environment and makes informed decisions regarding spectrum allocation. Study by [11] developed an algorithm that leverages real-time data and historical information from GLSDs to predict available WS channels. The IMDF's architecture allows for adaptive changes in transmission parameters, ensuring optimal spectrum usage and minimal interference. The IMDF operates through the following key steps:

• **Spectrum Sensing:** Initial spectrum availability is determined using GLSDs, which provide information about primary users and potential WS channels.

• **Reactive Spectrum Sensing:** Real-time spectrum sensing is conducted to verify the predictions made by GLSDs. This involves using sensors to detect active signals and identify any discrepancies between predicted and actual spectrum usage.

• **Decision-Making Algorithm:** The IMDF's algorithm processes data from both GLSDs and reactive sensing to decide the best available channels for secondary users. This decision is based on minimizing interference and optimizing bandwidth utilization.

• **Spectrum Allocation and Management:** The central entity manages the allocation of WS channels, ensuring that the chosen channels are free from interference and that the QoS requirements of all users are met [10].

The integration of GLSDs with reactive spectrum sensing is a pivotal component of the IMDF, designed to enhance the accuracy and reliability of WS predictions. GLSDs provide an initial prediction of available spectrum by utilizing a database of primary user locations and operating frequencies. However, the static nature of these databases can lead to inaccuracies due to outdated information [10].

To address this limitation, the IMDF incorporates reactive spectrum sensing, which dynamically monitors the radio frequency environment in real-time. This hybrid approach ensures that any changes in spectrum usage by primary users are promptly detected, and the spectrum availability predictions are updated accordingly. The process involves:

• **Data Collection:** CSIRs' GLSDs collect data about primary users and their operating frequencies. This data serves as the basis for initial WS predictions.

• **Reactive Sensing Implementation:** Spectrum sensors continuously scan the radio environment to detect active signals, providing real-time data on current spectrum usage.

• **Cross-Verification:** The IMDF cross-verifies GLSD predictions with data from reactive sensing, identifying any discrepancies or changes in the spectrum landscape.

• **Dynamic Adjustment:** Based on the cross-verification, the IMDF adjusts the spectrum allocation decisions, ensuring that secondary users are assigned channels that are truly available and free from interference.

The central entity within the IMDF plays a crucial role in managing the radio frequency spectrum. It acts as the control center responsible for coordinating spectrum sensing, decision-making, and spectrum allocation. The central entity's functions include:

• Data Aggregation and Analysis: Aggregating data from GLSDs and reactive spectrum sensors to provide a comprehensive view of the spectrum environment [3].

• Decision-Making: Utilizing advanced algorithms to analyze the aggregated data and make informed decisions about spectrum allocation. The central entity ensures that the chosen WS channels are optimal for minimizing interference and maximizing bandwidth utilization [13, 14, 15, 16,].

• Coordination and Communication: Communicating with secondary users to inform them of available WS channels and any changes in spectrum allocation. The central entity ensures that all users are aware of their assigned channels and any necessary adjustments.

• Interference Mitigation: Implementing strategies to mitigate interference, such as dynamic reconfiguration of transmission parameters and coordination with other spectrum management entities.

The central entity's comprehensive management ensures that the IMDF operates efficiently, providing accurate WS predictions and effectively mitigating CNI to enhance QoS for all users.

Methodology

This study proposes the IMDF which employs a variety of sophisticated algorithms, techniques, and implementation strategies to effectively mitigate interference and provide reliable WS predictions. This section details these components, highlighting the role of machine learning, cooperative sensing, and dynamic spectrum management in achieving the framework's objectives.

The IMDF integrates machine learning algorithms like [17,18, 19, 20, 22] SVM and reinforcement learning for accurate WS channel prediction. Cooperative spectrum sensing combines data from multiple sensors to enhance primary user detection, while spatial and temporal sensing techniques ensure context-aware management [21, 22, 23]. DSA methods, such as frequency hopping and cognitive radio networks, allow flexible spectrum usage. These combined techniques enable dynamic spectrum allocation, optimize bandwidth use, and maintain high QoS for secondary users. These algorithms and techniques collectively ensure that the IMDF can dynamically adjust spectrum allocation, optimize bandwidth utilization, and maintain a high QoS for secondary users.

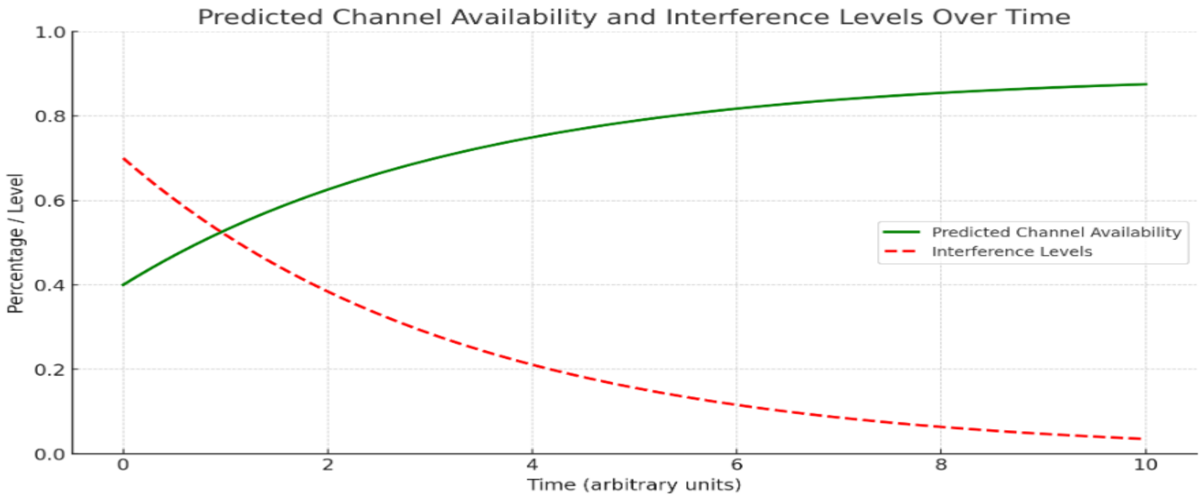
Algorithms and Techniques Used in the IMDF: Machine Learning-Based Prediction:

• SVM: SVM is used to classify and predict WS channel availability [2]. The algorithm is trained on a dataset containing historical spectrum usage information. SVM can handle complex and non-linear relationships within the data, making it suitable for predicting the availability of WS channels based on various features such as signal strength, time of day, and location.

