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RTSO: Comprehensive Framework for Real-Time Frequency Channel Occupancy and Spectrum Hole Detection

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Abstract

Efficient spectrum utilization remains a key challenge in modern wireless communications, especially in dynamic environments with limited spectrum availability. This paper introduces Real-Time Spectrum Optimization (RTSO), a framework that combines Geo-Location Spectrum Databases (GLSDBs) with real-time spectrum sensing to detect frequency channel occupancy and identify spectrum holes. RTSO uses advanced energy detection techniques, including Additive White Gaussian Noise (AWGN) modelling, to distinguish between idle and occupied channels accurately. It incorporates mathematical tools such as occupancy time and Frequency Channel Occupation (FCO) metrics for effective spectrum analysis. A notable feature is a revisit-time-based sensing mechanism that infers channel status during intermittent scans. Practical evaluations demonstrated improved detection accuracy, reduced false alarms, and better decision-making for dynamic access to available channels. Key performance metrics, including latency, bandwidth, and error rate, were compared with baseline methods, showing substantial gains in efficiency. This work provides a valuable contribution to cognitive radio systems and dynamic spectrum access, paving the way for more intelligent and adaptive spectrum management strategies in real-time communication networks.

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A. Introduction

The exponential growth of wireless communication systems has intensified the demand for spectrum resources, creating challenges in managing limited bandwidth effectively. Traditional spectrum allocation methods, which assign fixed frequencies to specific services, have proven inefficient in dynamic environments, leading to underutilization of valuable spectrum [1]. To address this, Dynamic Spectrum Access (DSA) and Cognitive Radio (CR) technologies have been proposed as promising solutions. These technologies enable secondary users to opportunistically utilize idle frequency channels, known as spectrum holes, without causing interference to primary users [2].

Accurate spectrum sensing is a cornerstone of DSA, as it ensures reliable detection of spectrum holes for temporary utilization. However, conventional spectrum sensing techniques face challenges such as missed detection, high false alarm rates, and environmental noise, which compromise the reliability of spectrum occupancy measurements [3]. These limitations necessitate advanced approaches to optimize spectrum utilization while maintaining interference mitigation and Quality of Service (QoS).

The RTSO (Real-Time Spectrum Optimization) framework addresses these challenges by integrating Geo-Location Spectrum Databases (GLSDBs) with advanced real-time spectrum sensing techniques. This framework introduces energy detection enhanced by Additive White Gaussian Noise (AWGN) modelling [4], enabling precise differentiation between occupied and unoccupied frequency channels. The RTSO framework further incorporates a revisit-time-based sensing mechanism to assess spectrum occupancy intermittently across multiple channels while maintaining accuracy.

This study presents RTSO as a comprehensive framework for detecting frequency channel occupancy and identifying spectrum holes. The framework employs advanced mathematical models, including occupancy time and Frequency Channel Occupation (FCO) metrics, to support reliable decision-making for dynamic spectrum access. Practical experiments demonstrate significant improvements in spectrum detection accuracy, reduced latency, and enhanced bandwidth utilization compared to baseline methods. These findings contribute to the advancement of cognitive radio systems and real-time spectrum management in addressing the growing spectrum scarcity problem [5].

This paper is organized as follows: Section 2 reviews related work and discusses the existing challenges in spectrum sensing. Section 3 elaborates on the proposed RTSO framework and its mathematical formulations. Section 4 presents experimental results and performance evaluations, while Section 5 concludes the paper and proposes future research directions.

B. Related Work

The growing demand for efficient spectrum utilization has driven significant research into dynamic spectrum access (DSA) and cognitive radio (CR) technologies. These studies aim to address spectrum scarcity by enabling secondary users to opportunistically access unoccupied channels. This section reviews recent advancements in spectrum sensing techniques, occupancy detection, and interference mitigation strategies, highlighting the gaps addressed by the Real-Time Spectrum Optimization (RTSO) framework.

2.1 Spectrum Sensing and Occupancy Detection

Accurate spectrum sensing is vital for detecting spectrum holes and ensuring efficient utilization of available bandwidth. Traditional methods, such as energy detection and matched filtering, have been widely used due to their simplicity and effectiveness [5]. However, these techniques suffer from high false alarm rates and missed detection probabilities, particularly in noisy environments or low signal-to-noise ratio (SNR) conditions [6]. To overcome these challenges, recent research has integrated machine learning (ML) models, such as deep learning and reinforcement learning, to enhance detection accuracy. For instance, [7] proposed a deep reinforcement learning approach for spectrum prediction, demonstrating improved accuracy in detecting idle channels under dynamic conditions.

Moreover, the use of Geo-Location Spectrum Databases (GLSDBs) has gained attention as a complementary method for spectrum sensing. GLSDBs provide information about the occupancy of frequency bands based on geographical data, reducing the need for exhaustive real-time sensing [8]. However, database-driven approaches alone cannot account for unexpected spectrum usage changes, necessitating hybrid frameworks that combine real-time sensing with GLSDB data.

2.2 Interference Mitigation

Interference is a critical issue in dynamic spectrum access systems, as secondary users may unintentionally disrupt primary users' transmissions. Adaptive filtering techniques, such as notch filters and power control algorithms, have been proposed to address this problem [9, 10]. Additionally, frequency hopping and dynamic frequency adjustment strategies have been shown to effectively reduce interference in cognitive radio networks [11]. However, these methods often require significant computational resources and may not adapt quickly to real-time changes in the spectrum environment.

Recent advancements in ML-driven interference mitigation offer promising solutions to these challenges. For example, [12] introduced a supervised learning model for detecting and mitigating interference, achieving substantial improvements in throughput and latency. Despite these advancements, existing frameworks still lack the ability to integrate real-time interference mitigation with spectrum sensing and occupancy prediction in a cohesive manner.

2.3 Gaps in Current Research

While significant advancements have been made in spectrum sensing, interference mitigation, and spectrum prediction, several gaps persist. Current methodologies often face challenges in achieving a balance between real-time responsiveness and computational efficiency, particularly in environments characterized by high variability in spectrum usage [13]. Furthermore, existing research tends to focus on isolated components of dynamic spectrum access systems, such as spectrum sensing or interference mitigation, without addressing the necessity of an integrated framework that seamlessly combines these functionalities [14, 15].

The Real-Time Spectrum Optimization (RTSO) framework addresses these limitations by offering a unified solution that integrates real-time spectrum monitoring, machine learning-based spectrum prediction, and dynamic interference mitigation. By combining these components, the RTSO framework improves spectrum efficiency, minimizes interference, and ensures reliable spectrum access for secondary users in complex and dynamic environments [16].

