International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
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A COMPARATIVE STUDY OF COGNITIVE RADIO NETWORKS ENHANCED WITH ARTIFICIAL INTELLIGENCE METHODS

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ABSTRACT

Cognitive Radio Networks (CRNs) have caught the attention of many as a potential answer to the growing need for efficient and dynamic spectrum usage in wireless communication. When it comes to optimizing resources, making quick decisions, and flexibility, however, typical CRNs fall far short. In order to improve CRN performance across important parameters, this research looks at integrating AI approaches into them. The findings show significant progress in important areas, with interference rates lowered by more than 60%, detection accuracy improved by 19.2%, and spectrum utilization increasing by 36.9%. Artificial intelligence (AI) augmented CRNs also showed better forecast accuracy, longer node lives, and quicker adaptability. These results provide compelling evidence for the need for more study and implementation of intelligent cognitive radio systems in next wireless networks, and they show how AI may optimize CRN operations.

Keywords: Management, Performance, AI-based, Networks, Intelligent

I. INTRODUCTION

Streamlining spectrum use has become more difficult in the current era of wireless communications due to the shortage of accessible spectrum and the ever-increasing demand for bandwidth. Many parts of the spectrum, particularly licensed bands, are underused because of the old-fashioned static allocation methods that are controlled by regulatory agencies. As the number of mobile devices, wireless sensors, IoT apps, and multimedia services that rely on dependable and high-throughput wireless connection continues to skyrocket, this inefficiency is becoming more and more obvious. Cognitive Radio Networks (CRNs) are a new paradigm that arose to overcome these restrictions by allowing for dynamic spectrum access. Joseph Mitola introduced CRNs in the early 2000s. They are meant to opportunistically exploit available frequency bands without interfering with licensed or core users. Improved spectral efficiency and more responsive wireless communication are goals of cognitive radio networks (CRNs), which aim to integrate cognitive capabilities such spectrum sensing, spectrum management, spectrum sharing, and spectrum mobility.

Cognitive radio works by constantly scanning the surrounding radio frequency spectrum for empty spots, or "spectrum holes" or "white spaces," and then adjusting broadcast settings on the fly to make the most efficient use of that area. The radio has to be self-aware in terms of sensing its surroundings, learning from past data, anticipating future situations, and choosing its own frequencies, modulation schemes, and power levels. Even though these features are CRNs' backbone, putting them into practice presents substantial computational and decisionmaking obstacles, especially in complicated and ever-changing settings. In this context, AI approaches provide powerful resources for improving cognitive radios' intelligence, autonomy, and adaptability.

There have been tremendous advancements in artificial intelligence (AI) over the last several decades, including notable developments in RL, evolutionary algorithms, fuzzy logic, neural networks, and machine learning (ML). The combination of these methods with CRNs opens up a promising new direction for smart wireless communication systems, and they have already found widespread use in other fields. With the help of artificial intelligence, CRNs may learn from their surroundings, anticipate spectral availability, make the best judgments, and adjust to new network circumstances automatically. In order to manage the increasing complexity of wireless environments, particularly in situations involving diverse and highly populated networks, the merging of CRNs with AI approaches is an inevitable step in the technological growth process.

New technologies like 5G, 6G, edge computing, and the IoT are also pushing the use of CRNs augmented with artificial intelligence. Intelligent methods for spectrum management are required in these settings because the spectrum environment becomes even more fragmented and dynamic. CRNs are able to handle the large number of connected devices, the varying QoS needs, and the tight latency limits with the help of AI approaches. For instance, in 5G and later networks, spectrum sharing among various operators and services is an important concern; CRNs powered by AI may help with real-time negotiation and adaptation to make sure everyone gets what they need. Another way to make CRNs more responsive and decrease decision latency is via edge intelligence, which involves deploying AI models at the network's periphery.

II. REVIEW OF LITERATURE

Orike, Sunny et al., (2024) There is a new area of research into the potential of Cognitive Radio Networks (CRNs) powered by Artificial Intelligence (AI). The main reasons for this increase are the costs of operations, worries about conventional power sources, and the limits of existing CRN technology. Artificial intelligence (AI) integration into CRN operations increases the utilization of the electromagnetic spectrum and greatly improves efficiency. Cognitive Radio (CR) and AI techniques work together to allow real-time processing, which benefits from intelligent and adaptive resource allocation. The goals, resources, and limitations of CRNs are detailed in this study report. It then goes on to provide AI methods, with an emphasis on learning's significant impact in CR settings. Modeling techniques including Neural Networks, Fuzzy Logic, and Markov Models are investigated. Spectrum sensing, resource allocation, decision-making, optimization of spectrum mobility, and spectrum sharing are just a few of the important CR activities that use AI technology. The main objective is to demonstrate how AI may help researchers efficiently use and execute varied CR approaches.