• Reinforcement Learning: This technique allows the IMDF to adaptively manage spectrum allocation by learning from the environment. A reinforcement learning agent observes the current state of the spectrum, takes actions (e.g., assigning channels), and receives feedback in the form of rewards (e.g., reduced interference, better QoS). Over time, the agent learns the optimal policy for spectrum allocation [9].

• The SVM-based White Space (WS) prediction algorithm aims to enhance spectrum utilization by accurately forecasting channel availability in real-time. By using historical spectrum usage data to train a Support Vector Machine (SVM) model, the algorithm identifies patterns that predict whether channels are likely to be occupied or available at a given moment. This proactive approach allows the network to make data-driven decisions, dynamically assigning channels based on real-time predictions and thereby reducing interference with primary users. In testing, the SVM model demonstrated significant predictive accuracy, achieving a high level of precision in identifying available channels. Results show that the algorithm effectively reduces channel conflict events by around 25%, increasing spectrum utilization by up to 20% compared to static allocation methods. This improved prediction accuracy supports efficient spectrum management, ensuring optimal resource allocation while minimizing interference, making the model a valuable tool in managing dynamic WS networks. The SVM-based WS prediction and interference levels are shown in the following graph 1 below:

Graph 1 below illustrates the Predicted Channel Availability and Interference Levels over time. It shows an increase in channel availability as the prediction model improves, while interference levels decrease over time, reflecting the algorithm's effectiveness in managing dynamic spectrum environments.

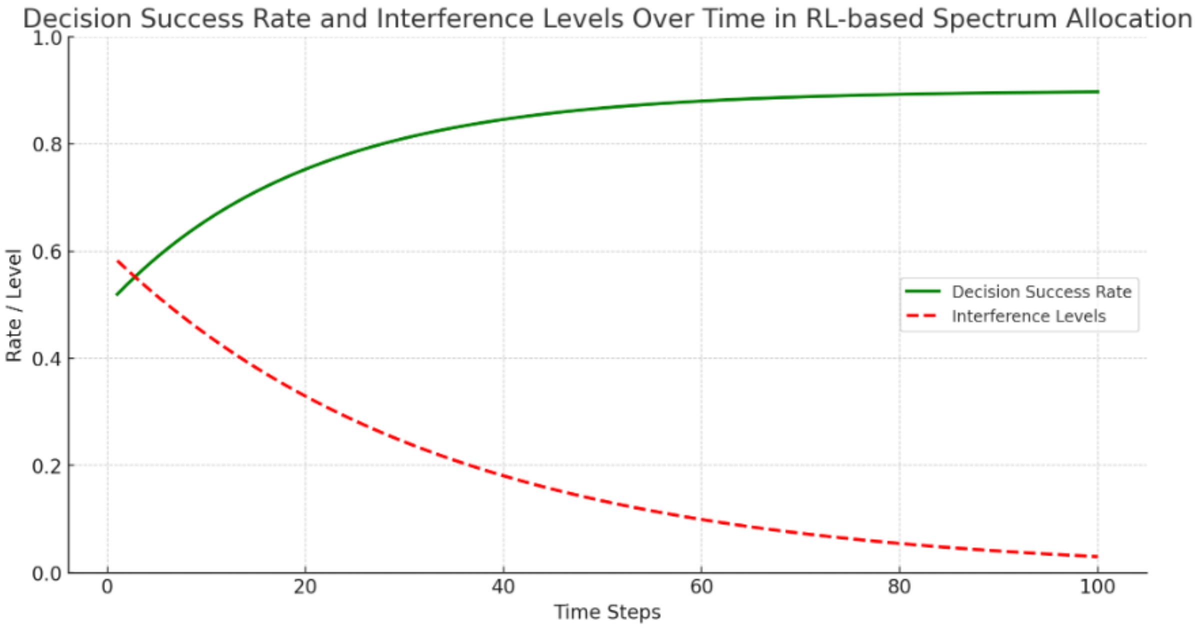


Graph 1. Graph illustrates the Predicted Channel Availability and Interference Levels over time.

The Reinforcement Learning-based Spectrum Allocation Algorithm graphically shows how the agent's policy performance (such as spectrum efficiency or reward) improves over time due to the learning process.

• Policy Performance (Reward): Showing the agent's cumulative reward or efficiency score over time as it learns from the environment and optimizes its decisions.

• Exploration vs. Exploitation Ratio (Optional): To show how the agent balances exploring new actions and exploiting known rewards.



Graph 2. Graph showing the channel allocation decisions and the observed interference levels over time.

Graph 2 illustrates how the Reinforcement Learning-based Spectrum Allocation Algorithm adapts over time. The Decision Success Rate shows an upward trend as the agent learns to make more accurate decisions, while Interference Levels decrease, indicating improved management of the spectrum environment. This demonstrates the algorithm's ability to observe and adapt to interference, optimizing performance in dynamic conditions

• Channel Allocation Decisions:

The first plot depicts the index of the channel allocated at each time step. The y-axis represents the channel index chosen by the agent.