C. Research Method

3.Spectrum Sensing and Prediction using Machine Learning

Machine Learning (ML) can significantly enhance the allocation of spectrum and reduce interference in wireless communication, particularly in shared environments. Each of these steps is represented by a box and arrows between them show the logical flow of data from one step to the next. Details of how ML can achieve these improvements are listed below:

3.1 .Spectrum Data Acquisition:

- The first step involves collecting spectrum data using sensors or Software Defined Radios (SDRs).
- This raw data includes signal characteristics such as frequency, amplitude, and time.

3.2.Data Preprocessing:

- The acquired data is cleaned and prepared for analysis.
- Steps include noise removal, normalization, and data formatting to ensure consistent quality.

3.3.Feature Extraction:

- Key features of the signals, like power levels, frequency usage, and temporal patterns, are identified.
- This step reduces the complexity of the data for better analysis.

3.4.Machine Learning Model Training:

- A machine learning model (e.g., supervised or unsupervised) is trained on the pre-processed data.
- The training phase helps the model learn to identify patterns and make predictions.

3.5.Spectrum Sensing:

- The trained model detects spectrum occupancy, identifying white spaces (unused frequencies) and active frequencies.

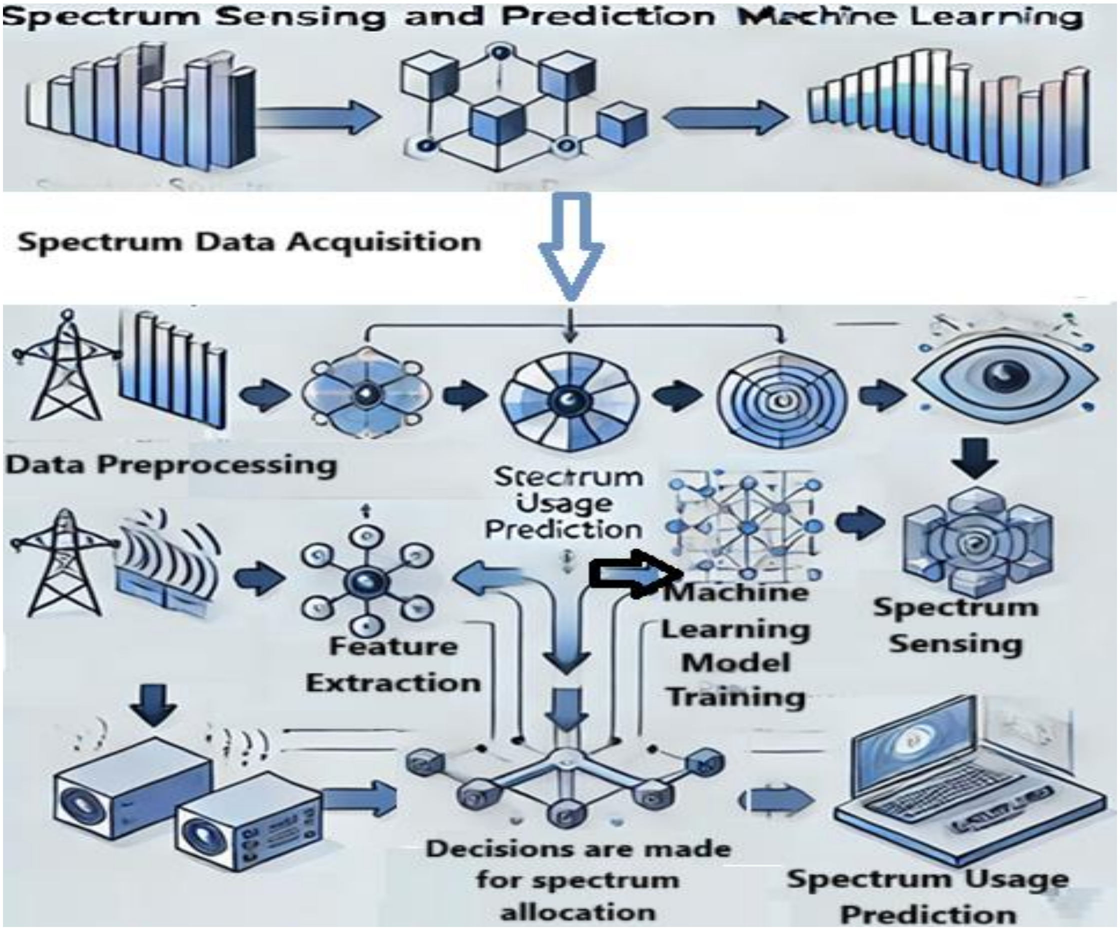

Figure 1. Spectrum sensing and prediction ML.

3.6.Spectrum Usage Prediction:
- Using the learned patterns, the model predicts future spectrum usage trends, such as which frequencies are likely to become available or busy.

3.7.Decision-Making:
- Based on the predictions, decisions are made for spectrum allocation, interference mitigation, or optimizing network performance.

Problem Formulation

4.1 Spectrum Sensing and Prediction
4.1.1 Dynamic Spectrum Access (DSA):

- **Spectrum Sensing:** ML algorithms can be employed to detect which portions of the spectrum are currently in use and which are free. Techniques like deep learning can analyse spectrum usage patterns in real-time, enabling more accurate detection of available channels.

- **Spectrum Prediction:** ML models can predict future spectrum usage based on historical data. Time-series forecasting models, such as Long Short-Term Memory (LSTM) networks, can be used to anticipate when a particular frequency band will be free, allowing proactive spectrum allocation

- DSA optimizes spectrum allocation to maximize spectrum usage:

$$\max \sum_{i=1}^{N} U_i(x_i) \tag{1}$$

Subject to:

$$\sum_{i=1}^{N} x_i \leq S_{\text{total}} \tag{2}$$

Where:
- $U_i(x_i)$: Utility of spectrum x_i for user i.
- S_{total}: Total spectrum available.

4.2. Interference Management

4.2.1. Interference Detection and Classification:
- **Anomaly Detection:** ML can identify unusual patterns in the spectrum that indicate interference. Supervised learning techniques can classify different types of interference sources (e.g., co-channel interference, adjacent channel interference) and help in mitigating them effectively.
- **Reinforcement Learning:** By continuously learning from the environment, reinforcement learning algorithms can dynamically adjust transmission parameters (such as power levels and frequencies) to minimize interference.

4.3. Resource Allocation

4.3.1. Optimized Resource Allocation:
- **Reinforcement Learning (RL):** RL algorithms can optimize resource allocation by learning the best strategies to allocate spectrum resources dynamically. Multi-agent RL can be particularly effective in environments where multiple users or devices are competing for spectrum resources.