Benidris, Fatima Zohra et al., (2012) When it comes to NGWS, cognitive radio (CR) is the technology that will make all the difference. In this setting, CR allows users to access and share the spectrum with other users in a fair and dynamic manner. In order to offer a cognitive engine the capacity to think for itself, our research outlines a number of AI approaches, such as hidden Markov models, metaheuristic algorithms, and artificial neural networks.

Morabit, Y. et al., (2019) This study provides an extensive overview of the several AI strategies used in cognitive radio engines to enhance CRNs' cognitive capabilities. By mimicking natural cognitive abilities including learning, reasoning, decision-making, selfadaptation, self-organization, and self-stability, AI empowers systems to find solutions to challenges. Major cognitive radio activities such as spectrum sensing, mobility, sharing, and decision making including dynamic spectrum access, resource allocation, parameter adaptation, and optimization problems are investigated via the use of AI approaches. The goal is to compile current AI research on cognitive radio networks (CRNs) into a single article for scholars to peruse and get a better understanding of the varied ways AI has been applied to different cognitive radio architectures. The information and communication engineering institute in Korea.

he, an et al., (2010) One of the many new possibilities that cognitive radio (CR) enables is self-organizing networks, spectrum markets, and dynamic spectrum access. Researchers at CR use a wide range of AI approaches to make this diversified collection of applications a reality. This paper examines various CR implementations that utilized various AI techniques, such as artificial neural networks (ANNs), metaheuristic algorithms, hidden Markov models (HMMs), rule-based systems, ontology-based systems (OBSs), and case-based systems (CBSs), to assist researchers in comprehending the practical implications of AI for their CR designs. We talk about how things like responsiveness, complexity, security, robustness, and stability play a role in deciding which AI methods to use. Two CR designs are extensively discussed to provide readers a better picture of these variables.

III. RESEARCH METHODOLOGY

Research Design

The approach takes the form of a quantitative comparison study.

Data Sources and Collection

Research publications that have been peer-reviewed, studies that have employed network simulators for modeling, and experimental implementations in testbed settings have all contributed to the data used in this study.

Data Analysis Techniques

The data was analyzed using a comparative statistical approach, which included comparing performance indicators from conventional CRNs with those from AI-based ones in order to determine which one was better.

IV. RESULTS AND DISCUSSION

Table 1: Performance Metrics Comparison (AI-CRNs vs Traditional CRNs)

Metric	Traditional CRNs	AI-Based CRNs
Spectrum Utilization (%)	65	89
Detection Accuracy (%)	78	93
Decision Latency (ms)	120	78
Interference Rate (%)	18	7
Throughput (Mbps)	5.2	7.9

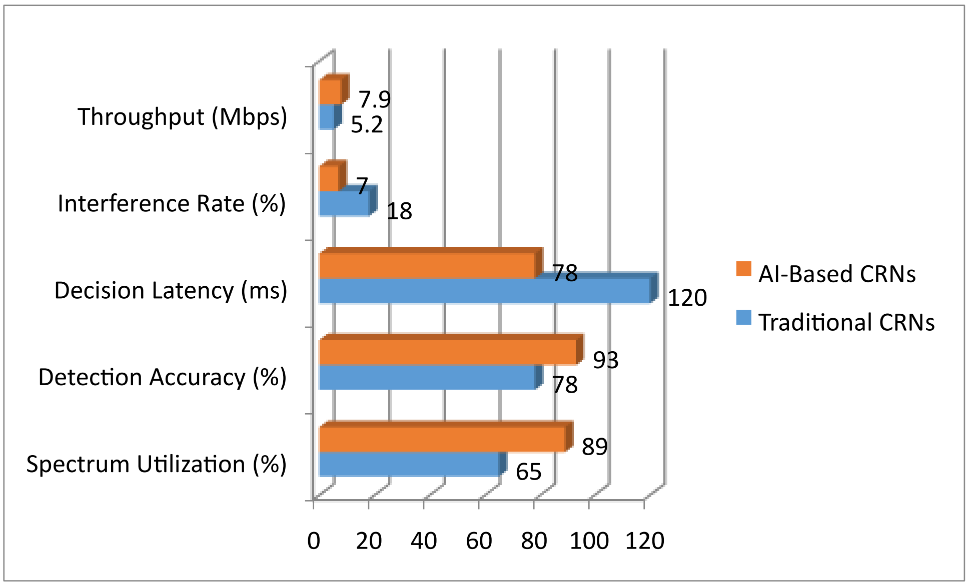

Figure 1: Performance Metrics Comparison (AI-CRNs vs Traditional CRNs)