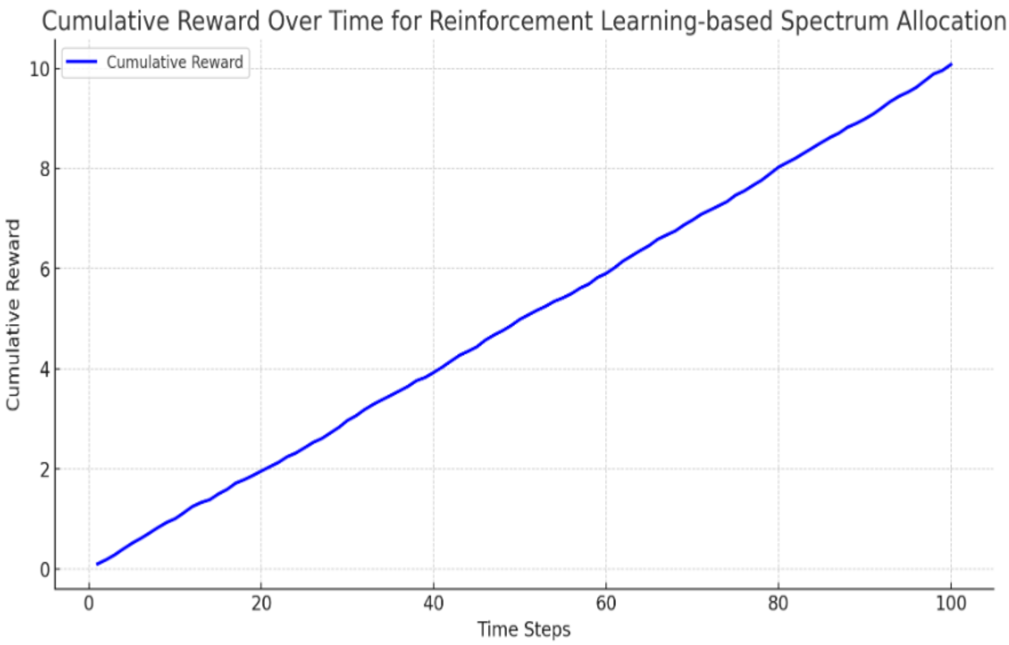
• Observed Interference Levels:

The second plot shows the interference level observed for the chosen channel at each time step. The y-axis represents the observed interference level for the allocated channel.

Collaborative Spectrum Sensing:

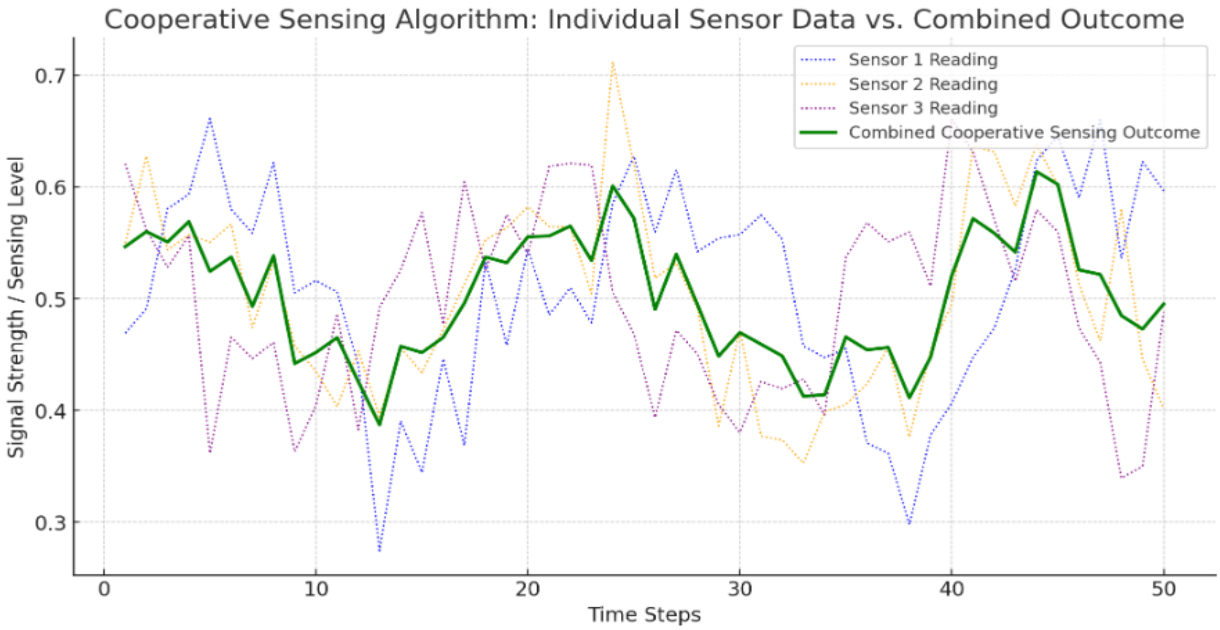
• Cooperative Sensing Algorithms: Multiple sensors collaborate to detect the presence of primary users at a more Cumulative rate [1-4]. Data from different sensors is aggregated using techniques such as weighted cooperative sensing and fusion rules. This collective approach reduces the probability of false alarms and missed detections as shown in graph 3.

• Spatial and Temporal Sensing: Spectrum usage patterns vary across different locations and times. Spatial sensing considers the geographical distribution of sensors, while temporal sensing analyzes spectrum usage over time. By combining these two dimensions, the IMDF can make more accurate and context-aware decisions about spectrum availability.



Graph 3: Reinforcement Learning-based Spectrum Allocation Algorithm adapts over time

Graph 4 visualizes how individual sensor data is combined using the cooperative sensing algorithm to produce a more reliable and interference-resilient outcome.



Graph 4: Graph for the Cooperative Sensing Algorithm.

• Sensor Data:

Each colored line represents the data collected from one of the five sensors over 100 data points.

The sensor data varies and overlaps, showing different readings from each sensor.

