STM JOURNALS

Journal of
Artificial Intelligence Research & Advances

ISSN: 2395-6720
Volume 8, Issue 2, 2021
DOI Journal: 10.37591/JoAIRA

http://computers.stmjournals.com/index.php?journal=JoAIRA&page=index

Review JoAIRA

Artificial Intelligence Based Hierarchical Cognitive Radio Network

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Abstract

Faced with ever-increasingly complex communication network architectural difficulties and rising traffic demand across wireless systems, cognitive radio (CR) technology alone is insufficient for dynamic spectrum resource allocation in 5th-generation (5G) networks. A distributed cognitive cellular network is presented in this research work for an efficient real-time procedure, which merges artificial intelligence with CR technology into a sophisticated multi-agent system (MAS). It is a new approach to 5G cellular communication networks. For dynamic time-frequency-space resource allocation to increase the usage of spectrum resources in the cognitive cellular network, balancing resource allocation among primary users, secondary users, and base stations is critical. In this study, a hierarchical MAS model is built and a four-layer distributed networking system is introduced. The study also describes the essential approaches and technologies and evaluates their efficacy by using numerical simulations.

Keywords: Cognitive Radio Network (CRN), Multi-Agent Reinforcement Learning (MARL), Multi-Agent System (MAS)

INTRODUCTION

One of the key factors in the information and communications technology (ICT) business is the emergence of 5G cellular networks [1]. 5G wireless networks, in particular, are projected to handle exceptionally high data rates and new applications to improve service provisioning and meet the demands of future diversification, consequently offering customers with greater Quality of Service (QoS) and Quality of Experience (QoE) [2]. In order to efficiently provide high-quality services in 5G cellular networks, wireless networks must adopt more candidate technologies and incorporate multiple types of functional networks, such as densified cells and massive multiple-input multiple-output (MIMO), narrowband Internet of Things (NB-IoT), CR, device-to-device (D2D) technologies, software defined networking (SDN), etc. [3]. The obstacles for 5G wireless networks, however, are diverse, including the explosive increase of mobile data services and traffic, as well as acute spectrum shortages, as a result of the convergence and development of various emerging technologies. Because it can overcome or at least partially alleviate the foregoing difficulties, CR has attracted the attention of both business and academics as one of the most promising technologies in 5G wireless networks [4].

Furthermore, 5G networks outperform 3G and 4G networks in a variety of communication scenarios, data volumes, and device accesses. It is vital to improve intelligence and autonomy in 5G cellular networks in order to address the more complicated configuration difficulties and burgeoning new service requirements of the 5G

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Received Date: April 21, 2021
Accepted Date: September 28, 2021
Published Date: October 20, 2021

Citation: Neeta Nathani, Vijay Kumar Khatri. Artificial Intelligence Based Hierarchical Cognitive Radio Network. Journal of Artificial Intelligence Research & Advances. 2021; 8(2): 13–21p.

wireless network. CR is a smart and intelligent technology that will be the next wireless communication system with sensing, analysis, and decision-making capabilities for dynamic resource allocation and spectrum management [5]. Even so, several issues remain in cognitive radio networks (CRNs) when it comes to real-time resource allocation, such as global limited optimization [6], long computation times, and complexity. By interacting with the environment, CR users are projected to have smarter learning and decision-making abilities, reducing the formation of these difficulties. Thankfully, the age of artificial intelligence (AI) has come up with a bang and is approaching at a faster rate.

Machines in the AI age have perception and learning abilities by interacting with the environment in the same way that humans do. Furthermore, swarm intelligence in an AI system can help basic individuals achieve important abilities. As a result, the AI system is projected to bring intelligence to communication networks, the Internet of Things (IoT), and the Internet of Vehicles (IoV) to maximize the benefits of individuals and groups [7]. Meanwhile, a slew of AI technologies have opened the road for better communication network optimization and resource allocation. Furthermore, 5G cellular networks can benefit from the combination of AI and CR, providing the network with the same intelligence and autonomy as humans. Abbas *et al.*, in their research work introduced AI and machine learning approaches, emphasizing the importance of learning in CR [5]. Reinforcement learning (RL) has been applied to most schemes in cognitive radio networks (CRNs), such as dynamic channel selection, channel sensing, and routing, as an unsupervised learning approach and online AI technology. To increase spectrum resource usage, RL allows main users (PUs) and secondary users (SUs) of CRNs to intelligently distribute dynamic resources by online learning behaviors and executing the best actions in their separate local operational settings at any time [8].

The study proposes a hierarchical distributed networking framework that utilizes AI technologies to both channel resource allocation and BSs resource management in 5G cellular networks to ensure CR users' QoS requirements, maximize spectrum resource usage, and improve BSs resource control approach.

