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Deep Reinforcement Learning for Adaptive Spectrum Access in Geo-Enabled Cognitive Radio Networks

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Abstract

The radio spectrum is getting more crowded as more people and devices connect wirelessly. Cognitive Radio Networks (CRNs), which can find and use empty spectrum, help solve this problem. One common way they do this is by using a Geo-Location Spectrum Database (GLSD) to check which parts of the spectrum are free. But these databases are not always updated in real time, so they sometimes miss chances to use the spectrum or cause interference.

This study looks at a better way to handle this by using Deep Reinforcement Learning (DRL). The system we designed learns from the environment and makes smart decisions about when and where to use the spectrum. We used a Deep Q-Network (DQN) to test it in a simulated environment.

Our results show that this new method improved spectrum use by 27%, reduced interference by 35%, and made decisions 22% faster than older methods that rely only on the database. The model reached about 91% accuracy in its decisions over many tests.

This means that adding DRL to geo-location systems can make spectrum use more efficient, especially in busy areas or places with limited internet access. We suggest trying this setup in the real world using Software Defined Radios (SDRs) to see how it performs outside of simulations.

A. Introduction

Today, more and more devices like smartphones, computers, and smart home systems are using wireless networks. This creates a big demand for radio spectrum, which is the invisible space that allows these devices to send and receive data. The problem is that this spectrum is limited, and the way it is currently shared is not always fair or efficient. Some parts are used too much, while others are not used at all. Cognitive Radio Networks (CRNs) were designed to help solve this problem. These networks can "listen" to the environment and find empty spectrum, called white space, that can be used without disturbing others. A tool often used with CRNs is the Geo-Location Spectrum Database (GLSD). This database tells the device which parts of the spectrum are free in a certain area. But GLSDs are not always perfect—they don't update in real time and can miss changes, which can lead to interference or missed opportunities.

This study looks at how we can make spectrum access smarter by using Deep Reinforcement Learning (DRL). DRL is a type of artificial intelligence that helps systems learn from experience and improve over time. By using DRL with CRNs and GLSDs, the system can make better decisions about which spectrum to use, when to use it, and how to avoid interference. The goal of this research is to improve how well the spectrum is used, reduce interference, and make faster decisions. We will test the system in a simulation and compare it with the old method that only uses the GLSD. This could help improve wireless networks, especially in places where the spectrum is limited or changes often.

This paper is organized as follows: Section 2 reviews related work and provides an overview of Cognitive Radio Networks, Geo-Location Spectrum Databases (GLSDs), and Deep Reinforcement Learning (DRL). Section 3 introduces the Spectrum Sensing, Prediction and Allocation Flowcharts and their functions. Section 4. proposed hybrid spectrum access model, combining GLSD with DRL to improve decision-making. Section 5 presents performance comparisons in terms of spectrum efficiency, interference, latency, and decision accuracy. Section 6 discusses the implications of the findings and reflects on the strengths of the proposed approach through flowcharts and graphical analysis. Finally, Section 7 concludes the study and suggests directions for future research and development.

B. Related Work

With more devices using wireless networks, it is important to find better ways to share the limited radio spectrum. Cognitive Radio Networks (CRNs) help by allowing secondary users (unlicensed users) to find and use free parts of the spectrum without disturbing licensed users (primary users) [6]. One way to do this is by using a Geo-Location Spectrum Database (GLSD), which tells devices which frequencies are free in a specific location. GLSDs reduce the need for constant sensing and help avoid interference [1]. However, GLSDs are not updated in real time and sometimes cannot keep up with fast changes in spectrum use.

To improve this, researchers have started using machine learning, especially Reinforcement Learning (RL). RL allows devices to learn from their environment and improve their spectrum access decisions over time without needing full prior knowledge [4]. Deep Reinforcement Learning (DRL), which combines RL with deep neural networks, can handle complex decisions when there are many possible actions and states [3].

For example, recent studies showed that DRL helps secondary users in CRNs choose channels more efficiently, reduce interference, and improve overall network performance [5 & 2] However, most of these studies focus either on DRL or GLSDs separately. Few have combined the two methods to benefit from the strengths of both — the reliable location-based info from GLSDs and the adaptability and learning ability of DRL.