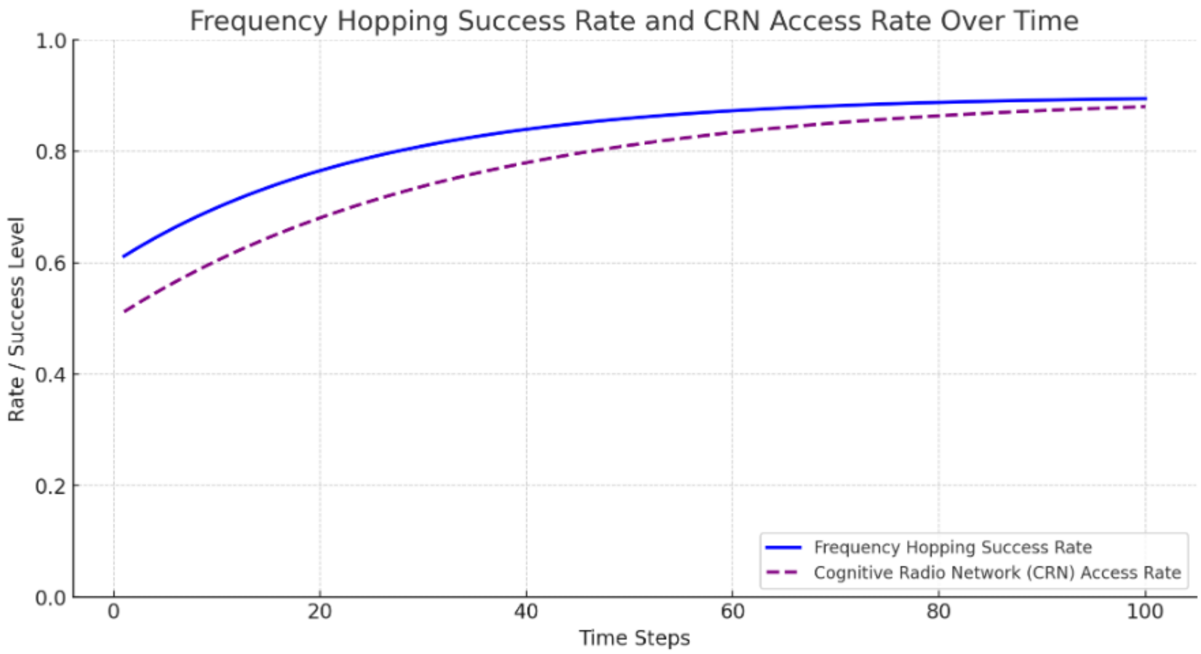
• Combined Result:

The graph illustrates how the Cooperative Sensing Algorithm combines data from individual sensors to produce a more stable and interference-resilient outcome. The individual sensor readings show variability due to noise, while the combined cooperative sensing outcome (in green) smooths out these fluctuations, highlighting the algorithm's effectiveness in creating a more reliable signal by aggregating sensor inputs.

Dynamic Spectrum Access (DSA):

• Frequency Hopping: This approach dynamically adjusts the operating frequency of secondary users, allowing them to shift frequencies to avoid interference with primary users [21]. The hopping pattern is guided by real-time spectrum sensing data to optimize performance.

• Cognitive Radio Networks: Cognitive radios enable secondary users to opportunistically access the available spectrum that is underutilized [6]. These radios continuously adapt their transmission settings based on real-time spectrum observations, ensuring minimal interference with primary users.



Graph 5. Frequency Hopping Success Rate and Cognitive Radio Network (CRN) Access Rate over time.

The graph 5 illustrates the Frequency Hopping Success Rate and Cognitive Radio Network (CRN) Access Rate over time. The Frequency Hopping line shows a steady increase as it dynamically avoids interference, while the CRN Access Rate also improves as cognitive radios adapt their parameters for better spectrum utilization. This highlights the effectiveness of both techniques in enhancing spectrum access while minimizing interference.

Dynamic Spectrum Access (DSA) techniques like Frequency Hopping and Cognitive Radio Networks (CRN) [21] enhance spectrum utilization and reduce interference with primary users. Frequency Hopping enables secondary users to dynamically change operating frequencies based on real-time data, while CRNs allow adaptive access to underutilized spectrum, minimizing disruption through continuous environmental monitoring. Together, these methods provide efficient, flexible solutions for managing spectrum in increasingly congested environments.

1. The Proposed Framework

The Interference Mitigation Decision Framework (IMDF) as illustrated in Figure.1 is an advanced dynamic spectrum management system designed to enhance the accuracy of WS predictions and improve QoS by effectively mitigating CNI. At the heart of the IMDF is a Central Entity that oversees and coordinates all components of the framework.