Although the RL algorithm performs well in CRNs, learning strategies are also influenced by network characteristics such as single-agent, multi-agent, centralized, and decentralized networks. Because many realistic communication scenarios are partially observable systems and multi-agent systems (MASs) [9], AI research in multi-agent environments and distributed networks has grown in popularity in recent years. [10], for example, used multi-agent reinforcement learning (MARL) to allocate cooperative power in CRNs. In addition, in CRNs, an RL algorithm is used to estimate throughput and detect accessible idle channels [11], and in the study by Wu *et al*. [12], an RL base station (BS) multi-agent model is presented. In addition, Wang *et al*. proposes a distributed optimization technology for a heterogeneous small cell network [13]. All of the strategies listed above are employed in communication networks to solve the problem of resource allocation efficiency or network optimization. However, there is no hierarchical distributed networking framework for multi-agent settings that we are aware of. Artificial intelligence-based hierarchical and distributed network technologies are viable solutions for improving resource usage and ensuring QoS for CR users. As a result, based on two MARL mechanisms, the present study proposes a four-layer distributed networking system.

The following are the important contributions summarized in this research work:

i. Based on a combination of AI and CR technologies, the study proposes a four-layer distributed networking framework that separates 5G cellular networks into four tiers.
ii. The authors of this research work primarily build a three-level MAS model for SUs, PUs, and BSs in the proposed hierarchical networking framework.
iii. To achieve AI-based resource allocation and optimization in distributed cellular networks, an intelligent BS control mechanism and a channel resource allocation mechanism are presented.

The following is how the rest of the paper is structured: In 5G cellular networks, the paper introduces the hierarchical distributed networking architecture and proposes a three-level MAS model. The essential implementation technologies in the MAS paradigm are then introduced. Following that, the paper describes the benefits and drawbacks of the impending 5G cognitive wireless communications.

HIERARCHICAL NETWORK FRAMEWORK AND MAS MODEL

The study proposes a hierarchical distributed networking framework that utilizes AI technologies to both channel resource allocation and BS resource management in 5G cellular networks to ensure CR users' QoS requirements, maximize spectrum usage, and optimize BSs' resource control approach. The three-level MAS model and hierarchical networking framework are depicted as given below:

The Hierarchical Distributed Networking Framework

The hierarchical distributed networking framework, as depicted in Figure 1, is built on 5G cellular networks, which are divided into four tiers: CR users (Tier 1), Cellular BSs (Tier 2), Cloud processing (Tier 3), and Application (Tier 4). The explanation of all of these tiers is mentioned below:

- Tier 1: In the CR user layer, a 5G cellular network framework of the cognitive radio scenario is considered, which is composed of multiple cells with many CR users who attempt to transmit data to the cellular BSs in each cell. In general, CR users include multiple PUs and SUs, where PUs have higher priority for channel resource usage. In each cell, the AI technologies and CR are combined to allocate channel resources in CRNs. An agent is assigned to each cellular subscriber. PUs and SUs are two separate types of heterogeneous agents, and each cell's BSs allocate resources to PUs first, and then to SUs. Each cell is thought to be a complex MAS containing both PUs and SUs. Each agent interacts with the CRN's environment and learns each other's behaviors to perform dynamic resource allocation, which increases resource efficiency and optimizes communication networks so that data may be uploaded to the BSs as rapidly as possible. In addition, to realize PUs' and SUs' online learning intelligence, these agents use the MARL algorithm, which is detailed in the next section.
- Tier 2: The BS plays an essential function in communication networks as the wireless cellular infrastructure. Small cell base stations (SBSs) and classic macro-cell base stations (MBSs) are common in 5G wireless networks. As a result, a two-tier hierarchical cell network exists. However, in the proposed hierarchical distributed networking framework, only one type of BS is included in the cell structure to simplify the network model. There are several BSs, as shown in Figure 1, each of which covers one cell of the CR user layer (the two layers are labeled with corresponding numbers in the figure). This layer connects the CR user layer and the cloud processing layer, allowing the CR user layer to distribute channel resources and transmit data to the cloud processing layer. Each BS can be considered an agent in this layer, and the BSs in the same layer form a MAS of the isomorphic agents.
- Tier 3: Cloud computing is well known for its benefits, which include lower computing costs, resource integration, and flexibility. A cloud processing centre is a location where centralized data processing using cloud computing and AI algorithms takes place. The BSs send a variety of data to the cloud processing centre, where servers store and process data centrally. To be more specific, cognitive algorithms such as machine learning and deep learning can be used to classify and prioritize data. Higher-priority data can be delivered as rapidly as possible to local users, while lower-priority data can be temporarily kept in the cloud, which can increase data storage capacity and reduce data transmission time and loss from BSs to users.
- Tier 4: The cloud processing centre subsequently processes data in networks, which is then delivered to this tier for local storage and application in domains such as education, health, and transportation.