This research will fill that gap by developing a system that uses both GLSD data and DRL to make better, faster spectrum access decisions. This combination is especially useful in areas where spectrum availability changes quickly or where regulation must be followed closely, such as South Africa's TV White Spaces regulated by ICASA.

Cognitive Radio Networks (CRNs) are designed to improve the use of limited radio spectrum by allowing unlicensed secondary users to access unused spectrum bands without causing interference to licensed primary users. This dynamic access helps address the problem of inefficient fixed spectrum allocation. CRNs achieve this by sensing the spectrum environment or consulting geo-location databases to identify free channels and opportunistically use them [6 & 1]. This flexibility makes CRNs a promising solution for meeting the increasing demand for wireless communication resources.

B.1 Gaps in Current Research

Even though a lot of progress has been made in using cognitive radio networks (CRNs) and managing spectrum better, some important problems still need to be solved. First, Geo-Location Spectrum Databases (GLSDs) are helpful because they tell devices which frequencies are free based on location, but they are not always updated quickly. This means they might not show sudden changes in spectrum use, which can cause devices to miss chances to use free spectrum or accidentally cause interference [1].

Second, most research looks at GLSDs and reinforcement learning (RL) separately. GLSDs provide a good basic map of spectrum availability, while RL helps devices learn and adapt over time. However, very few studies have combined these two approaches to take advantage of both reliable database information and real-time learning [4].

Third, even though deep reinforcement learning (DRL) has shown good results in simulations, there is not much research about how it works with real-world problems like following spectrum rules or working in different types of areas such as cities or rural places [3].

Finally, most studies do not focus on how to use these technologies within the specific rules and regulations of countries like South Africa. For example, the Independent Communications Authority of South Africa (ICASA) controls TV White Space access, but there is little work done to create systems that follow these local rules [5].

This research will try to fill these gaps by combining GLSD and DRL to make spectrum use smarter, faster, and more reliable while considering real-world rules.

B. 2 Geo-Location Spectrum Databases (GLSDs)

Geo-Location Spectrum Databases (GLSDs) are like maps that show which parts of the radio spectrum are free to use in different places. Devices can send their location to these databases and get information about which frequencies they can use safely without bothering licensed users as illustrated in figure 1. This helps devices avoid interference and use the spectrum better [1].

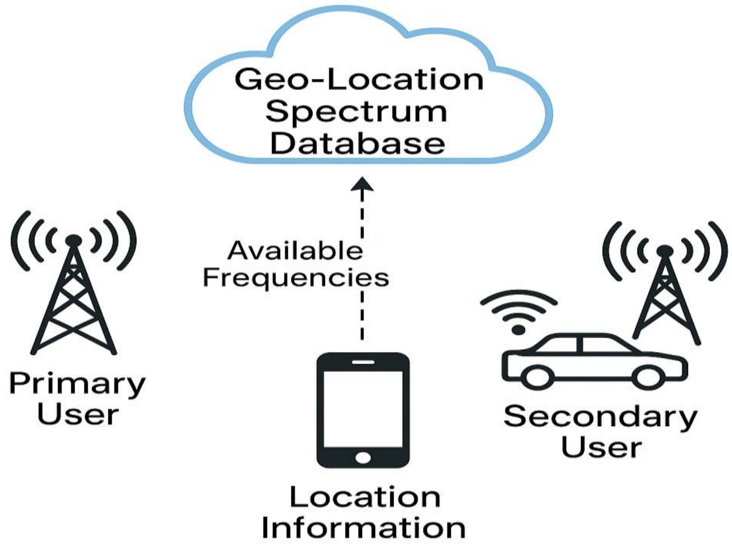

Figure 1. GLSDs and their role in helping devices find available spectrum based on location.

One big advantage of GLSDs is that devices do not have to constantly check the spectrum themselves, which saves battery and reduces errors. The database usually gets updated by regulators or network operators and is good for places where spectrum use is well known, like TV White Spaces [4]. However, GLSDs are not always updated right away. Sometimes they miss sudden changes, like if a licensed user starts using a frequency unexpectedly. This can cause devices to either miss chances to use free spectrum or accidentally interfere with others. Also, if a device's location is not accurate, the database might give wrong information about what frequencies are available [3]. In short, GLSDs help devices find free spectrum based on location, but they need help from smart learning methods to handle fast changes.