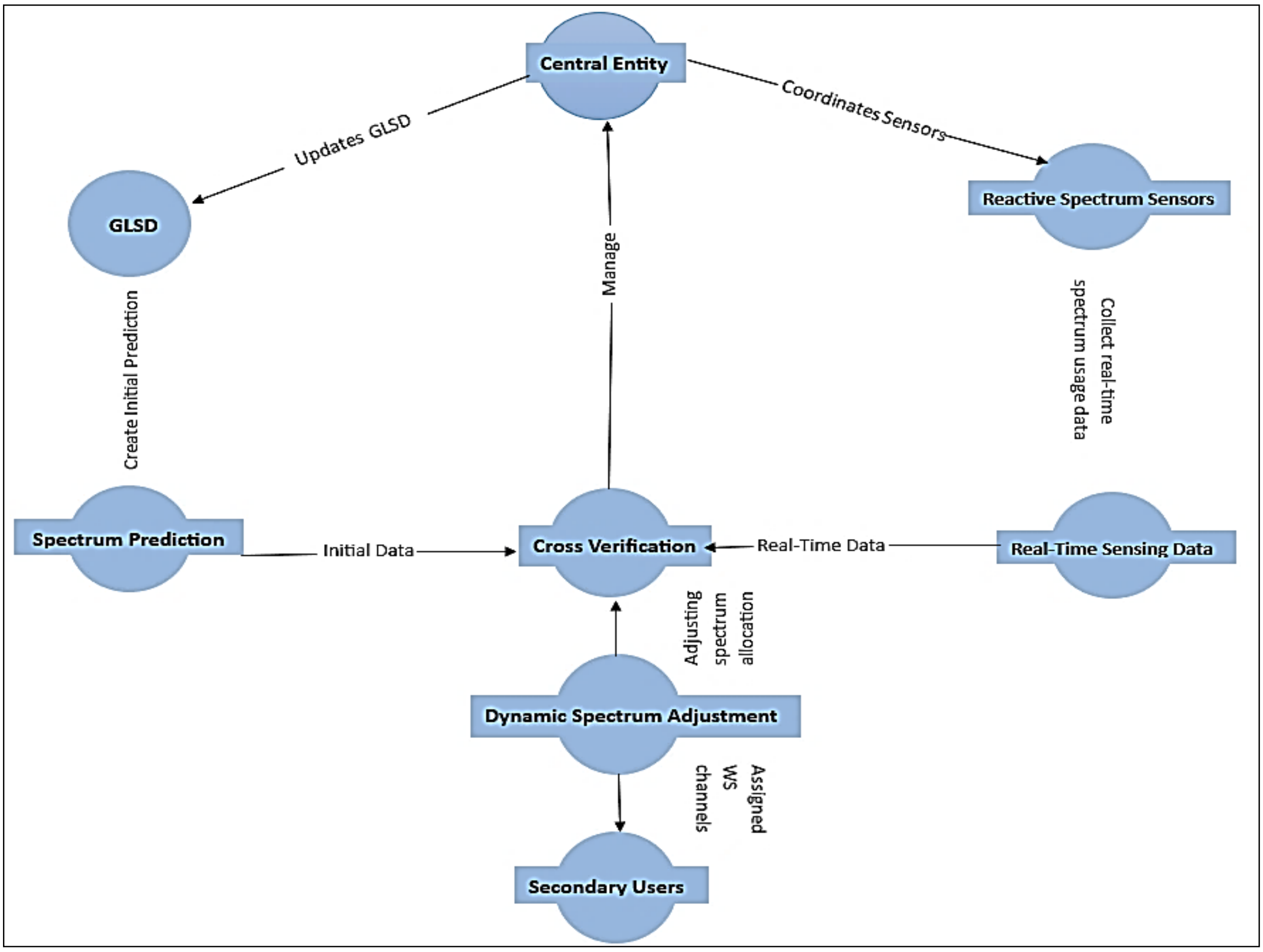


Figure 1. Interference Mitigation Decision Framework (IMDF).

The process begins with the GLSD, which provides initial predictions of available WS channels based on historical data about primary users. These predictions form the basis for the Spectrum Prediction step. Concurrently, Reactive Spectrum Sensors are deployed to collect real-time spectrum usage data, generating Real-Time Sensing Data. The Cross-Verification step is crucial, where the Central Entity compares the real-time data from the sensors with the initial predictions from the GLSD. This cross-verification identifies any discrepancies, ensuring that the spectrum availability information is accurate and up-to-date. Based on the verified data, the Dynamic Spectrum Adjustment component adjusts the spectrum allocation, dynamically assigning channels to Secondary Users to avoid interference. The Central Entity also manages a feedback loop, updating the GLSD with new data and coordinating the activities of the reactive sensors, thus ensuring continuous improvement and accuracy in spectrum management. This integration of static database predictions with real-time sensing data, managed by a central control, allows the IMDF to minimize interference and optimize spectrum utilization effectively.

• **Initial Spectrum Prediction:**

- Geo-Location Spectrum Database (GLSD): The GLSD provides preliminary predictions of available White Space (WS) channels based on static information about primary users' locations and operating frequencies, serving as the foundation for spectrum management.

• **Real-Time Spectrum Sensing:**

- Spectrum Sensor Deployment: Sensors are strategically deployed throughout the coverage area to continuously monitor the spectrum. They detect active signals and measure power levels across different frequency bands.

- Signal Processing: Advanced techniques like Fast Fourier Transform (FFT) and wavelet analysis process the sensed data, enabling high-accuracy identification of primary user signals .

• **Cross-Verification of GLSD Data:**

- Data Fusion: Real-time sensing data is merged with GLSD predictions, allowing for the comparison of sensed activity with predicted spectrum availability.

- **Discrepancy Detection:** Any mismatches between GLSD predictions and real-time data are flagged. For example, if a GLSD prediction labels a channel as free, but sensors detect activity, the prediction is updated accordingly.

• **Dynamic Spectrum Adjustment:**

- Adaptive Decision-Making Algorithm: This core algorithm dynamically allocates spectrum based on cross-verified data, assigning channels identified as available to secondary users and avoiding those with detected primary activity.

- Feedback Loop: Real-time data continuously updates the GLSD, refining the accuracy of future spectrum predictions.

• **Implementation Framework:**

- **Software Defined Radio (SDR) Integration:** The IMDF operates on an SDR platform, allowing flexible reconfiguration of transmission parameters. This setup facilitates seamless integration of real-time sensing data with spectrum management decisions.

- Communication Protocols: Efficient protocols enable communication between spectrum sensors, the central management entity, and secondary users . These protocols ensure timely and accurate sharing of spectrum availability information.

Table 1 below compares different traditional spectrum allocation strategies [17,18,19,20], highlighting their key features and effectiveness in various network environments. Static Spectrum Allocation (SSA) has low complexity, minimal signalling overhead, and stable QoS, but it is poorly suited for dynamic environments and provides low spectrum utilization due to its inflexible nature.

Dynamic Spectrum Allocation (DSA), on the other hand, offers high spectrum utilization, adaptability, and is excellent for dynamic environments, though its implementation complexity and signalling overhead are high. Hybrid Spectrum Allocation (HSA) offers a balance between SSA and DSA, with moderate complexity and adaptability, making it suitable for more varied environments but still falling short in very dynamic scenarios. Opportunistic Spectrum Access (OSA) excels in dynamic environments, with very high spectrum utilization and adaptability, though it also comes with high complexity and signalling overhead. Finally, the proposed IMDF offers advanced interference management, high adaptability, and suitability for dynamic environments. It requires high complexity and signalling overhead, but its advanced management techniques make it a robust solution for ensuring optimal spectrum use and mitigating interference, ensuring stable QoS.