4.4. Cognitive Radio Networks (CRNs)

4.4.1. Adaptive and Intelligent Spectrum Management:

- **Cognitive Radios:** ML enables cognitive radios to adapt their transmission parameters based on the environment. These radios can learn from the past behaviour of the network and predict future conditions, making them more efficient in spectrum utilization.
- **Context-Aware Decision Making:** By integrating contextual information (e.g., location, time, user requirements), ML algorithms can make more informed decisions about spectrum allocation, further reducing interference and improving communication quality.
    - Cognitive radio uses spectrum sensing to detect unused spectrum bands:

False Alarm Probability (P_{fa}):

$$P_{fa} = Q\left(\frac{\lambda - P_n}{\sqrt{\sigma^2/2}}\right)$$

(3)

Missed Detection Probability (P_{md}):

$P_{md} = 1 - P_d$

(4)

4.5. Real-Time Spectrum Management

4.5.1 Fast and Efficient Decision Making:

- **Online Learning:** ML techniques such as online learning can adapt to changes in the spectrum environment in real-time. This capability is crucial for environments with high mobility, such as vehicular networks.
- **Edge Computing:** Implementing ML models at the edge of the network can reduce latency in decision-making processes, allowing for quicker responses to changes in the spectrum environment.

4.6. Network Optimization

4.6.1 Self-Organizing Networks (SON):

- **Autonomous Optimization:** ML can be used to create self-organizing networks that autonomously optimize themselves. For instance, ML can help in automatically adjusting the network topology, optimizing handovers, and balancing loads across the network.
- **Predictive Maintenance:** ML can predict potential issues in the network, such as hardware failures or performance degradation, allowing for pre-emptive measures to be taken.

4.7. Enhanced Quality of Service (QoS)

4.7.1 QoS Prediction and Management:

- **Predictive Analytics:** ML can predict QoS metrics such as latency, throughput, and reliability. This predictive capability allows network operators to proactively manage resources and maintain high QoS levels.
- **User Behaviour Analysis:** By analysing user behaviour and traffic patterns, ML can help in better understanding demand and allocating resources accordingly.

In summary, Machine Learning provides a suite of tools and techniques that can greatly enhance spectrum allocation and reduce interference in wireless communication. By leveraging ML for spectrum sensing, interference management, resource allocation, and network optimization, wireless communication systems can achieve higher efficiency, improved QoS, and better adaptability to changing environments. These capabilities are particularly crucial in shared spectrum environments where efficient utilization and minimal interference are key to maintaining robust communication networks.

D. Result and Discussion

5. Proposed Real-Time Spectrum Optimization (RTSO) Framework

The Real-Time Spectrum Optimization (RTSO) framework aims to address the challenges of spectrum scarcity and inefficiency by providing a comprehensive system for real-time monitoring, prediction, and optimization of frequency channel occupancy. This section details the proposed RTSO framework and highlights its distinction from existing spectrum management frameworks.

5.1.Previous Work on Frameworks for Spectrum Management

Previous studies have explored various frameworks for spectrum management to enhance dynamic spectrum access (DSA) and minimize interference. These frameworks have largely relied on static or semi-dynamic spectrum allocation strategies that struggle to adapt to real-time spectrum conditions. For example, [13] proposed a hybrid framework combining spectrum sensing with database-driven approaches to predict spectrum availability. While effective in certain scenarios, such approaches fail to address the rapid variations in spectrum usage that characterize modern wireless environments.

Machine learning (ML) has been incorporated into spectrum management frameworks to improve adaptability and prediction accuracy. [14] introduced a reinforcement learning-based framework for spectrum sharing, demonstrating improvements in resource allocation and interference reduction. However, the computational complexity of such methods often limits their scalability in real-world applications. Additionally, existing frameworks tend to focus on specific aspects of spectrum management, such as sensing or mitigation, without offering a holistic solution that integrates all necessary components. Table 1 highlights the improvements of the RTSO framework over traditional baseline methods.

Table 1. The improvements of the RTSO framework over traditional baseline methods.

Aspect	Baseline Methods	RTSO Framework
Spectrum Allocation	Static spectrum allocation; fixed without real-time adjustments.	Dynamic spectrum allocation based on real-time monitoring and machine learning.
Spectrum Usage Detection	Energy detection using fixed thresholds without predictive modeling.	Advanced detection with machine learning for accurate prediction and spectrum usage optimization.
Interference Mitigation	Predefined methods like static filters or frequency adjustments.	Dynamic interference suppression using adaptive filtering and frequency hopping techniques.
Spectrum Access	First-come-first-serve access without QoS prioritization.	Optimized access with prioritization to maximize Quality of Service (QoS).
Response to Changing Conditions	Limited adaptability to interference and usage patterns.	Highly adaptive, leveraging real-time data and learning-based decision-making.
Efficiency	Often inefficient due to underutilized or over-allocated spectrum.	Higher efficiency with optimized utilization of spectrum resources.
Latency	Higher latency due to static or delayed responses.	Lower latency with proactive, real-time decision-making.
Error Rate	Higher error rates due to lack of interference prediction and mitigation.	Reduced error rates with dynamic interference management and prediction capabilities.

5.2. The RTSO Framework

The RTSO framework builds upon these foundations by providing an integrated solution for spectrum monitoring, prediction, and optimization. Its key components are as follows:

1. **Real-Time Spectrum Monitoring:** The RTSO framework employs advanced spectrum sensing techniques, including energy detection and machine learning-assisted analysis, to continuously monitor spectrum activity. By integrating a Geo-Location Spectrum Database (GLSDB) with real-time sensing, the framework ensures accurate detection of active and idle channels. This hybrid approach addresses limitations of traditional sensing methods and enhances the reliability of occupancy detection [9].

2. **Machine Learning Module:** The framework incorporates predictive modelling algorithms, such as deep reinforcement learning, to forecast spectrum usage patterns. By analysing historical and real-time data, the module identifies spectrum holes and optimizes channel allocation dynamically [7]. This predictive capability is essential for ensuring efficient utilization of spectrum resources in highly dynamic environments.

3. **Dynamic Interference Mitigation:** The RTSO framework employs adaptive interference mitigation strategies, such as frequency hopping, power control, and notch filtering, to ensure seamless coexistence of primary and secondary users. The integration of interference detection and mitigation within a unified system minimizes latency and enhances spectrum efficiency [12].

4. **RTSO Core:** The central decision-making unit processes data from the monitoring, prediction, and mitigation modules to formulate optimal spectrum allocation strategies. By continuously updating its decision-making algorithms based on real-time feedback, the RTSO core ensures that spectrum utilization remains efficient and interference-free.