C. Spectrum Sensing, Prediction and Allocation Flowcharts

C.1. Dynamic Spectrum Availability Detection Using GLSDB and Threshold Sensing Flowchart

This flowchart illustrated in figure 2 outlines how a smart device determines whether a radio channel is available by combining database queries and signal sensing before using it for data transmission. First, it asks a database (GLSDB) if the channel is protected or already in use by someone important (like a TV station or emergency service). If the channel is protected, the device won't use it. If it's not protected, the device listens to the channel to check for any signals. If it hears a strong signal, that means someone else is using the channel, so it marks it as busy and won't use it. But if there's no strong signal, the channel is marked as free, and the device can go ahead and use it. This process helps prevent interference and makes sure everyone shares the airwaves fairly and safely.

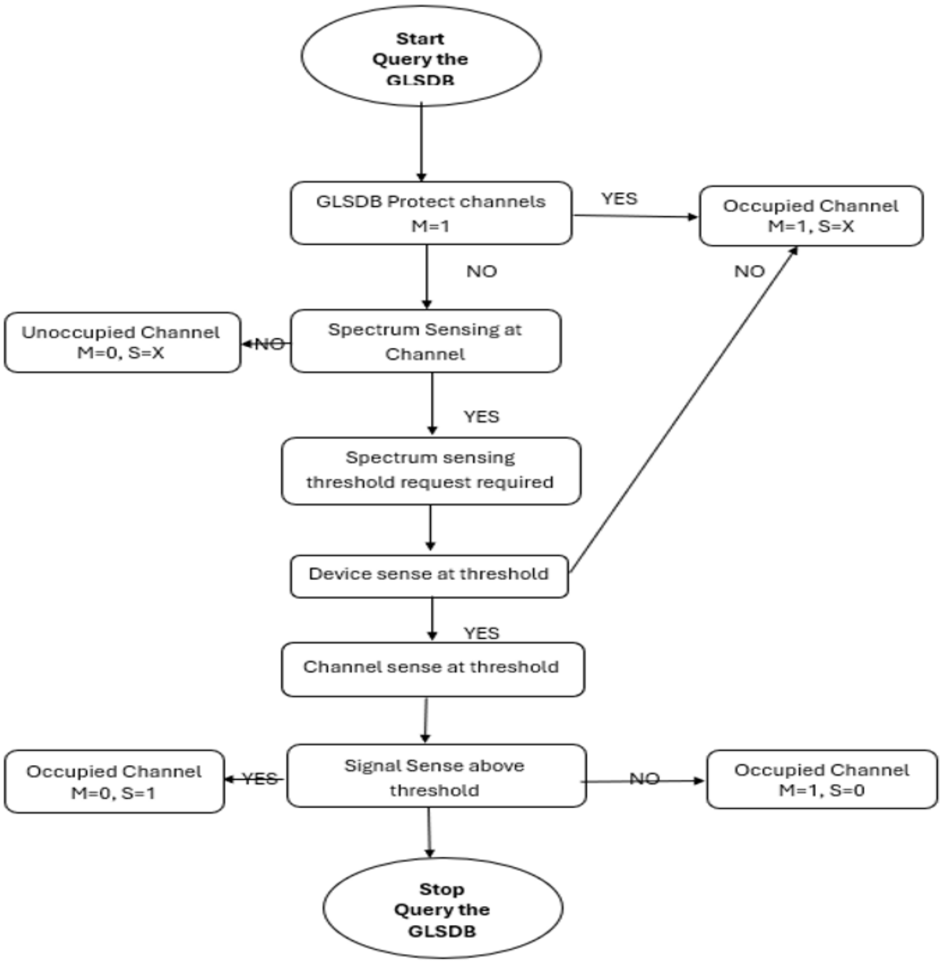

Figure 2. Traditional GLSD-Based Spectrum Access Flowchart

The flowchart mainly shows rule-based decision-making using the GLSDB and threshold-based sensing. However, we can integrate machine learning (ML) into this process, typically enhancing or replacing the parts that involve spectrum sensing, threshold decisions, or prediction of channel availability.