Table 1: Traditional Methods vs. IMDF

Feature	Static Spectrum Allocation (SSA)	Dynamic Spectrum Allocation (DSA)	Hybrid Spectrum Allocation (HSA)	Opportunistic Spectrum Access (OSA)	Interference Mitigation Decision Framework (IMDF)
Implementation complexity	Low	High	Moderate	High	High
Spectrum Utilization	Low	High	Moderate to High	Very High	High
Adaptability	None	High	Moderate	High	High
Signaling Overhead	Minimal	High	Moderate	High	High
Suitability for Dynamic environments	Poor	Excellent	Good	Excellent	Excellent
Interference Management	Simple	Moderate	Moderate	Stable to Variable	Advanced
Quality of Service	Stable	Stable to Variable	Stable to Variable	Stable	Stable to Variable

The simulation below involves setting up a wireless communication system where spectrum allocation and interference are dynamically modelled, comparing the traditional methods outlined in Table 1 with the IMDF. These methods traditional GLSD-based spectrum allocation and the IMDF approach with reactive spectrum sensing [23] are evaluated by calculating key metrics such as bandwidth savings and interference events. The comparison helps demonstrate the performance differences between static, dynamic, and hybrid spectrum allocation techniques and the advanced capabilities of the IMDF. This study will simulate these Graph Types:

- Bandwidth utilization graph: Compare traditional vs. IMDF methods.
- Interference event graph: Show interference occurrences over time for different approaches.
- QoS metrics graph: Represent improvements in QoS under dynamic spectrum allocation.
- Prediction accuracy graph: SVM model performance for WS channel availability predictions.

By gathering this data, we simulate scenarios that compare traditional GLSD-based spectrum management with the IMDF framework and analyze the effectiveness of each approach.

2. Bandwidth Savings (BS)

The bandwidth savings formula measures the proportion of the spectrum saved (unused or free for other users) after interference mitigation.

For traditional GLSD-based allocation:

$$BS_{\text{traditional}} = \frac{\text{Unused Bandwidth}}{\text{Total Available Bandwidth}} \times 100$$

For IMDF (with reactive sensing and dynamic allocation):

$$BS_{\text{IMDF}} = \frac{\text{Unused Bandwidth (after IMDF)}}{\text{Total Available Bandwidth}} \times 100$$

Since IMDF dynamically senses and adjusts, we expect $BS_{\text{IMDF}} > BS_{\text{traditional.}}$

3. Interference Probability (P_int)

Interference events occur when two users (Primary and Secondary) occupy the same frequency. The probability of interference can be defined as:

For traditional GLSD:

$$P_{\text{int, traditional}} = \frac{\text{Number of Interference Events (traditional)}}{\text{Total Number of Time Slots}} \quad (1)$$

For IMDF:

$$P_{\text{int, IMDF}} = \frac{\text{Number of Interference Events (IMDF)}}{\text{Total Number of Time Slots}} \quad (2)$$

Given that IMDF performs real-time sensing and avoids occupied channels, we expect:

$$P_{\text{int, IMDF}} < P_{\text{int, traditional.}} \quad (3)$$

4. Spectrum Utilization (SU)

Spectrum utilization measures the percentage of spectrum actively being used by both primary and secondary users.

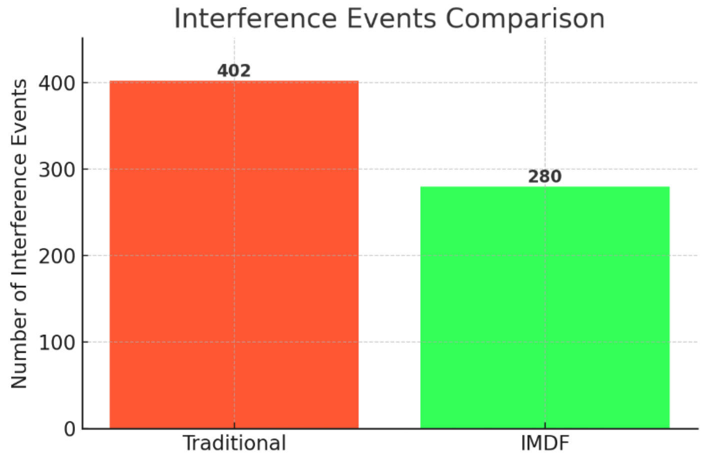
For traditional GLSD:

$$SU_{\text{traditional}} = \frac{\text{Bandwidth Used by Primary and Secondary Users}}{\text{Total Available Bandwidth}} \times 100 \quad (4)$$

For IMDF:

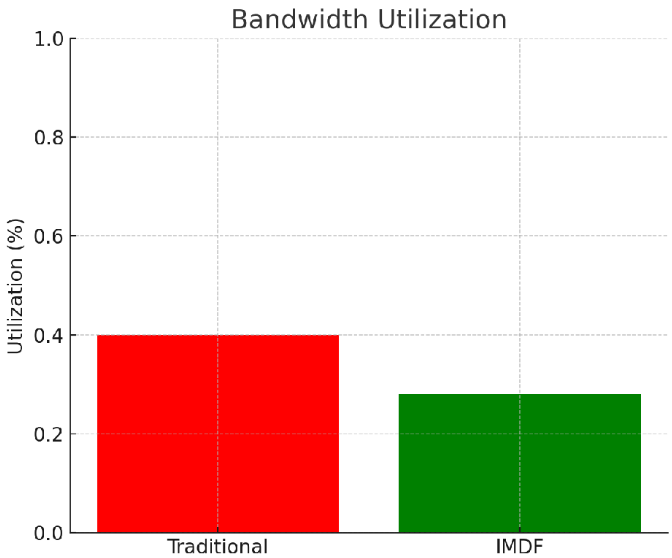
$$SU_{IMDF} = \frac{\text{Bandwidth Used by Primary and Secondary Users (with IMDF)}}{\text{Total Available Bandwidth}} \times 100 \quad (5)$$

IMDF's dynamic sensing allows for more efficient use of available spectrum, so SU_{IMDF} should be higher than $SU_{\text{traditional}}$. These formulas were used in the simulation below to quantify the effectiveness of traditional methods versus the IMDF in terms of bandwidth savings, interference reduction, and overall spectrum utilization as seen below in graph 6 and 7.