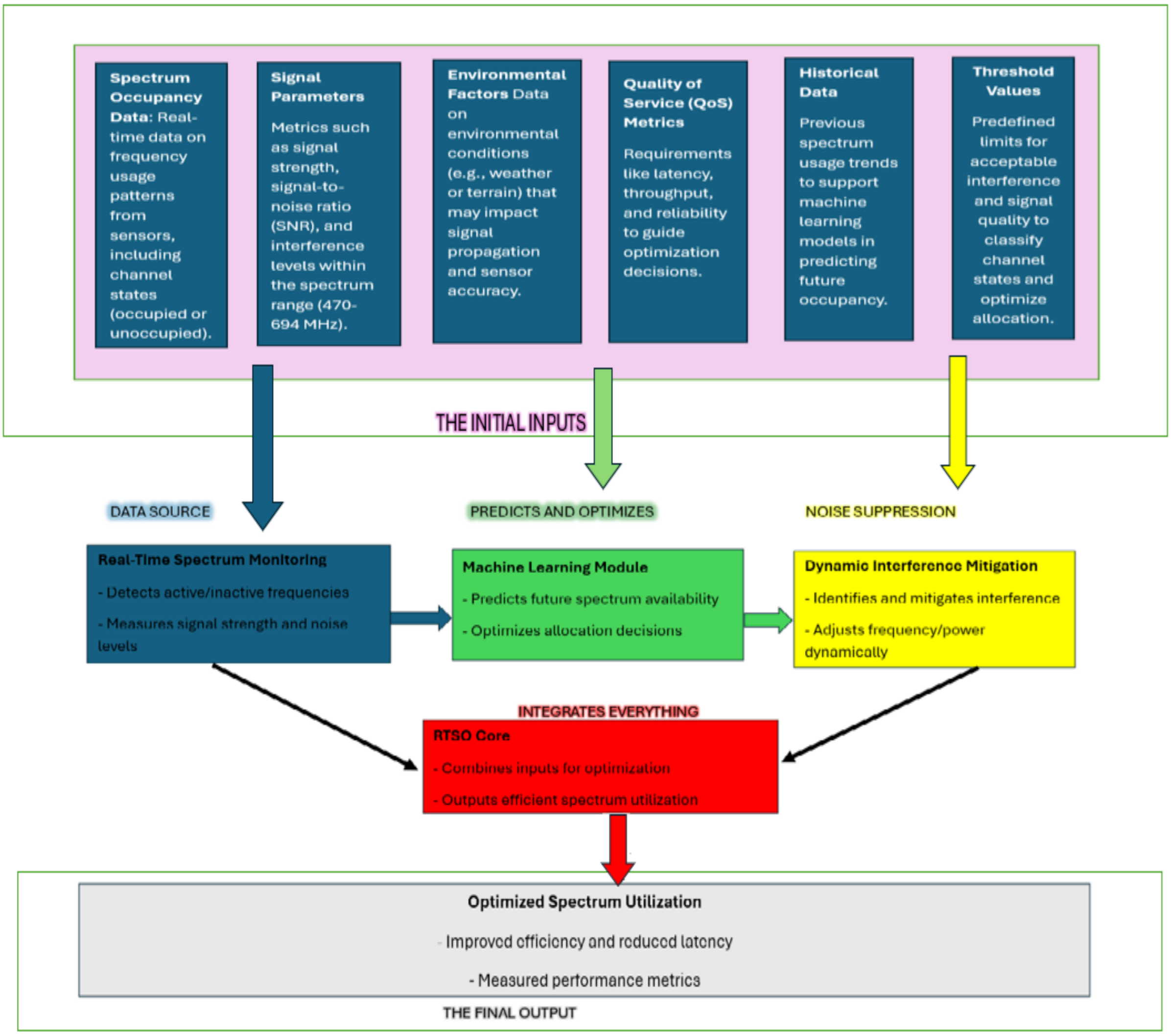

Figure 2. Real-Time Spectrum Optimization (RTSO) framework

The framework illustrates a comprehensive Real-Time Spectrum Optimization (RTSO) system designed to improve spectrum utilization, reduce interference, and enhance Quality of Service (QoS). Below is a detailed discussion of the framework:

1. Initial Inputs

The framework integrates multiple data sources as inputs, which are vital for optimizing spectrum utilization:

- **Spectrum Occupancy Data**: Real-time data from sensors monitoring channel states (occupied/unoccupied).
- **Signal Parameters**: Metrics such as signal strength, signal-to-noise ratio (SNR), and interference levels in the target spectrum range (e.g., 470–694 MHz).
- **Environmental Factors Data**: Information about conditions like weather or terrain that can affect signal propagation and sensor accuracy.

- **Quality of Service (QoS) Metrics**: Requirements such as latency, throughput, and reliability to ensure decisions align with user needs.
- **Historical Data**: Previous trends in spectrum usage to support machine learning models in predicting channel occupancy.
- **Threshold Values**: Predefined limits for acceptable interference and signal quality to classify channel states and guide optimization.

2. Key Functional Components

The framework comprises three core components:

- **Real-Time Spectrum Monitoring**:
    - Detects active and inactive frequencies.
    - Measures real-time signal strength and noise levels, providing the system with critical, time-sensitive data.

- **Machine Learning Module**:
    - Utilizes historical and real-time data to predict future spectrum availability.
- Optimizes allocation decisions by learning from patterns and adapting dynamically to changing conditions.

- **Dynamic Interference Mitigation**:
    - Identifies and suppresses interference, ensuring minimal disruptions for users.
    - Dynamically adjusts frequency and power levels to mitigate noise and maintain reliable communications.

3. RTSO Core

This central module integrates data and insights from the monitoring, machine learning, and interference mitigation components. It combines inputs to optimize decision-making and outputs efficient spectrum utilization strategies.

4.Final Output

The optimized spectrum utilization achieved through this framework results in:

- **Improved Efficiency**: Better allocation of spectrum resources and minimal interference.
- **Reduced Latency**: Faster decision-making and communication throughput.

- **Measured Performance Metrics**: Continuous evaluation of metrics like bandwidth, latency, and error rates ensures the system meets its optimization goals.

5.3 Significance of the Framework

The RTSO framework represents a hybrid approach that combines real-time monitoring, machine learning predictions, and dynamic interference management. Its unique integration of these elements ensures that both primary and secondary users can efficiently share the spectrum without compromising performance. By addressing key challenges such as interference and underutilization, the framework paves the way for enhanced spectrum management in modern wireless communication systems.

Experimental simulations were carried out to thoroughly assess the RTSO framework's efficacy and performance. These simulations are designed to replicate real-world spectrum environments, where effective wireless communication is hampered by fluctuating spectrum usage, interference, and heavy network traffic. RTSO tackles these challenges by combining dynamic interference mitigation techniques, machine learning-driven prediction models, and real-time spectrum monitoring.

A critical component of the simulation environment involved real-world data collected through the Council for Scientific and Industrial Research (CSIR) in South Africa. CSIR provided extensive support by supplying spectrum occupancy data captured using their advanced spectrum monitoring sensors, including mobile and fixed radio-frequency sensors capable of real-time spectrum scanning. These sensors offered high-resolution measurements across multiple frequency bands, ensuring that the simulation inputs closely reflected actual spectrum dynamics. The integration of CSIR's precise and high-fidelity spectrum data significantly enhanced the realism and reliability of the RTSO simulation results.