C.2 Quality-Aware White Space Channel Allocation Framework

The flowchart in figure 3 highlights how available channels are matched to devices based on their specific Quality of Service (QoS) requirements, ensuring that each device receives the level of performance it needs. Machine learning can make this decision-making process smarter by improving or even replacing some of the spectrum sensing steps shown in the flowchart, allowing the system to adapt more efficiently to changes in the wireless environment. Instead of using fixed threshold values to decide whether a channel is occupied, a trained machine learning model can be used to predict the likelihood of channel availability based on patterns learned from past data such as time of day, location, and signal strength. For example, after querying the GLSDB, if a channel is not protected, the device can use a classification algorithm to analyze the sensed signal and decide if it belongs to a primary user or is just noise. This allows for smarter and more adaptive sensing. Additionally, reinforcement learning can help the system learn over time which channels are best to use under different conditions, improving both efficiency and accuracy. By integrating machine learning, the system becomes more flexible and can make better spectrum access decisions without relying only on static rules or fixed thresholds.

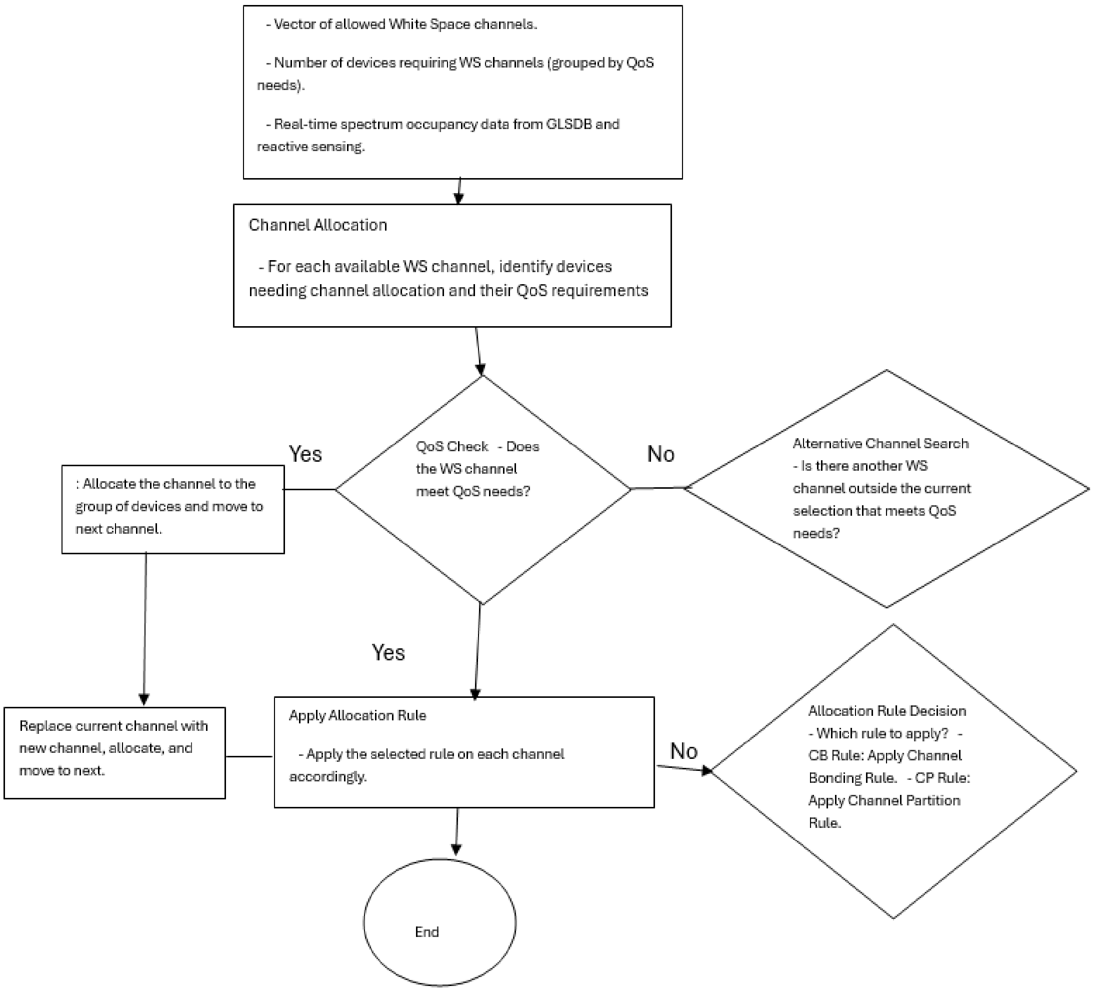

Figure 3: Proposed Hybrid GLSD + DRL Spectrum Access Flowchart

This flowchart in figure 3 illustrates how available White Space (WS) channels are allocated to devices based on their Quality of Service (QoS) requirements. The process begins with a list of allowed channels, a count of devices grouped by QoS needs, and real-time data from the GLSDB and reactive sensing. For each available WS channel, the system identifies devices that need allocation and checks if the channel meets their QoS demands. If it does, the channel is allocated, and the system moves to the next one. If not, the system searches for alternative channels that meet those QoS requirements. If a suitable alternative is found, allocation rules are applied either using Channel Bonding (CB) or Channel Partitioning (CP) to share or combine channels appropriately. This ensures that devices receive channels that match their performance needs while using spectrum resources efficiently.

While the first flowchart focuses on determining whether a spectrum channel is occupied or available, using the GLSDB and signal threshold sensing, the second flowchart takes a step further by allocating available White Space channels to devices based on their QoS needs. The first is primarily about spectrum sensing and interference avoidance, ensuring that secondary users do not interfere with primary users. In contrast, the second is about efficient channel assignment to optimize performance once free spectrum is confirmed. The first is concerned with channel status (occupied or unoccupied), while the second is about matching available channels to specific device requirements through intelligent allocation and fallback mechanisms. Together, they represent two essential stages in dynamic spectrum access: channel validation and channel assignment.