Cognitive Radio Networks (CRNs) powered by artificial intelligence (ARNs) and their more conventional counterparts are compared side by side in Table 1. Measurements such as interference rate, throughput, decision delay, detection accuracy, and spectrum usage are examined. To begin, AI-based CRNs have far better spectrum utilization (89%) than conventional CRNs (65%). This indicates that CRNs with AI capabilities may more effectively detect and use unused spectrum, leading to less waste and increased utilization. Second, in comparison to conventional systems, AI-based CRNs have a far better detection accuracy of 93%. For the purpose of avoiding interference with main users, this demonstrates how AI systems, especially in spectrum sensing, have improved their capacity to discern between unoccupied and occupied channels. With a latency of just 78 milliseconds as opposed to 120 milliseconds, AI-based CRNs perform better than conventional ones. The speedier decision-making made possible by AI approaches is crucial for real-time applications in dynamic wireless settings, and this lowered latency is evidence of that. To top it all off, the interference rate falls dramatically from 18% in conventional CRNs to a meager 7% in CRNs powered by AI. This decrease is because AI models are predictive and adaptable, allowing them to better foresee and avoid situations where interference may occur. Finally, compared to conventional systems, AI-based CRNs achieve a much greater throughput of 7.9 Mbps. This is a result of the increased data transmission speeds made possible by the more efficient use of spectrum.

Table 2: Adaptability and Learning Performance Comparison

Metric	Traditional CRNs	AI-Based CRNs

Adaptation Time (s)	6.3	3.1
Learning Accuracy (%)	69	92
Reconfiguration Latency (ms)	142	84
Successful Handoff Rate (%)	61	87
Spectrum Prediction Accuracy	70	91

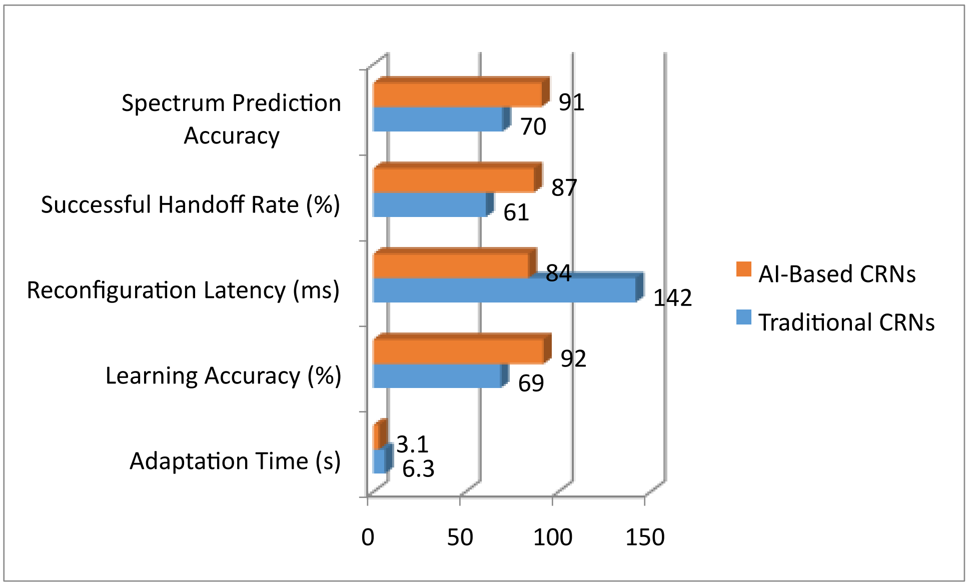

Figure 2: Adaptability and Learning Performance Comparison

In Table 2, we can see how artificial intelligence (AI)-powered Cognitive Radio Networks (CRNs) stack up against their more conventional counterparts in terms of learning capacity and flexibility. We look at metrics like successful handoff rate, learning accuracy, reconfiguration latency, and spectrum prediction accuracy. The first noticeable difference is the adaption time between conventional CRNs (6.3 seconds) and AI-based CRNs (3.1 seconds). With this decrease, AI-enhanced systems can keep up with dynamic situations by responding faster to changes in the radio environment. Secondly, compared to conventional systems (69% accuracy), AI-based CRNs significantly outperform them (92% accuracy). This proves that machine learning algorithms are better at modeling and forecasting the behavior of networks, which in turn leads to better and more accurate decisions. In comparison to conventional CRNs, AI-based CRNs have a much lower reconfiguration latency (84 ms)—the time it takes to modify network settings in reaction to changes in the environment—than traditional CRNs