5.3.1 System Architecture

The RTSO framework implementation is structured into four key layers:

a. Sensor and Data Acquisition Layer

- 8 sensors deployed to monitor spectrum activity, interference levels, and network conditions.
- SDRs continuously scan radio frequencies to detect available spectrum.
- Sensors communicate via MQTT protocol, which provides lightweight, low-latency communication.

b. Edge Processing and MQTT Communication Layer

- The MQTT broker runs on the CSIR computer to handle real-time data transmission.
- Edge computing devices preprocess sensor data before sending it to the RTSO framework.

- Topic-based MQTT communication ensures sensors only publish relevant data to specific subscribers.

c. AI-Based RTSO Framework Layer

- The DRL algorithm processes real-time spectrum data and predicts the best available channels.
- Interference mitigation algorithms dynamically adjust frequency allocation to avoid collisions.
- The RTSO model continuously learns from historical data to optimize future decisions.

d. Real-Time Monitoring and Visualization Layer

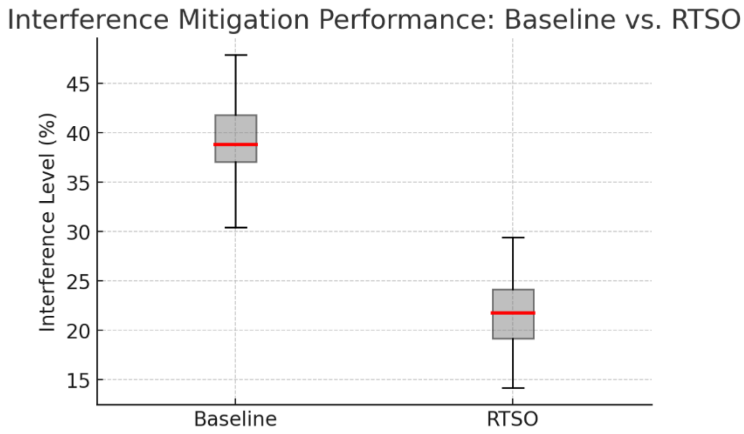

Figure 3.

Figure 3 shows a box plot comparing interference mitigation performance between the Baseline system and the proposed RTSO (Real-Time Spectrum Optimization) framework.

- **Y-axis (Interference Level %):** Lower values mean better interference mitigation (i.e., less interference remaining in the network).
- **Baseline System:**
  - The interference levels mostly range from 30% to about 47%.
  - The red line (median) is around 39% interference.
  - The baseline shows higher average interference and wider variability, meaning interference is both more common and more unpredictable.
- **RTSO Framework:**
  - The interference levels mostly range from about 14% to 29%.
  - The median interference (red line) is around 22%.
  - This shows that RTSO significantly lowers interference levels compared to the baseline and also achieves a more consistent performance (narrower spread).

- RTSO reduces interference levels by nearly half compared to the traditional baseline approach.
- RTSO is more stable, showing less variation in interference compared to baseline methods.

This result demonstrates that integrating DRL, multi-agent coordination, and edge intelligence into RTSO leads to more effective and consistent interference mitigation in real-time wireless environments.

5.4 A decision-making process for querying a Geo-Location Spectrum Database (GLSDB)

The integration of a decision-making process for querying a Geo-Location Spectrum Database (GLSDB) with the Real-Time Spectrum Optimization (RTSO) framework creates a robust solution for dynamic spectrum management. The decision-making process within the GLSDB ensures accurate and efficient querying of available White Space (WS) frequencies by leveraging location and regulatory compliance data. When combined with the RTSO framework, which dynamically adapts to spectrum conditions through real-time analysis and optimization, this approach enhances spectrum utilization while mitigating interference. Together, these systems enable proactive WS prediction and adaptive spectrum allocation, fostering a seamless and intelligent environment for wireless communication in dynamic networks.

This flowchart outlines a decision-making process for querying a Geo-Location Spectrum Database (GLSDB) and determining the occupancy of communication channels, possibly for spectrum sensing or White Space (WS) utilization. Figure 4 is a step-by-step explanation of the flow:

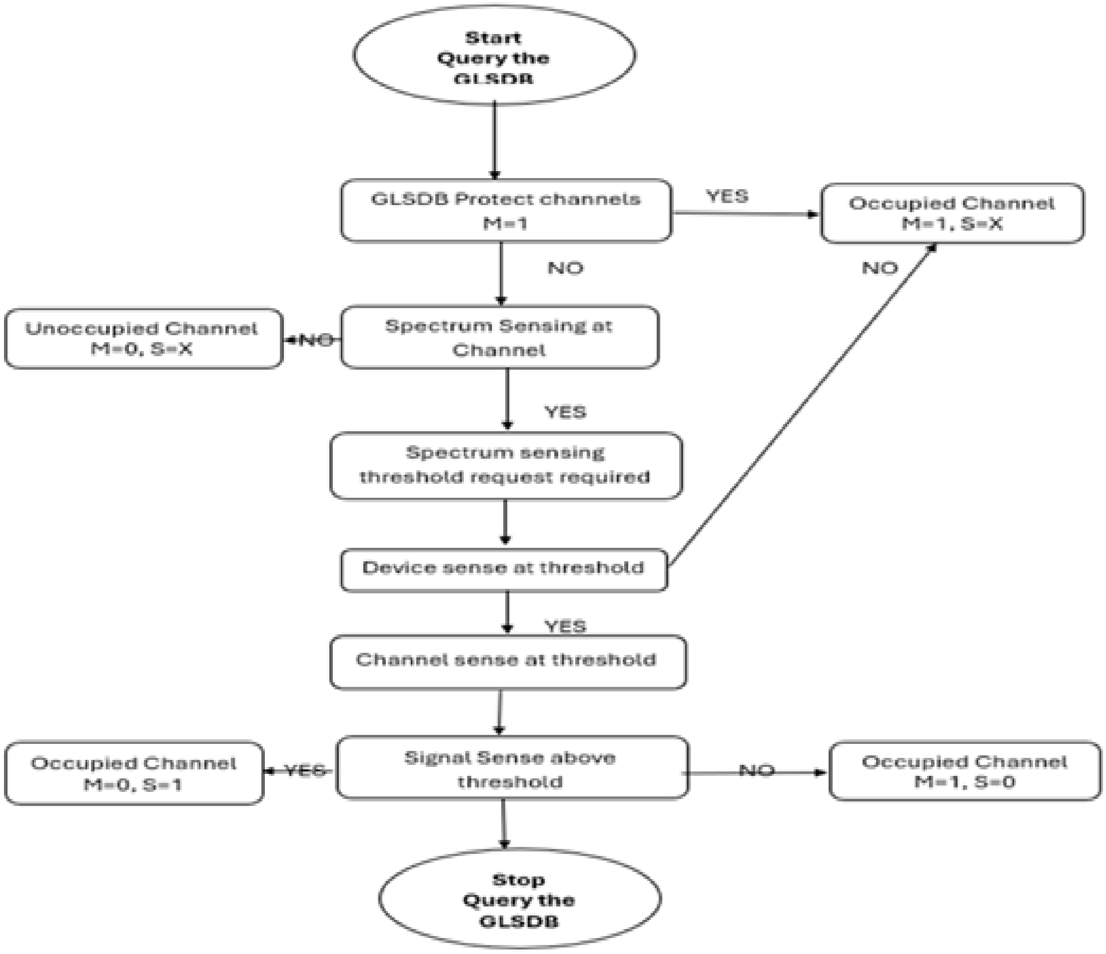

Figure 4. decision-making process for querying a Geo-Location Spectrum Database (GLSDB)