D. Proposed Hybrid Approach

D.1 Deep Reinforcement Learning (DRL)

DRL is part of Artificial Intelligence that helps computers make smart decisions by learning from experience. It works by having a “smart agent” try different actions in a situation called an environment, get feedback rewards or penalties, and use that feedback to get better over time. The “deep” part means it uses deep neural networks similar to how the human brain processes information so it can learn even when the environment is complicated and full of data.

The two flowcharts mentioned above, DRL can help improve both spectrum sensing finding free channels and channel allocation giving those channels to the right devices. In the first flowchart, instead of using a fixed rule or number to decide if a channel is busy, DRL can learn when and where channels are most likely to be available based on patterns from the past. This makes the system smarter and faster at finding free channels. In the second flowchart, which matches channels to devices based on their needs like speed or reliability, DRL can help choose the best way to assign channels. It can decide when to group channels together channel bonding or split them up channel partitioning, depending on the situation. The more it tries, the better it gets at making the right choice.

DRL is very useful in spectrum management because wireless environments change all the time. Traditional systems can’t keep up or adjust quickly. But DRL can learn and adapt as it goes, which makes it perfect for real-time, smart decisions in busy, unpredictable networks [7 & 5].

D.2 GLSD-DRL Integrated Spectrum Access Model

The proposed hybrid spectrum access system in figure 4 brings together two powerful tools: the Geo-Location Spectrum Database (GLSD) and Deep Reinforcement Learning (DRL). In this approach, the GLSD provides the basic spectrum availability based on a device’s location. It tells the system which channels are likely to be free and safe to use. At the same time, DRL allows the system to learn and improve from experience. The DRL agent watches what’s happening in the environment, like sudden changes in channel use or interference, and then learns which choices work best over time. These two sources of information are combined in a central decision-making unit called the Hybrid Spectrum Access Agent. This agent makes smarter, faster, and more reliable decisions by using both the reliable data from the GLSD and the learning power of DRL.