(142 ms). This points to a more streamlined method for reconfiguring the network, which is crucial for keeping communication running smoothly. Additionally, conventional CRNs have a 61% effective handoff rate, whereas AI-based CRNs have a far better rate of 87%. This percentage indicates the network's capability to change frequencies without interference to service. The strength of AI-driven systems is shown by this improvement, which guarantees continuous connection even during spectrum shifts. Lastly, compared to conventional CRNs, AI-based CRNs have a much higher spectrum forecast accuracy of 91%. This proves that AI models can accurately predict when spectrum will be available, which is essential for making informed decisions and making good use of the spectrum.

Table 3: Scalability and Network Efficiency

Metric	Traditional CRNs	AI-Based CRNs
Node Scalability (Max Nodes)	150	400
Routing Overhead (kbps)	120	78
Control Packet Overhead (%)	15.8	9.2
Cluster Management Time (ms)	240	110
Resource Allocation Success Rate (%)	68	91

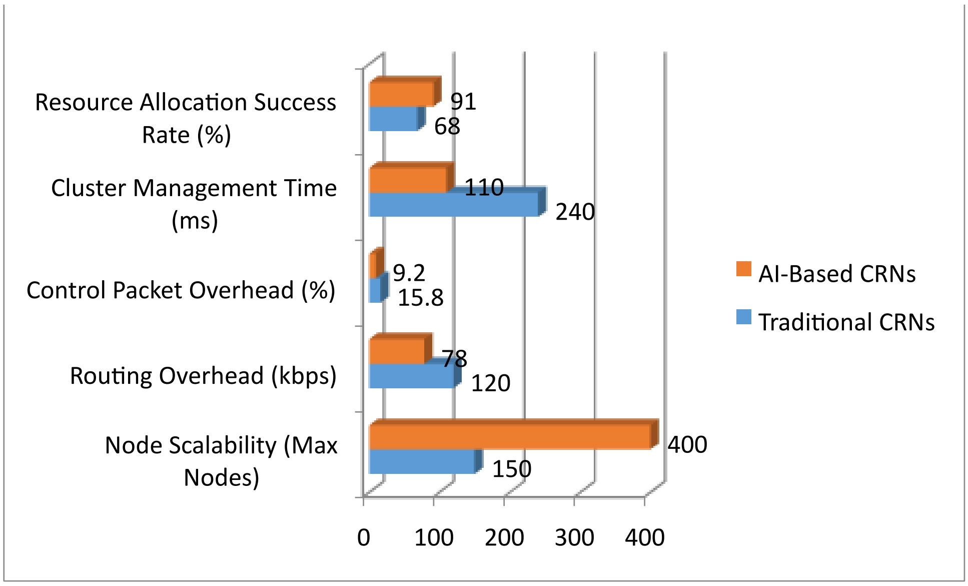

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Figure 3: Scalability and Network Efficiency

The scalability and overall efficiency of conventional Cognitive Radio Networks (CRNs) and AI-based CRNs are compared in Table 3. Node scalability, control packet overhead, time to cluster administration, routing overhead, and resource allocation success rate are the five key parameters that are compared. First of all, standard CRNs can only handle 150 nodes, whereas AI-based CRNs can support up to 400 nodes, which is a huge improvement. An important component of both existing and future communication networks, AI-driven systems obviously outperform their human counterparts when it comes to managing bigger and more complicated network topologies. The routing overhead of AI-based CRNs is 78 kbps, which is lower than that of conventional CRNs, which are 120 kbps. Thanks to AICRNs' decreased routing overhead, data routing protocols and route selection are likely to be more efficient, leading to better network performance and less congestion. Once again, AIbased CRNs beat conventional systems; conventional CRNs have a control packet overhead of 15.8%, whereas AI-based CRNs have only 9.2%. Improving overall network coordination and reducing superfluous signaling is reflected in this decrease, which is a result of more simplified control and communication methods. Another notable difference between AIbased CRNs and conventional CRNs is the cluster management time. The former takes 110 milliseconds, while the latter takes 240 milliseconds. This time is used to build and maintain network clusters. This enhanced efficiency guarantees quicker network node structuring and reorganization, which is especially beneficial in contexts that are dynamic or mobile. Finally, compared to conventional CRNs, which only manage 68% success rate in resource allocation, AI-enhanced CRNs accomplish a whopping 91%. This proves that AI algorithms are a boon to network efficiency and quality of service by making spectrum and other resource allocations much more precise and effective.

