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RESEARCH

Harvesting cognitive radio networks using artificial intelligence

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The utilization of Artificial Intelligence (AI) in leveraging Cognitive Radio Networks (CRNs) represents an emerging field of study. This surge is primarily driven by operational expenses, concerns over traditional power sources, and limitations inherent in current CRN technologies. Furthermore, integrating AI into CRN operations significantly enhances efficiency and maximizes the application of the electromagnetic spectrum. To enable real-time processing, Cognitive Radio (CR) is paired with AI methodologies, fostering adaptive and intelligent resource allocation. This research paper outlines CRNs: their objectives, available resources, and constraints. It subsequently introduces AI techniques, emphasizing the profound influence of learning within CR contexts. The application of model methods such as Markov Model, fuzzy logic, and Neural Network is explored. AI technology is employed in critical CR tasks like spectrum sharing, spectrum sensing, resource allocation, optimization of spectrum mobility, decision-making processes, and more. The overarching goal is to showcase how AI can assist researchers in harnessing and implementing diverse CR designs effectively.

Keywords: artificial intelligence, cognitive radios, cognition cycle, harvester, network, sensor

1. Introduction

Electromagnetic spectrum is an exceptional resource that exists naturally and is allocated to several licensed holders called Primary Users (PUs) depending on the assigned spectrum policy. However, it was discovered that a large percentage of the assigned spectrum was not utilized. To mitigate this problem, CR was suggested to opportunistically exploit the spectrum in the absence of the PU. Cognitive radio refers to wireless communication systems and devices that have the ability to autonomously adapt radio characteristics and behavior in order to optimize the utilization of spectrum resources. This technique seeks to enhance the efficiency of the limited and irreplaceable radio frequency spectrum (1).

In cognitive radio technology, the term "harvesting" refers to the intelligent discovery and use of dormant or underutilized parts of the spectrum. Cognitive radios have the capability to detect unoccupied frequency bands, enabling them to opportunistically use these bands without causing interference to authorized main users (2). Cognitive radio systems use spectrum sensing, dynamic spectrum management, and adaptive modulation methods to adjust their transmission parameters according to changing spectrum circumstances. This enables them to optimize spectrum consumption and coexist well with current users (3). These proficiencies are achieved by incorporating AI systems in the heart of the CR. AI assists CR consumers to resolve glitches by imitating human biological processes like reasoning, self-adaptation, learning, self-stability, self-organization, and decision-making.

Due to the increasing need for wireless communication and the limited availability of spectrum, cognitive radio technology becomes very important. This adaptability allows cognitive radios to improve the utilization of spectrum and efficiently share the spectrum with existing users (3). The concept of using cognitive network (CN) capacity is a potential area of study and advancement in wireless communications. Cognitive radio technology aims to optimize spectrum use by intelligently adjusting transmission and reception settings. The progression of this idea entails using AI and machine learning methodologies, particularly dynamic Spectrum Access (1).

Considerable progress in radio technology has led to the extensive implementation of CR, a sophisticated software-driven radio system, as documented in Bello-Salau et al. (4). This CR system incorporates techniques from information theory (IT), statistical signal processing (SSP), game theory (GT), artificial intelligence (AI), and broad-spectrum multiple-antenna methodologies. The exceptional dynamism that this fusion imparts to the transceivers empowers them to learn, adapt, and exhibit self-awareness. CR is a prospective technology for the next era of wireless systems due to these characteristics.

The paper provides an in-depth analysis of various AI strategies that enhance the intelligence of cognitive radio systems within cognitive radio networks (CRNs), as explained in Morabit et al. (2). AI enables these systems to address complex difficulties by imitating human cognitive processes such as decision-making, self-adaptation, reasoning, self-organization, learning, and self-stability. This work investigates the use of artificial intelligence (AI) methods in critical tasks of CR. These activities include spectrum sensing (SS), spectrum sharing (SSh), mobility management (MM), decision-making (DM) in dynamic-spectrum-access (DAC), resource allocation (RA), parameter adjustments, and optimization problems. The main objective of this resource is to offer a comprehensive reference for academics to better comprehend the many applications of AI in various cognitive radio designs. It also aims to guide interested readers toward contemporary AI-focused research in CRNs (2).