Three-Level MAS Model

The architecture of hierarchical and distributed networks is described by the suggested three-level MAS model. The MASs used in Tiers 1 and 2 of the hierarchical distributed networks are MASs using the MARL algorithm. The suggested approach is meant to achieve the following two elements in a multi-agent scenario in CRNs. On one hand, given that the AI technology MARL is being applied to CR users in 5G cellular networks, a new channel resource allocation mechanism is proposed to assist PUs and SUs in efficiently utilizing channel resources, with the goal of improving CR users' channel resource utilization and QoS. The proposed work suggests an intelligent BS control system that facilitates perceptual performance among BSs and intelligently regulates the proportion of each channel resource.

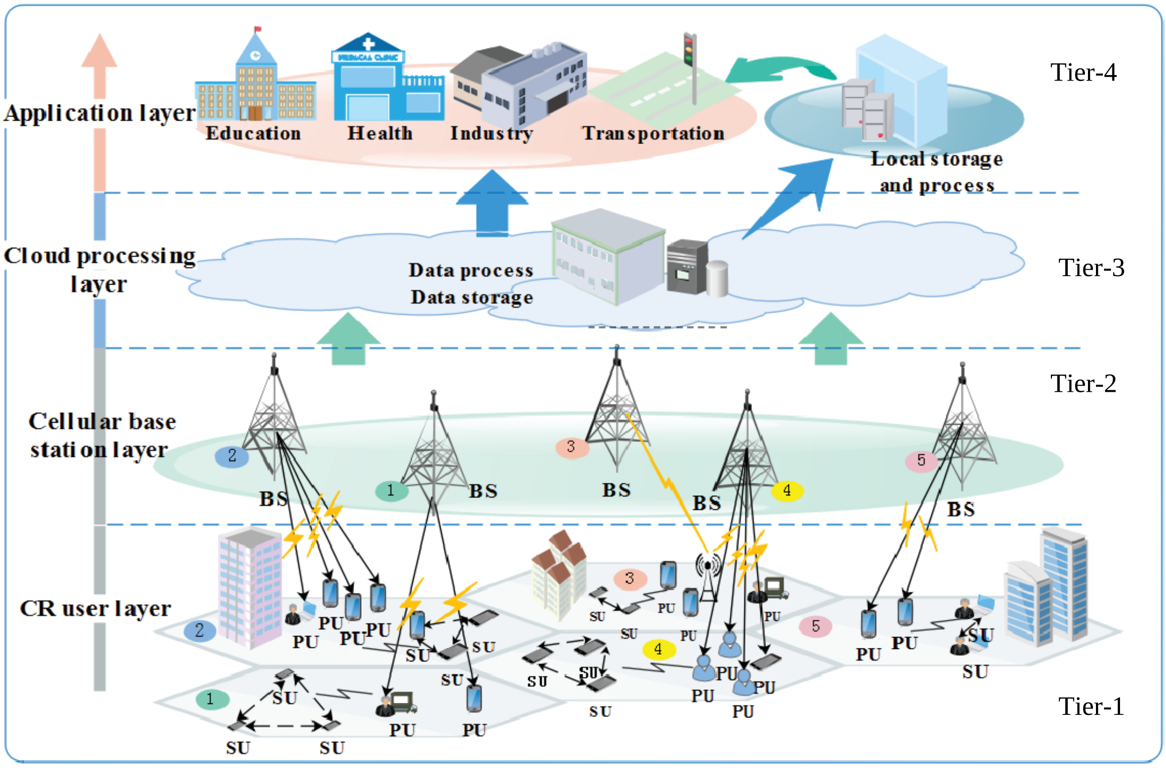

Figure 1. Architecture of the hierarchical distributed cognitive network (PU: Primary User; SU: Secondary User; BS: Base Station).

Isomorphic and heterogeneous agents, in general, create a sophisticated MAS. The majority of real-life circumstances are made up of incredibly complex MASs. As a result, under the suggested paradigm, we primarily construct two clever algorithm techniques to address resource allocation and smart channel concerns.

In Figure 2, the three-level MAS model is depicted, with (i) representing the actual communication scenario in CRNs and (ii) representing an abstracted model. Generally, the agents are capable of perceiving their surroundings. The MAS is made up of many single agents that are self-contained and can communicate internally via a connection topology or communication. Collaboration, competitiveness, or knowledge exchange can all be used as interaction models. There is a layering phenomenon among them in the proposed hierarchical distributed networking system, as shown in Figure 2b, according to the type and behaviour of agents. PUs and SUs are the two types of agents in Tier 1. The isomorphic agent is the SU, while another isomorphic agent is the PU. They are heterogeneous agents. The isomorphic agents have a competitive interaction in the proposed paradigm, while the two layers of heterogeneous agents have a cooperative relationship.