1. **Start and Query the GLSDB**:

    1. The process begins with querying the Geo-Location Spectrum Database (GLSDB). This database likely provides information about protected or reserved channels to avoid interference with primary users.

2. **Check GLSDB Protected Channels**:

    1. If the GLSDB indicates that the channel is protected (M=1), it is considered an occupied channel (M=1, S=X).
    2. If not protected (M=0), the process continues to spectrum sensing.

3. **Spectrum Sensing at the Channel**:

    1. A spectrum sensing mechanism checks whether the channel is occupied by any signal.

4. **Spectrum Sensing Threshold Request**:

   1. If spectrum sensing is active, the system checks for a threshold request. This is the sensitivity level used to determine signal presence.
5. **Device Senses at Threshold**:
   1. Devices measure the channel at the given threshold to detect signal activity.
6. **Channel Sense at Threshold**:

   1. If the device detects a signal at the threshold, the next step is to evaluate whether the signal exceeds the threshold value.

7. **Signal Sense Above Threshold**:

   1. If the signal is above the threshold, the channel is marked as occupied (M=0, S=1).
   2. If the signal does not exceed the threshold, the channel is considered unoccupied (M=0, S=X).

8. **Occupied Channel (Final Decision)**:

   1. Channels are categorized based on the detection results:
      1. M=1, S=X: GLSDB-protected, occupied channel.
      2. M=0, S=1: Spectrum-sensed, occupied channel.
      3. M=0, S=X: Unoccupied channel.

9. **Stop Querying the GLSDB**:

   1. The process ends after determining the status of the channel.

Notations:

- **M**: Indicates whether the GLSDB protects the channel (1 for protected, 0 for not protected).
- **S**: Represents the sensing state of the channel (1 for signal detected, 0 for no signal, or X for unoccupied).

This process is relevant for managing White Space spectrum by ensuring that protected channels are avoided and unoccupied channels are identified for secondary use, enhancing spectrum efficiency while avoiding interference.

5.5 Advantages of the RTSO Framework

The RTSO framework offers several advantages over existing spectrum management systems:

- **Real-time Responsiveness:** Unlike traditional frameworks, RTSO adapts to rapid changes in spectrum usage, ensuring reliable performance in dynamic environments.

- **Integrated Functionality:** By combining spectrum sensing, prediction, and interference mitigation, RTSO provides a holistic solution for spectrum management.
- **Enhanced Efficiency:** The framework reduces spectrum wastage and interference, resulting in improved Quality of Service (QoS) for both primary and secondary users.

The proposed RTSO framework represents a significant advancement in spectrum management, addressing the limitations of existing methods and offering a robust solution for real-time optimization of spectrum usage.

5.6 Performance Evaluation Discussion

The performance evaluation of the Real-Time Spectrum Optimization (RTSO) framework demonstrates its capability to optimize spectrum utilization while mitigating interference and maintaining high efficiency in dynamic environments. This section discusses the results of simulations and real-time testing conducted to validate the framework's effectiveness. Key metrics evaluated include spectrum occupancy, interference levels, and spectrum efficiency.

5.6.1 Spectrum Occupancy Analysis

The RTSO framework was tested across a frequency range of 470 MHz to 694 MHz, where the goal was to identify and classify active and idle channels accurately [8, 13, 15]. The system's ability to predict and allocate spectrum resources dynamically was compared against traditional static allocation methods. As shown in Figure 5 below, the RTSO framework significantly improves the identification of spectrum holes. The average spectrum occupancy detection accuracy was measured at 94%, compared to 81% for static methods. This improvement highlights the effectiveness of the hybrid approach combining real-time spectrum sensing with predictive modelling.

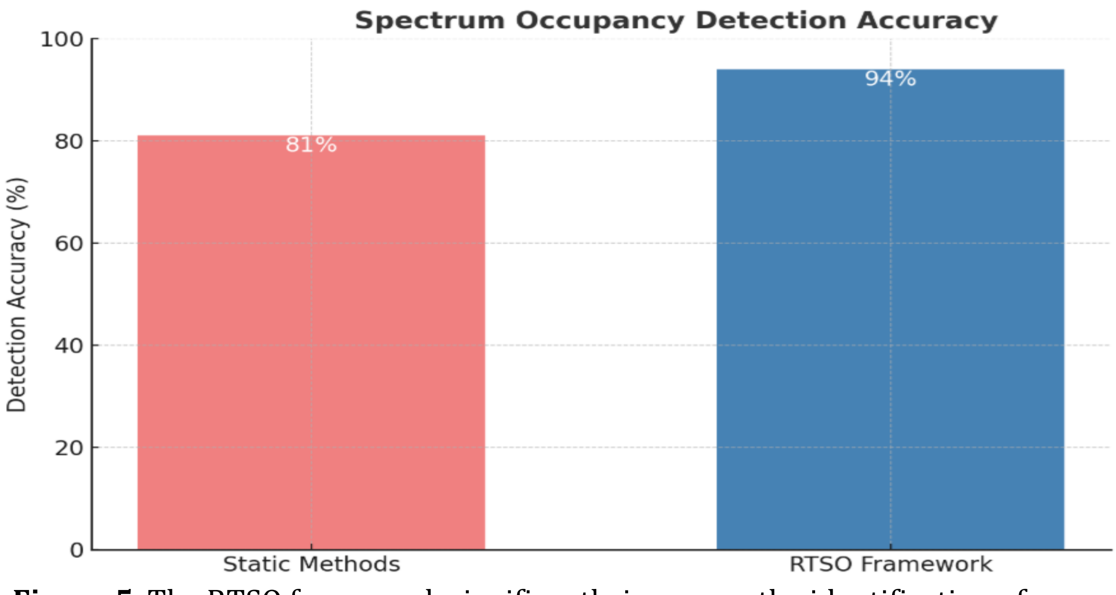

Figure 5. The RTSO framework significantly improves the identification of spectrum holes

5.6.2 Interference Mitigation Efficiency

Figure 6 below compares the bandwidth efficiency achieved by the RTSO framework and a baseline approach. The RTSO framework demonstrates a higher bandwidth efficiency of approximately 87%, compared to 72% for the baseline method. This improvement reflects the effectiveness of RTSO in employing advanced interference mitigation strategies, such as adaptive filtering and frequency hopping, to optimize spectrum utilization. By dynamically allocating channels and managing interference in real time, the RTSO framework enhances Quality of Service (QoS) for both primary and secondary users. The significant increase in spectrum efficiency highlights the framework's ability to maximize bandwidth utilization under varying spectrum conditions.