According to Abbas et al. (1), CRs are poised to perform a crucial role in meeting with the growing need for wireless systems. These nodes use their perception of the surroundings and analysis of environmental data to make well-informed judgments about how to allocate and manage time, frequency, and space resources. This ultimately improves the efficiency of spectrum usage. Widely used in real-time operations, the combination of artificial intelligence and machine learning methods attains optimal efficiency. This results in the ability to allocate resources in an adaptable and intelligent manner. This research endeavor begins by providing a comprehensive introduction to CRNs, including their resources, aims, restrictions, and obstacles. Subsequently, it presents AI and machine learning (ML) methodologies, highlighting the significance of learning in CR. This text presents a thorough examination of the most advanced ML techniques used in CRs. The existing literature is put into different groups based on different AI methods, like fuzzy logic (FL), neural networks (NN), and Markov models (MM). In addition, the study explores the implementation of CR and the upcoming issues associated with learning in CR applications.

As highlighted in Benidris et al. (3), CR is a crucial enabler of NGWS (Next Generation Wireless Systems). It empowers users to efficiently and fairly access and distribute the spectrum among themselves. This study presents several artificial intelligence methodologies, including artificial neural networks (ANN), meta-heuristic algorithms (MHA), and hidden Markov models (HMM), that have been suggested to enhance cognitive engines with cognitive skills, thereby further enhancing CR technology.

2. Varieties of harvester

In different scenarios, the term "harvester" usually describes a device or system created with the purpose of collecting or accumulating specific elements. The particular kind of harvester may differ depending on its intended use. Here are several prevalent varieties of harvesters.

2.1. Energy harvester

Within the energy domain, a harvester is a mechanism devised to accumulate and store energy from the surroundings. This energy may stem from diverse sources like solar panels (solar energy harvester), piezoelectric materials (vibration energy harvester), or thermoelectric materials (heat energy harvester). These devices often serve to power low-energy electronics or sensors.

2.2. Radio frequency (RF) harvester

An RF harvester is a contrivance engineered to capture and transform ambient RF energy, such as Wi-Fi or cellular signals, into electrical power. This technology finds application in powering compact electronic devices or sensors sans reliance on conventional batteries.

2.3. Data harvester

In the realm of data mining or web scraping, a data harvester represents a software tool or script designed to automatically gather data from websites or other online sources. Its purpose is to accumulate information for various objectives, including market research or competitive analysis.

2.4. Harvester network architecture

The suggested CR Harvesting Network Architecture (CRHNA) is shown in **Figure 1**. CR routers are denoted with relay stations.

Important to note is a secondary service provider (SSP) or PU-assigned licensed spectrum bands to provide reliable communication services. The SSP could be independent wireless service provider or present wireless network operator which plans to improve its services. The CR-routers and BSs work collectively to handle the resources (licensed or unlicensed) in other to control the traffic in the coverage area. The CR-routers are CR meshes that transport data from the BSs to the end users or secondary users (SUs) so that spectrum can be more effectively used with potentially advanced frequency reuse (3).

3. Cognitive radio network

Cognitive Radio Networks (CRNs) are wireless communication networks that use cognitive radio technologies to maximize the efficiency of radio spectrum usage. The networks are engineered to adapt to changing spectrum conditions, maximizing spectrum efficiency, and offering heightened flexibility across various wireless communication applications. We hereby provide an overview of cognitive radio networks (1).

3.1. Cognitive radio technology

Cognitive radios, as devices or network nodes, possess the ability to perceive, learn from, and adjust to their radio surroundings. Their functionality includes detecting unused or underutilized spectrum regions known as "white spaces" and dynamically modifying transmission parameters to access available frequencies (1).