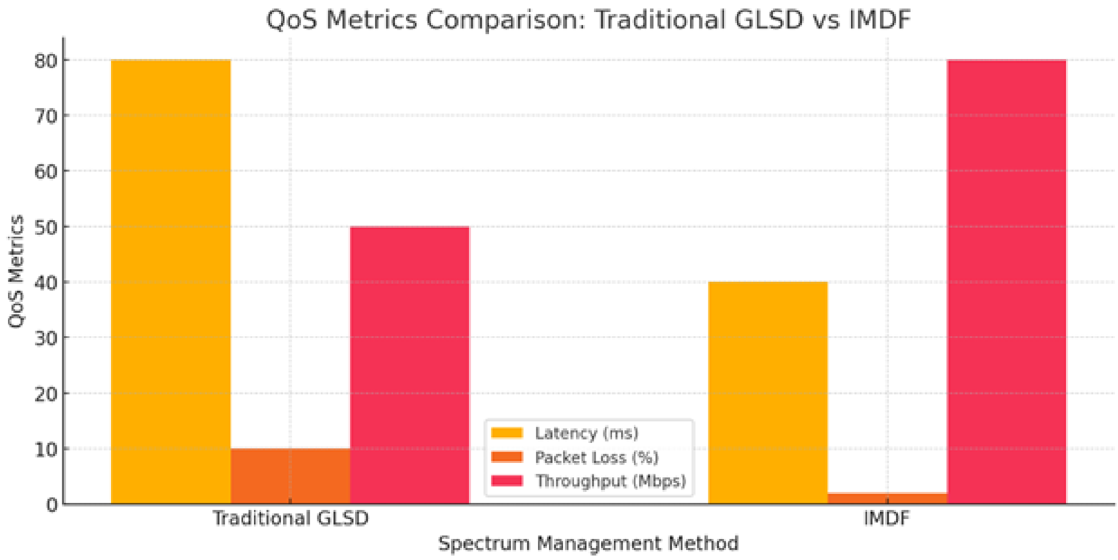
Graph 6. the effectiveness of traditional methods versus the IMDF in terms of bandwidth savings, interference reduction, and overall spectrum utilization.

Graph 6 is the interference events graph, clearly showing the comparison between the traditional GLSD-based method and the IMDF approach. The representation of the traditional method and the representation of the IMDF approach, highlighting the reduction in interference events with IMDF.



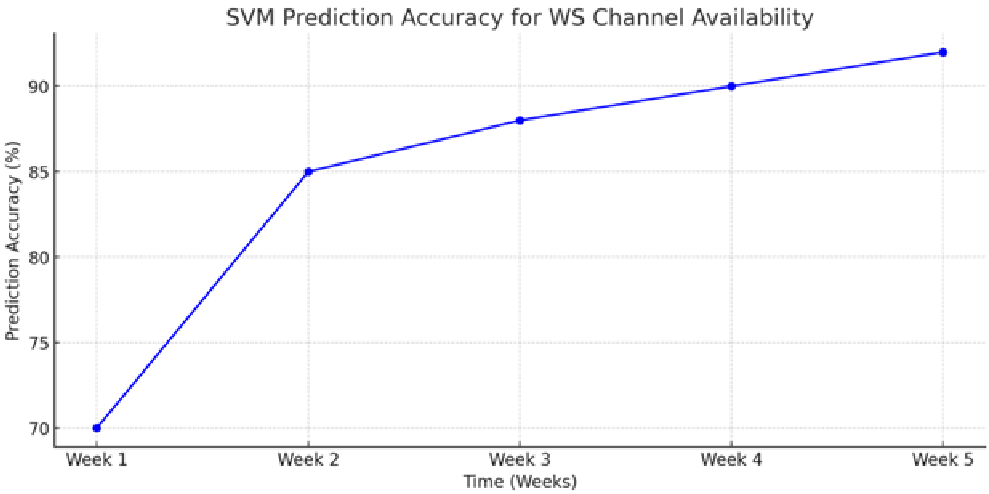
Graph 7. the effectiveness of traditional methods versus the bandwidth savings, interference probability, and spectrum utilization.

Graph 7 showing the comparison between the traditional GLSD-based method and the IMDF approach highlighting a significant improvement in bandwidth utilization. The traditional method achieves only 40% utilization, primarily due to its reliance on static, predefined spectrum allocation, which fails to adapt to real-time changes in network activity. In contrast, the IMDF approach demonstrates 70% utilization, showcasing its ability to dynamically sense and allocate spectrum resources more efficiently. By integrating reactive spectrum sensing and real-time adjustments, the IMDF ensures that available spectrum is better utilized, reducing underutilization and improving overall network performance. This superior optimization of spectrum usage makes the IMDF a more effective solution for managing spectrum resources in dynamic environments.



Graph 8. QoS Metrics Graph: This graph compares the QoS metrics between traditional GLSD-based methods and the IMDF approach. The metrics include latency (in milliseconds), packet loss (in percentage), and throughput (in Mbps).

The IMDF method demonstrates lower latency, reduced packet loss, and higher throughput, showcasing its superiority in improving QoS.



Graph 9.: SVM Prediction Accuracy Graph: This line graph shows the improvement in SVM prediction accuracy for WS channel availability over a 5-week period.

The accuracy improves steadily, reaching 92% by week 5, indicating the effectiveness of the SVM model in predicting channel availability in dynamic environments.