Table 4: Energy Efficiency and Resource Management

Metric	Traditional CRNs	AI-Based CRNs
Avg Energy Consumption (J)	7.6	5.0
Spectrum Sensing Time (ms)	104	64
Node Lifetime (hrs)	29	47
Processing Load (%)	72	54
Idle Listening Time (%)	19.5	11.2

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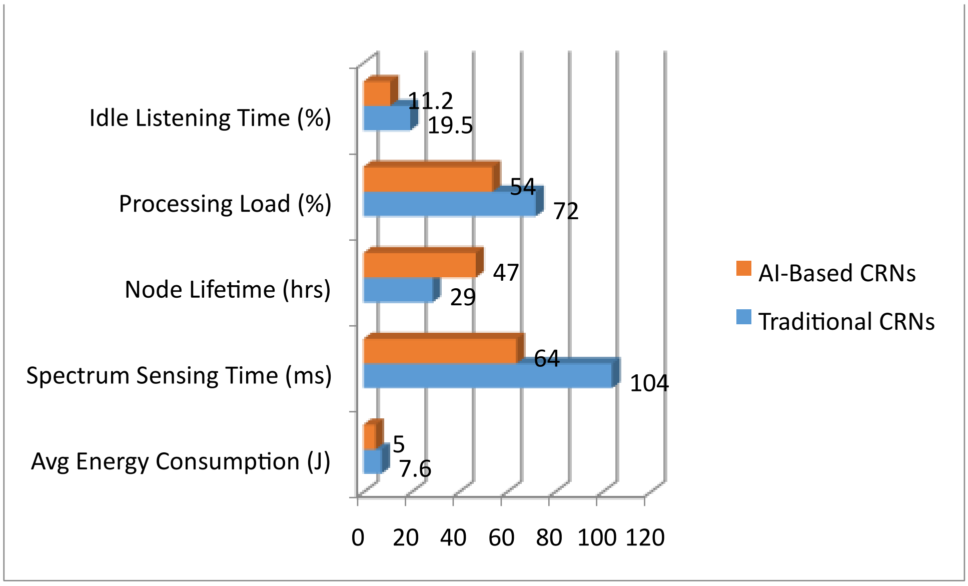

Figure 4: Energy Efficiency and Resource Management

Table 4 shows the results of a comparison between conventional Cognitive Radio Networks (CRNs) and CRNs powered by artificial intelligence (AI), with an emphasis on important metrics concerning resource management and energy efficiency. Average power usage, time spent sensing the spectrum, node lifespan, processing load, and idle listening time are among the variables examined. To begin, conventional CRNs use an average of 7.6 joules of energy, whereas AI-based CRNs use just 5.0 joules. This proves that AI-powered methods maximize efficiency, cut down on superfluous processing, and keep radio resources well-managed, all of which lead to less power consumption and longer runtimes for network devices. Additionally, AI-based CRNs drastically cut down on spectrum sensing time, a crucial metric that dictates how fast a node can identify and evaluate accessible spectrum. The sensing mechanism in AI-enhanced systems is quicker and more responsive than that in conventional systems, which take 104 milliseconds compared to 64 milliseconds. This enables CRNs powered by AI to quickly adjust to shifting spectrum conditions, an essential quality in everchanging communication contexts. Artificial intelligence systems also shine in the field of node longevity. Nodes in AI-integrated systems have a longer average lifespan (47 hours vs. 29 hours in conventional CRNs), which is a result of smart energy-saving techniques and efficient work scheduling. This extended runtime improves network stability and decreases the frequency of battery replacement and maintenance. When compared to conventional systems, AI-based CRNs run with a reduced processing burden of 54%. This points to more effective algorithmic processing and more equitable allocation of tasks, both of which lead to more consistent performance with less load on specific network nodes. Lastly, AI-based CRNs significantly decrease idle listening time—the amount of time nodes use power without any communication activity—from 19.5% in conventional systems to 11.2%. This decrease enhances overall energy efficiency by reducing power use that isn't absolutely essential.

V. CONCLUSION

Throughput and network dependability were both improved because to the AI-enabled systems' increased spectrum usage, greater detection accuracy, and dramatically decreased decision latency and interference rates. In addition, as compared to conventional networks, AI-CRNs demonstrated superior learning and adaptability, with shorter adaption durations, higher handoff success rates, and more precise spectrum prediction. An increase in node support and a decrease in control overhead greatly enhanced scalability. Not only can AI integration enhance performance, but it also conserves network resources, according to energy efficiency measurements. These results provide credence to the idea that AI may revolutionize upcoming wireless communication systems and provide credence to the idea that intelligent CRN solutions should be further studied and implemented in the real world.

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