3.2. Dynamic spectrum access (DSA)

Dynamic spectrum access (DSA) is a crucial characteristic of cognitive radio networks. Cognitive radios have the ability to detect and analyze the electromagnetic spectrum, allowing them to intelligently and strategically make use of the frequencies that are currently accessible. This results in substantial enhancement in the efficiency of spectrum utilization while simultaneously reducing the occurrence of interference.

3.3. Spectrum sensing

Cognitive radios find unoccupied frequency bands and identify principal users (licensed spectrum holders) using spectrum sensing methods. Typical sensing techniques include matched filtering, cyclo-stationary feature identification, and energy detection (4). Spectrum sensing is a necessary component of CRNs, as it ensures the rights of primary users are respected while facilitating efficient spectrum utilization and access to available frequency bands. Accurate spectrum sensing proves indispensable for the success of CR technology in wireless communication applications (4).

3.4. Cognitive cycle (CC)

The wireless communication system (WCS), as illustrated in **Figure 2**, consists of wireless radio networks and base stations (BS). Within this system, certain locations serve as primary users (PUs), while others operate as secondary users (SUs). PUs own the network, whereas SUs utilize the spectrum opportunistically when it is vacant. In **Figure 2** the SSP coordinates spectrum harvesting and optimization. PU is the device or system that has the licenses for a particular spectrum bands.

Base station (BS) is a system node providing essential support for coverage services, allowing the SSP to achieve supportive network services. It functions as an agent of control message exchange for the SSP. CR-router is a fixed relay/wireless router station furnished with several CR interfaces and can be tuned to countless accessible frequency bands for communications. CR mesh is a wireless mesh backhaul which could use basic bands and harvested bands to support BSs in delivering services through multi-hop transmissions. Basic band is the Spectrum bands that are licensed to the SSP (5). **Figure 3** shows CRN using the CC to enhance resource management and network functioning. In order to maximize the deployment of the electromagnetic ratio spectrum, CRNs function by detecting their surroundings, evaluating their exterior characteristics, and making decisions about the distribution and management of dynamic resources (5).

The processes involved in the cognitive radio cycle are discussed below:

3.5. Sensing the environment

Within a CRN, the primary network (PN) retains the primacy for spectrum usage over the secondary network (SN). While the SN can utilize available spectrum, it must avoid causing disruptive interference to the PN. The SN is tasked with sensing various environmental parameters such as Khan and Nakagawa (6):

a) Available spectrum and its power

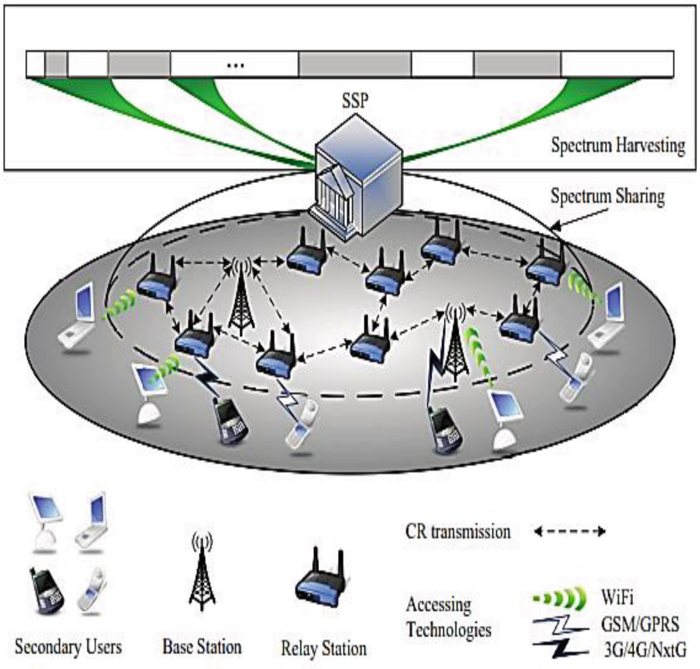

FIGURE 1 | Cognitive radio (CR) harvester network architecture (3).

b) Channel characteristics among base stations (BS) and users
c) Identification of vacant spectrum holes across time, frequency, and space
d) Power consumption,
e) Application and user demands
f) Local policies and constraints.