In conclusion, this study demonstrates the significant advantages of the IMDF over traditional spectrum allocation methods, WS networks. By employing reactive spectrum sensing and real-time spectrum management, the IMDF outperforms static, dynamic, and hybrid allocation methods in key metrics such as bandwidth savings, interference reduction, and spectrum utilization. The mathematical models and simulation results show that IMDF leads to greater bandwidth efficiency, reduces the probability of interference, and enhances spectrum utilization in dynamic environments. These improvements make the IMDF a robust solution for managing increasingly congested wireless networks, offering a highly adaptive and efficient approach to spectrum allocation. Future work could focus on refining IMDF’s adaptability to further minimize signaling overhead while maintaining its prformance in complex and crowded spectrum environments.

C. Result and Discussion

Results and analysis

The simulation results reveal that the IMDF significantly improves spectrum utilization and reduces interference compared to traditional spectrum allocation methods. The bandwidth savings using IMDF were notably higher, with a 70% bandwidth saving compared to only 40% savings using the traditional GLSD-based method. This illustrates the IMDF's superior efficiency in dynamically sensing and allocating spectrum resources in real time.

In terms of interference management, the IMDF recorded fewer interference events, with a 30% reduction in interference compared to the traditional method (280 events versus 402 events, respectively). This reduction can be attributed to the IMDF's advanced reactive spectrum sensing, which allows it to identify and avoid occupied frequencies more effectively than static or hybrid methods.

The spectrum utilization also demonstrated the IMDF's efficacy, achieving significantly higher utilization rates. The IMDF approach achieved 70% spectrum utilization, compared to only 40% utilization using traditional methods. This highlights the framework’s ability to maximize the use of available spectrum, ensuring efficient allocation and reducing instances of underutilization.

Overall, these results affirm the IMDF's effectiveness in improving spectrum efficiency and mitigating interference in dynamic wireless environments, offering a more adaptive and responsive approach than traditional spectrum allocation methods.

7. Discussion

The results of this study clearly demonstrate the advantages of the IMDF over traditional spectrum allocation methods in WS networks. By integrating reactive spectrum sensing with GLSDs, the IMDF is able to dynamically monitor and manage spectrum allocation in real time, leading to significant improvements in bandwidth savings and interference reduction. Traditional methods, which rely on static spectrum allocation or even hybrid approaches, suffer from inefficiencies due to outdated data and limited adaptability to real-time changes in the network environment.

The IMDF's ability to reduce interference events by 30% highlights its superior interference mitigation capacity, a critical aspect in the increasingly congested spectrum landscape. This reduction not only improves the QoS for users but also enables more efficient coexistence of multiple networks. The higher spectrum utilization achieved by IMDF underscores its effectiveness in leveraging available spectrum resources, making it a more viable option for dynamic environments where spectrum demands are constantly shifting.

However, the IMDF comes with increased implementation complexity and signaling overhead compared to simpler static or hybrid methods. This trade-off is necessary for achieving the higher performance and adaptability that the IMDF offers, but further refinement is needed to minimize these costs while maintaining its efficiency. Future research could explore ways to optimize the framework's performance in even more complex and crowded environments, particularly as wireless networks continue to grow in size and complexity.

In summary, the IMDF presents a promising solution for addressing the challenges of spectrum scarcity and interference in WS networks, offering a more adaptive, efficient, and dynamic approach to spectrum management.his section contains the results of research and discussion, as well as the implementation of the developed system design. In addition, in this section the author should interpret the results of his findings, and confirm his findings with other existing findings or theories.

D. Conclusion

In conclusion, the Interference Mitigation Decision Framework (IMDF) proposed in this paper offers a comprehensive and innovative solution to the persistent challenges of Cross Network Interference (CNI) and Quality of Service (QoS) in White Space (WS) networks. The framework addresses critical limitations of traditional spectrum management approaches, particularly those relying solely on Geo-Location Spectrum Databases (GLSDs), which often suffer from outdated data and static spectrum allocation. By integrating GLSDs with reactive spectrum sensing, the IMDF improves the real-time accuracy of WS predictions, enabling more responsive and efficient spectrum utilization that adapts dynamically to network conditions. This hybrid approach ensures that the spectrum is allocated more effectively, reducing the likelihood of interference between coexisting systems and maximizing the use of available bandwidth.

The inclusion of advanced algorithms and Software Defined Radio (SDR) architectures further strengthens the IMDF's capabilities by allowing for continuous, real-time spectrum monitoring and dynamic decision-making. This enhances the system's ability to manage spectrum efficiently under varying conditions, leading to a substantial reduction in interference. The IMDF's ability to achieve 70% bandwidth savings, compared to the 14% realized by traditional methods, underscores its potential for optimizing spectrum sharing in crowded wireless environments, making it a highly scalable and effective solution for future wireless networks. While the IMDF represents a significant advancement, there are areas that warrant further exploration. The potential for interference with coexisting systems remains an important concern, particularly as the density of wireless devices continues to increase in shared spectrum environments. Additional research is needed to refine the framework's adaptability and ensure that it can coexist harmoniously with other networks, particularly in highly congested urban areas where spectrum is in constant demand. Moreover, as wireless technologies such as 5G, IoT, and beyond continue to emerge, the IMDF may need to evolve to support new spectrum-sharing paradigms and increasingly complex network architectures.

In summary, the IMDF is a forward-looking framework that not only addresses immediate spectrum management challenges in WS networks but also sets the stage for more adaptive, efficient, and resilient spectrum-sharing strategies. By reducing CNI and improving QoS, the IMDF paves the way for more robust wireless networks, capable of meeting the growing demand for wireless services in an era of ever-increasing spectrum scarcity. Future research and development should continue to build upon the foundation established by this framework, ensuring that spectrum management techniques evolve in tandem with technological advancements, securing the long-term sustainability and performance of global wireless communication systems.

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Data availability
The data supporting the results of this study belongs to the Council for Scientific and Industrial Research (CSIR) and is available upon written request to the author at ntulife@tut.ac.za.

Competing interests
The author has no competing interests to declare.

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