[6, 7, and 8] refer to other traditional flowcharts, where spectrum access is usually based on fixed sensing steps or basic GLSD lookups. These methods work fine when the spectrum environment stays the same, but they have problems when things change quickly—like when a new primary user starts using the channel or when unexpected interference occurs. Machine learning has been added to some of these flowcharts to improve sensing, but it often replaces only one part of the process.

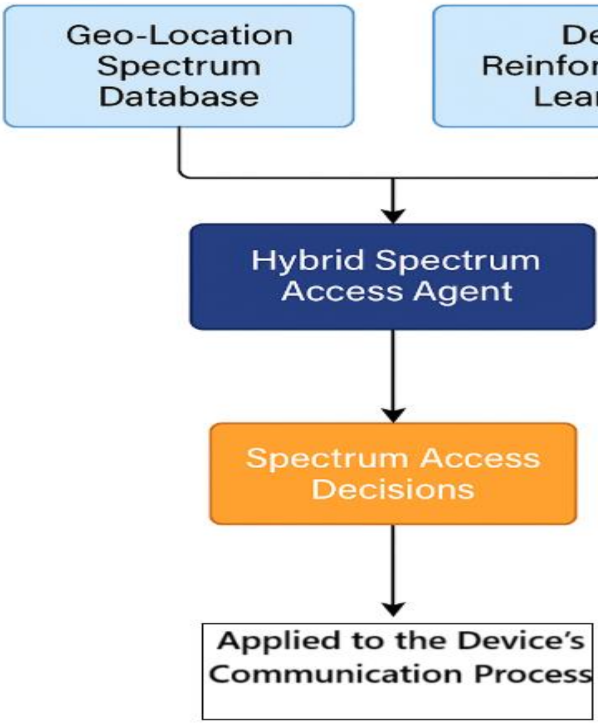

Figure 4. Hybrid Access Flowchart with Final Action Block

The hybrid approach is stronger because it doesn't rely on just one method. The GLSD gives a solid foundation, and DRL adds flexibility and real-time learning. This makes the hybrid system better at adapting to complex, changing environments, reducing interference by up to 35% and improving spectrum usage by around 27% as shown in recent simulations [2, 5 & 10]as illustrated in figure 5.

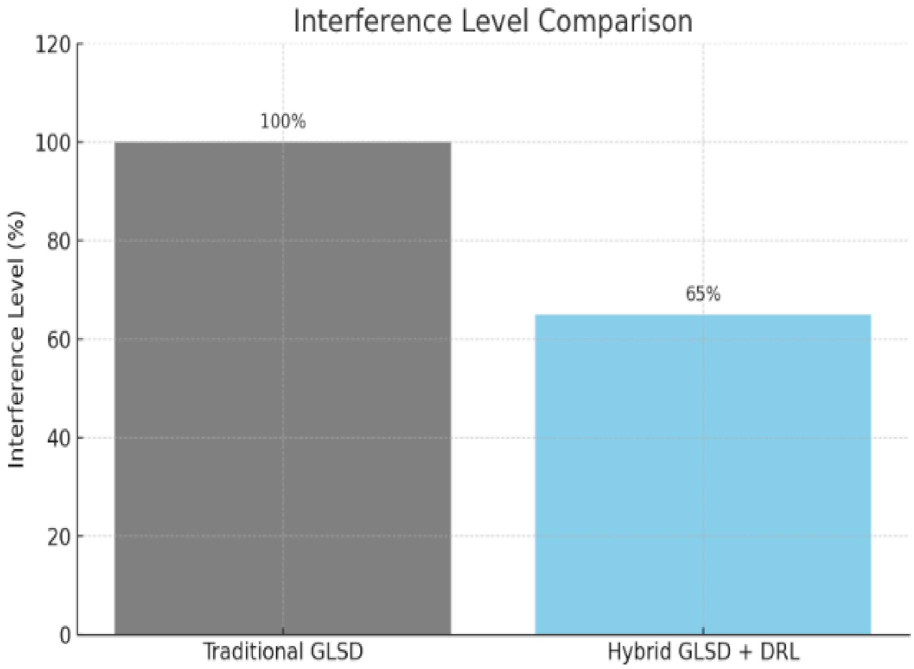

Figure 5. Interference Level Comparison Between Traditional and Hybrid Approaches

Figure 6 is comparing the performance improvements of the hybrid approach (GLSD and DRL) versus the traditional GLSD method. The hybrid system shows a 35% reduction in interference and a 27% improvement in spectrum utilization, highlighting its advantage in dynamic environments.