CR resource distribution/allocation objectives encompass the following (7):

a) Minimizing Bit Error Rate (BER),
b) Reducing power consumption,
c) Enhancing throughput,
d) Minimizing interference,
e) Optimizing spectrum efficiency
f) Enhancing Quality of Service (QoS).

3.6. Decision making

Decisions in a CRN are based on multiple variables aligned with the aforementioned objectives, where the CRN makes decisions on critical aspects including (8):

a) Distribution of frequency bands,
b) Power control,
c) Coding and adaptive modulation,

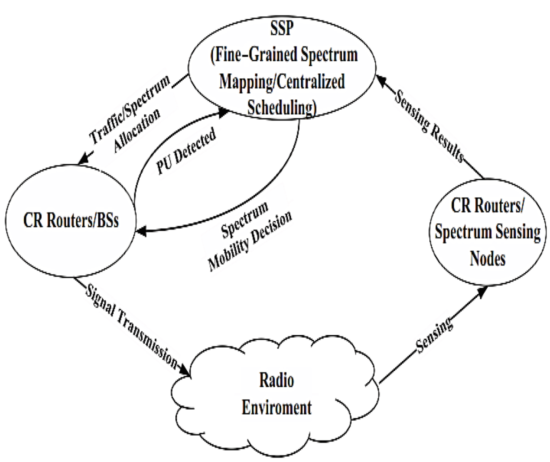

FIGURE 2 | The CR and typical operations (5).

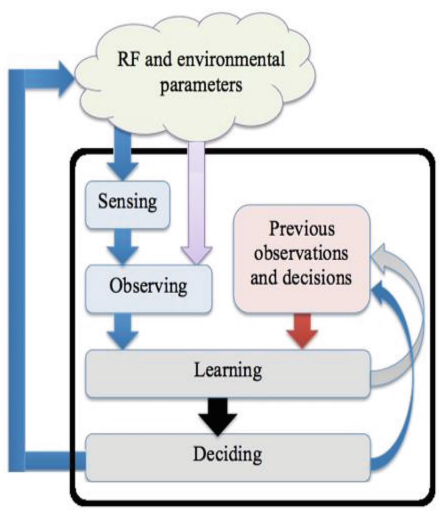

FIGURE 3 | Learning process in CRs (1).

d) Allocation of time slots,
e) Frame size and symbol rate,
f) Antenna selection and parameters,
g) Rate control,
h) Handover, scheduling, and admission control,
i) Load control, routing plans, base station utilization, and congestion control.

4. Cognitive radio tasks and challenges

Cognitive Radios (CRs) are primarily responsible for detecting spectrum gaps in several dimensions, including frequency, space, and time. Based on these gaps, CRs modify transmission parameters, including modulation, coding, frequency, time, antenna characteristics, slot allocation, and power management. In their role as a secondary user (SU), CRs effectively use their capacity for learning, capacity for reconfiguration, and capacity for cognitive processing, to methodically prevent them from causing noticeable disruption to the primary user (PU).

4.1. Cognitive capability

To reach CR's cognitive capacity, you need to be able to effectively sense and understand spectrum and the environment, which includes understanding operational concepts, network topology, spatial and position awareness, and RF environment (9). Some problems that these skills have, though, are finding spread spectrum primary signals, figuring out the background noise power, which can be hard when the SNR is low because of multipath fading and shadowing, and being accurate when figuring out spectrum availability, frequency, and periodicity. Suggestions for improving the spectrum sensing include the use of geo-location technology and cooperative sensing.