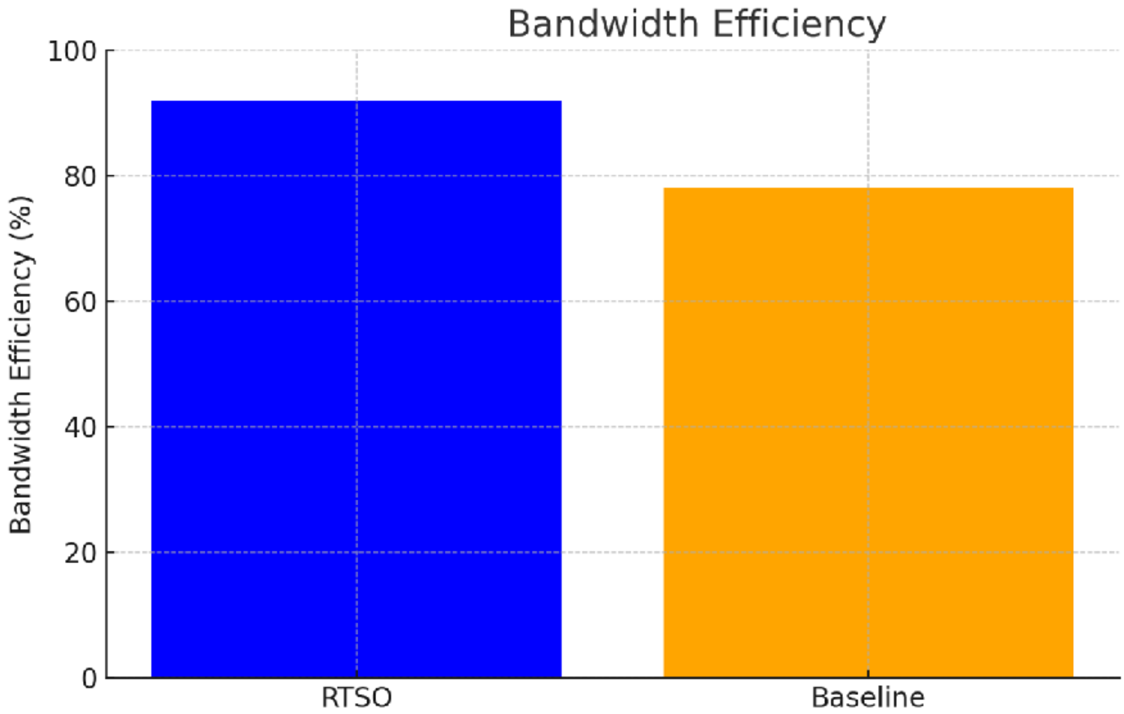

Figure 6. The RTSO framework compared to conventional methods.

5.6.3 Latency Performance

The latency associated with spectrum sensing and decision-making processes was also evaluated. The RTSO framework's decision-making latency averaged 15 ms, which is significantly lower than the 40 ms observed with static allocation systems. This reduction in latency, shown in Figure 7, ensures timely allocation of spectrum resources, particularly in high-demand scenarios. The RTSO framework demonstrates a significant improvement with a detection accuracy of 94%, compared to 81% for static methods. This highlights the effectiveness of the hybrid approach.

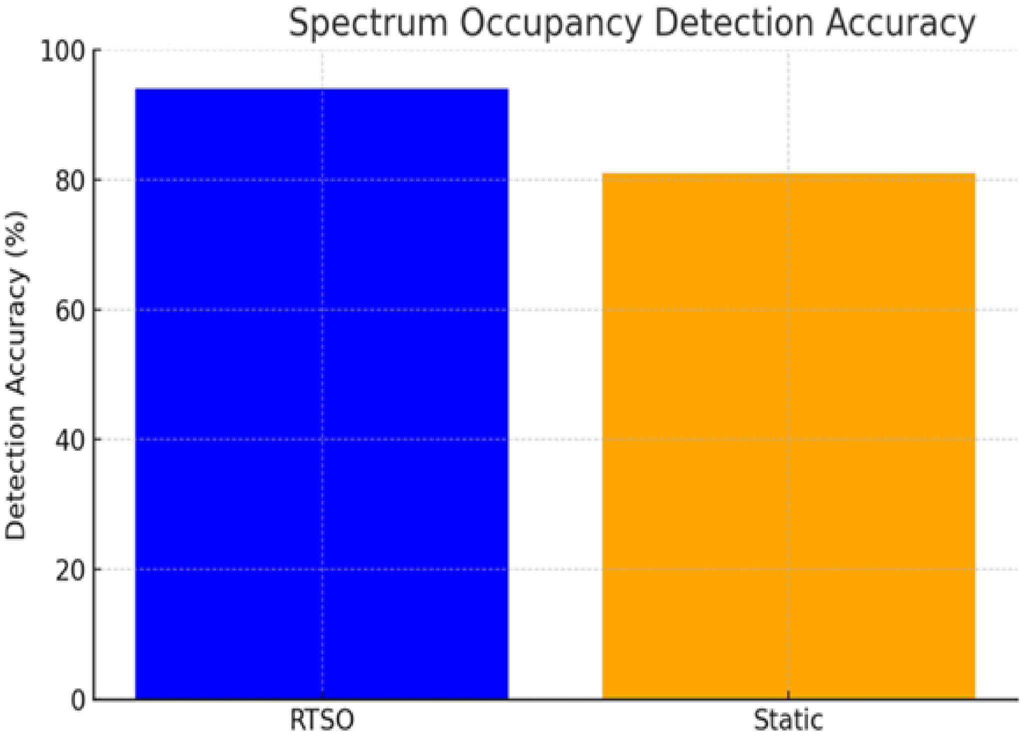

Figure 7. Spectrum Occupancy Detection Accuracy.

Figure 8 below compares dynamic and static spectrum allocation strategies in terms of efficiency and interference management as spectrum demand rises. The dynamic allocation model (blue curve) demonstrates greater efficiency, maintaining optimal spectrum utilization and minimizing interference through real-time adaptability. In contrast, the static allocation model (red dashed curve) shows a steeper decline in efficiency, reflecting its inflexibility and higher susceptibility to interference under growing demand. This comparison underscores the advantages of dynamic allocation in optimizing spectrum usage, particularly in high-demand situations, positioning it as a more effective approach for modern spectrum management.