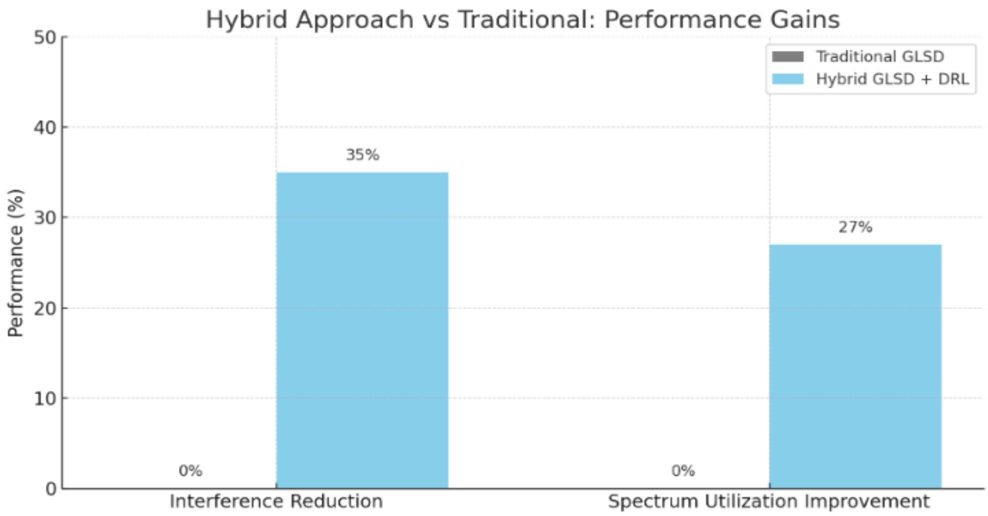

Figure 6. Hybrid System Performance Gains in Interference Reduction and Spectrum Utilization