4.2. Reconfiguration capability

In order to improve network performance by minimizing energy consumption, reducing interference, maximizing spectrum utilization, and throughput while meeting users' QoS demands such as delay, rate, and BER, reconfiguration capability systematically modifies operational processes and transmission parameters, including policies (10). Adaptive modulation, symbol rate, power control, frame size, frequency band assignment, rate control, and time slot allocation are all examples of reconfigurable parameters (1). The intricacy and rapid convergence of this technology provide a hurdle. CRNs use AI and machine learning based on cognitive learning models that are generated from surrounding information to solve this problem. CRNs should make decisions quickly and methodically (11). These issues need further research since they impair CRNs' capacity to reconfigure.

4.3. Learning capability (LC)

Learning capability (LC) is utilized in building and developing learning models for decision-making. Enabling systems to learn from prior choices and use this understanding to enhance performance is a major problem (1). However, it is considered challenging to select an accurate and efficient learning strategy for exact CR tasks (1). AI techniques are presented as potential schemes for CRs, gaining recent interest in CR learning (3).

5. Leveraging AI in CRN

In the field of computer science and engineering, AI is a broad, multidisciplinary area that focuses on creating tools and systems that can do activities that are normally associated with human intellect. Its range of methods includes many strategies, tactics, and uses, and it has advanced significantly in the last several years. Here's an overview of key facets of AI (3): AI aims to enable machines to assume tasks akin to an expert, perceiving their surroundings and executing actions to optimize utility. Challenges within AI include reasoning, knowledge representation, deduction, problem-solving, and learning (11). Crucial procedures in machine learning within CRs are depicted in **Figure 3**, emphasizing the following (12):

a) RF sensing, like channel quality assessment
b) Environment detection and analyzing feedback
c) Learning
d) Maintaining decisions and what was observed for refining future decision-making precision
e) Resource management and corresponding transmission error control.

AI techniques applicable to CRNs include genetic algorithms, fuzzy logic, neural networks, reinforcement learning, game theory, Bayesian methods, entropy, support vector machines, base colony algorithm meta-heuristic, Markov models, and multi-agent systems (12).

6. Notable applications of AI in CRN harvesting

Key learning concepts within cognitive radios are articulated using the following AI methods and techniques:

6.1. Fuzzy logic

Zadeh (13) first proposed this theory in 1965 as a means of representing imprecise, hazy, ambiguous, and uncertain information using empirical and mathematical models, as outlined in Abbas et al. (1). Contrary to crisp and classical sets that are limited to either true or false values (14), fuzzy logic is used in cognitive radio (CR) for many purposes, such as power management, interference control, bandwidth allocation, resource distribution, and evaluation of the available spectrum. This utilization is detailed in Kaur et al. (15), where a centralized fuzzy interference system that allocates bandwidth to cognitive users is presented, taking into account QoS priority, traffic intensity, and kinds. Secondary users (SUs) use fuzzy logic to request bandwidth from a master SU. This fuzzy logic system assesses the intensity of traffic and determines the allocation of bandwidth based on priority. The application of fuzzy logic in Matinmikko et al. (16) involves evaluating various available bandwidth sensing techniques. This evaluation is based on input parameters such as the required probability of sensing, the functional SNR, the time available for sensing, and prior knowledge. The results of this evaluation include energy sensing, correlation sensing, feature sensing, matched filtering, and cooperative energy sensing, all of which are determined using fuzzy input values.

6.2. Artificial Neural Networks (ANN)

In 1943, NNs were introduced by Walter Pitts and Warren McCulloch, drawing motivation from the human central nervous system. Analogous to biological counterparts, ANNs consist of interconnected nodes or neurons that constitute the network. Anomalies neural networks (ANNs) receive data from adjacent neurons and produce output in accordance with the mass and initiation functions of said neurons. Adaptive mass pertains to the degree of inter-neuronal connectivity, which is regulated in such a way that the output of the network closely resembles the anticipated output. ANNs can be utilized in CR to make decisions that improve the Quality of Service (QoS) in communication systems by learning from the environment (1).