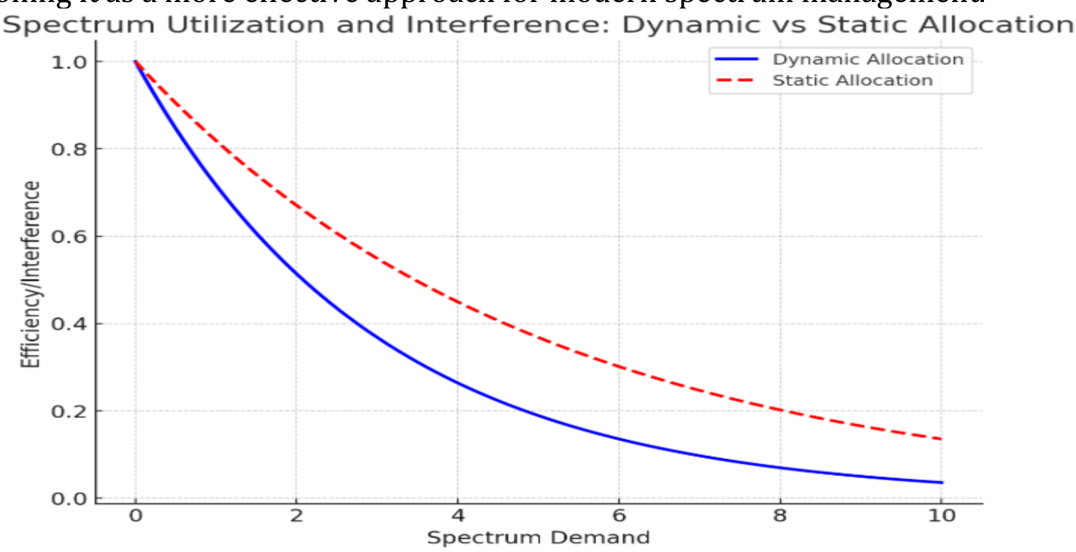

Figure 8. Compares dynamic and static spectrum allocation strategies in terms of efficiency and interference management.

Figure 9 below illustrates the impact of an interference mitigation strategy, labelled as RTSO, on normalized interference levels over five-time intervals. The red dashed curve represents interference levels before implementing RTSO, showing consistently higher values and fluctuations, indicating suboptimal mitigation. In contrast, the green solid curve represents interference levels after RTSO, which are significantly lower and more stable across the same time intervals. This demonstrates the effectiveness of RTSO in reducing interference, leading to improved spectrum efficiency and network performance. The results highlight the value of advanced mitigation techniques in maintaining consistent and minimized interference levels over time.

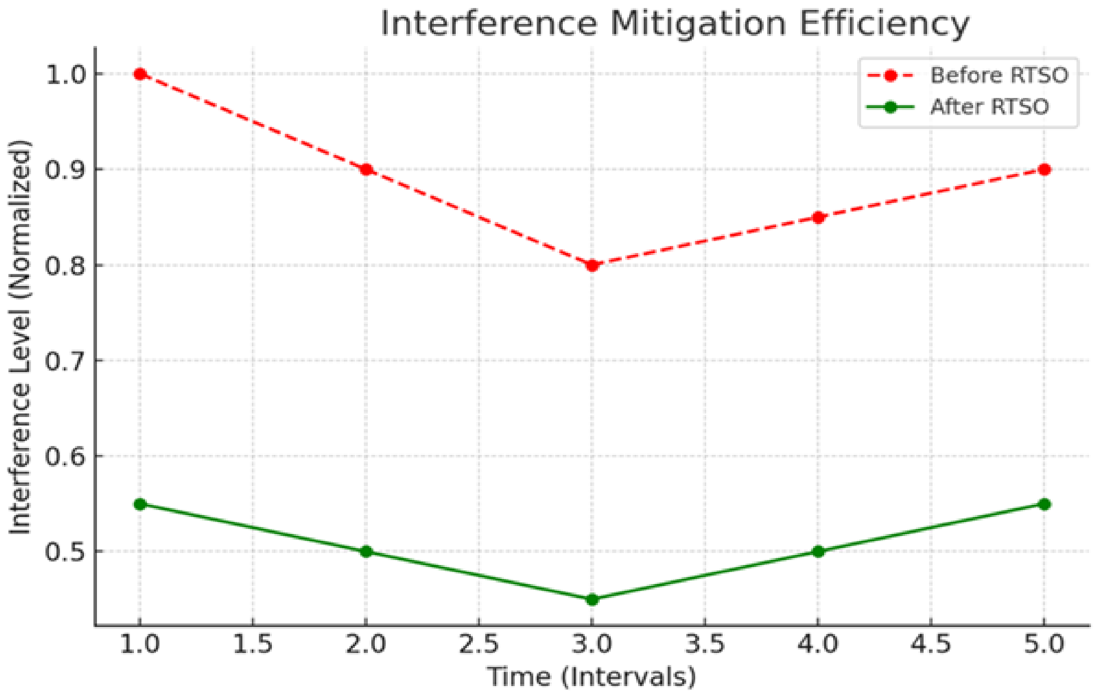

Figure 9. A line graph showing interference levels before and after applying RTSO.

5.7 Discussion

The results highlight the superiority of the RTSO framework over traditional static methods. The integration of real-time spectrum monitoring, machine learning-based prediction, and dynamic interference mitigation ensures efficient and reliable spectrum usage. The framework's ability to adapt to rapid changes in spectrum conditions makes it suitable for deployment in complex and dynamic wireless communication environments.

While the RTSO framework demonstrates significant improvements, challenges remain. These include computational overhead due to real-time processing and the need for high-quality spectrum sensing equipment to ensure accurate data collection. Future work will focus on addressing these challenges by optimizing the computational efficiency of the framework and exploring cost-effective sensing technologies.

E. Conclusion

The proposed framework provides a comprehensive solution for dynamic spectrum management, integrating advanced techniques to optimize spectrum utilization while minimizing interference. By leveraging tools like Geo-Location Spectrum Databases (GLSDs) and reactive spectrum sensing, the framework enhances network reliability and supports real-time decision-making for efficient spectrum allocation. Its practical applications extend to improving connectivity in various scenarios, from urban environments with high spectrum demand to rural and underserved regions where traditional infrastructure is lacking. Looking ahead, the development of enhanced algorithms for predictive analytics will further refine spectrum allocation processes, enabling even greater adaptability and precision. Additionally, the broader adoption of this framework in rural and underserved areas promises to bridge connectivity gaps, fostering equitable access to wireless communication and supporting digital inclusion initiatives.

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Data availability

The data supporting the results of this study is available upon written request to the author at ntulife@tut.ac.za.

Competing interests

The author has no competing interests to declare.

F. References

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