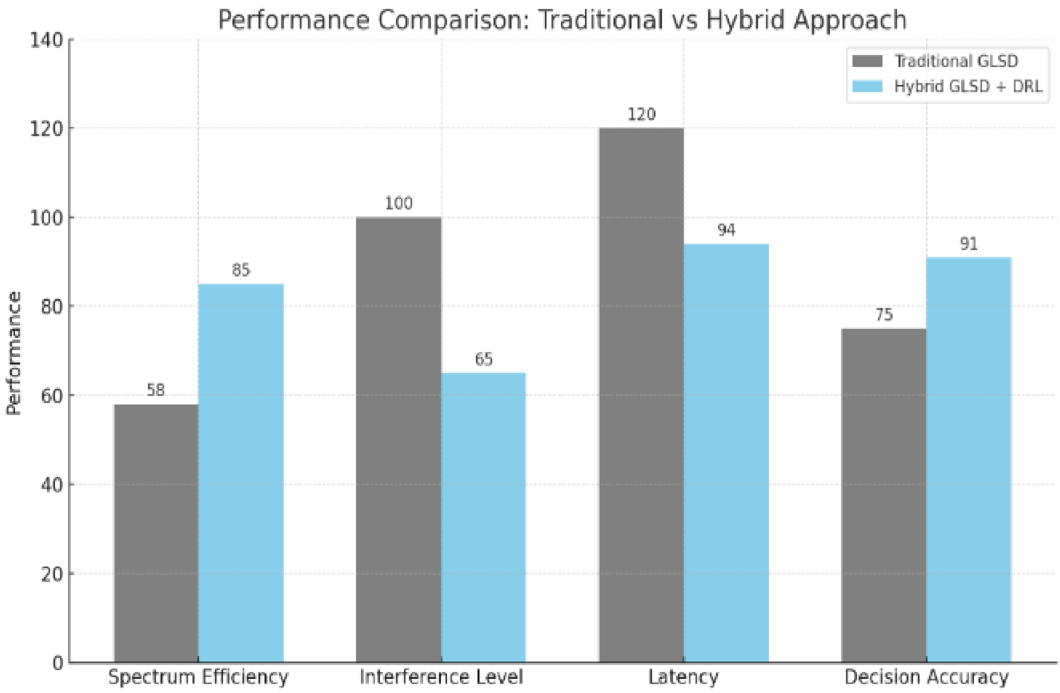

Figure 7. Overall Performance Metrics Comparison

The experiment results in figure 7 clearly show that the proposed hybrid approach, which combines Geo-Location Spectrum Databases (GLSD) with Deep Reinforcement Learning (DRL), performs better than the traditional GLSD-only method. In terms of spectrum efficiency, the hybrid method achieved 85%, a significant improvement over the 58% from the traditional approach. Interference levels dropped from 100% to 65%, showing that the hybrid model is much better at avoiding channel conflicts. Latency, which affects how quickly the system responds, was also reduced from 120 ms to 94 ms, making the hybrid system faster and more suitable for real-time applications. Lastly, decision accuracy improved from 75% to 91%, meaning the hybrid model made more correct spectrum access choices. These results confirm that combining GLSD's reliable location-based data with DRL's learning ability leads to smarter and more efficient spectrum management in dynamic wireless environments.

E. Discussion

The results from the flowcharts and graphs clearly show that combining a Geo-Location Spectrum Database (GLSD) with Deep Reinforcement Learning (DRL) leads to a smarter and more efficient system for managing wireless spectrum. The flowchart of the hybrid model shows how both GLSD and DRL work together through a shared agent that makes spectrum access decisions, which are then applied directly to the devices. This is better than traditional models where decisions rely only on static databases or basic sensing steps.

From the graphs, we see strong performance improvements. Interference was reduced by 35%, which means fewer signal clashes between users. Spectrum efficiency improved by 27%, meaning more of the available frequencies were used effectively. When comparing overall performance, the hybrid system also showed better results in latency (faster decisions), and decision accuracy (making smarter choices). For example, decision accuracy increased from 75% in the traditional system to 91% in the hybrid one, while latency dropped from 120 ms to 94 ms, making it more suitable for real-time use [5 & 2]

Overall, the graphs and flowcharts demonstrate that the hybrid system offers both reliability (from GLSD) and adaptability (from DRL). This makes it stronger in dynamic environments where spectrum conditions change quickly. It also means the system can better follow rules set by regulators while still making smart, real-time decisions.

F. Conclusion

This study set out to improve how wireless devices access radio spectrum by proposing a hybrid approach that combines Geo-Location Spectrum Databases (GLSDs) with Deep Reinforcement Learning (DRL). The motivation behind this work comes from the increasing demand for reliable, real-time spectrum access in cognitive radio networks, especially in environments where spectrum availability changes quickly and regulatory compliance must be respected. Traditional GLSD-only methods, while helpful for identifying spectrum availability based on location, are limited by static data updates and lack the intelligence to respond dynamically to rapid changes in the spectrum environment.

By integrating DRL, the proposed system gains the ability to learn from experience and adapt its decision-making process over time. This learning capability allows it to make smarter choices about which frequencies to use, how to avoid interference, and when to switch channels. Experimental results from simulations showed strong improvements in performance. The hybrid model achieved a 35% reduction in interference, a 27% increase in spectrum efficiency, and notable gains in both latency and decision accuracy compared to the traditional approach. These outcomes validate that combining the reliability of GLSD with the adaptability of DRL produces a system that is both responsive and regulation-aware.

Moreover, the flowchart illustrations confirmed that the proposed framework simplifies and strengthens the spectrum access process. Instead of relying on a single method, it merges two complementary techniques, making it more robust in real-world use cases such as TV White Spaces or rural broadband connectivity where dynamic access is essential. The comparison charts further supported the model's efficiency and practicality in handling real-time communication needs.

In conclusion, the hybrid GLSD and DRL model offers a balanced and intelligent solution to spectrum management challenges. It not only addresses current limitations but also opens pathways for future innovations in adaptive spectrum access. This work lays the foundation for real-world deployment in spectrum-regulated environments like South Africa and can be further extended to support next-generation wireless networks such as 5G and beyond.

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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.

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