The issue of spectrum scarcity in the current communication system was resolved by authors in Tan et al. (17) through the utilization of ANNs as a substitute for the current frequency distribution system. An endeavor was undertaken in Zhang et al. (18) to improve spectrum sensing in CRNs through the implementation of ANNs across Secondary Users (SUs) in order to forecast sensing probabilities. The objective was to develop innovative cooperative spectrum sensing methods by combining the capabilities of multiple SUs with expertise in artificial neural networks (ANNs) and a fusion center that utilizes the theory of propagation networks. Furthermore, authors of Popoola and Van Olst (19) introduced a range of spectrum sensing methodologies and put forth a suggestion for an automated sensing method that classifies modulation. The objective of this approach was to empower SUs to perceive a wide range of primary radio (PR) signals, irrespective of their strength, knowledge, familiarity, or lack thereof, without any prior knowledge of the PU's signals.

Anomalies neural networks (ANNs) possess the capability to perpetually learn and dynamically adapt, which enables them to comprehend the patterns and characteristics of the systems under analysis. During the learning process, neurons are stored in memory (computer memory), allowing for sequential control of outputs in response to new circumstances while preserving previous outputs. Analytically formulating functions or processes becomes a challenge due to their complex and non-linear characteristics. Furthermore, ANNs can facilitate adaptive problem-solving processes and recognize or classify received stimuli in CR (3).

6.3. Markov model

For modeling random processes that transition from one state to another over time and lack memory so that future conditions are determined solely by present conditions, this model is implemented. Unlike the Markov Model, the observer cannot directly observe the conditions of the Hidden Markov Model (HMM). HMM was utilized to improve spectrum sensing in CR in Ghosh et al. (20), where authors proposed the application of HMM in CR for processing signal cyclostationary characteristics and resolving spectrum sensing challenges, respectively. The HMM-based method has found extensive implementation in CR. The writers also looked into whether it would be possible to use the Hidden Bivariate Markov (BHMM) and Non-Stationary Hidden Markov (NSHMM) models to predict RF channel occupancy in CR systems (21). They did this through simulations and real-time implementations. The findings demonstrated the capacity to efficiently employ a substantial fraction of the accessible spectrum for secondary purposes.

7. Future directions and challenges

Artificial intelligence (AI) in CRN faces several known issues and impending challenges, including the exploration of beam forming's potential and its impact on human health. Some critical areas warranting future attention encompass: Optimizing secondary user throughput involves algorithms that currently pose high computational complexity. This complexity elongates transmission periods, diminishing sensing durations. Previous CRN studies have used strategies such as energy detectors or random PU channel access in relation to spectrum sensing (SS). On the other hand, energy detectors create significant uncertainty, and random PU channel access at low signal-to-noise ratios (SNR) impairs PU privacy. Therefore, it is essential to use stronger SS approaches. While improving SS accuracy is important, it also increases computing complexity, increases power consumption and sensing times, and lowers SU throughput. Embracing new cutting-edge methodologies such as Wireless Distributed Computing (WDC) introduces innovative paradigms for devices with constrained power sources. WDC potentially curtails power consumption when AI operates within CRN setups, potentially boosting SU throughput.

8. Conclusion

In addition to highlighting current developments in CRNs and AI, this study described AI methodologies incorporated into CR designs and stressed the critical role that learning plays in CR settings. The research examined CR tasks, evaluations, and the difficulties associated with learning approaches in CRNs, as well as cutting-edge advancements using AI learning methods in CR. The importance of AI techniques varies according to their use and execution. The best choice of AI methods for CR design depends on a number of variables, including application requirements, accuracy, computational complexity, resilience, and previous knowledge. Additionally, the selection of AI approaches in CR settings is influenced by hardware characteristics like speed, memory, and processor potential.

Author contributions

All the authors have accepted responsibility for the entire content of this manuscript and approved its submission to BOHR Journal of Computational Intelligence and Communication Network.

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