KEY IMPLEMENTATION TECHNOLOGIES IN THE MAS MODEL

This section introduces the channel resource allocation technique and the intelligent BS control mechanism. By employing MARL, the two methods strive to maximize the efficiency of resource allocation.

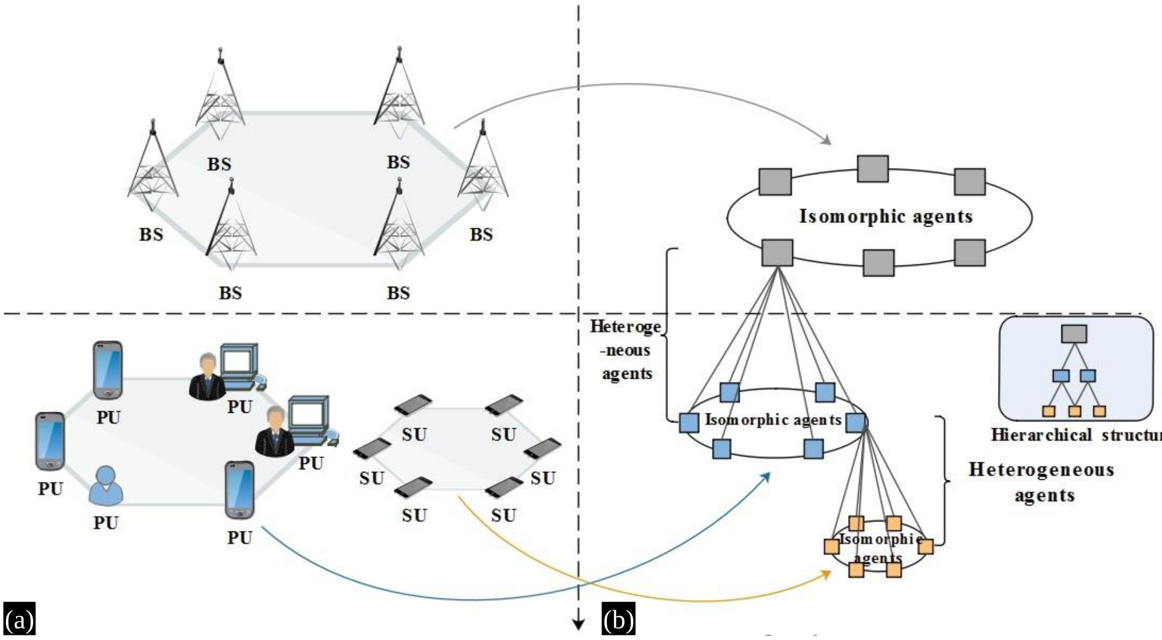

Figure 2. A three-level MAS in cognitive radio networks. **(a)** BSs, Pus and SUs, **(b)** Multi-agent system model.

Channel Resource Allocation Mechanism

We assume that the scenario is a MAS with various PUs and SUs in the channel resource allocation mechanism. Each cognitive user is treated as an agent, with the other users and the 5G wire-free network serving as the environment. Each agent interacts with the environment to learn and make decisions, and dynamically distributes spectrum resources to maximize the benefit of every agent. The MARL algorithm is thought to address a choice problem in the MAS based on this. In addition, we must examine agent behaviour and propose an appropriate MARL approach. Treatments must include three components: agent, environment, and rules, according to this viewpoint. The following are the specifics of these components:

Agent

Agents in the proposed model are simple and include PUs and SUs. Each agent is a unique individual with perception, observation, learning, and decision-making abilities. The BS, in general, covers the cellular region, and the cellular system's communication quality is determined by the number of resources possessed by each BS, the number of BSs, and so on. Switching between BSs can also make full use of channel spectrum resources. These agents interact with the environment of a CRN according to well-defined rules. Abstraction of a MAS model is done, which includes the channel resource allocation and the intelligent BS control model, as shown in Figure 3. There are numerous PUs and SUs in the channel resource allocation paradigm, and PUs can communicate with one another. Each agent obtains a perceptive state from the environment and then chooses on the next course of action by observing and learning online.

Environment

A partially observable Markov decision process (POMDP) is taken in the environment. However, when one agent makes a decision in this MAS model, other agents are fixed, and the environment becomes a Markov decision process (MDP). When a single PU agent interacts with the environment, all agents, including all PUs and SUs, are considered a part of the environment in CRNs.

Rules

In MARL, rules are extremely important. Isomorphic agent rules and heterogeneous agent rules are both considered. Isomorphic agents' rules are mostly PU-to-PU and SU-to-SU, whereas heterogeneous agents' rule is PU-to-SU. In the meantime, the PUs and SUs suggest the rewards and policies.

PU-to-PU: There is competition among PUs in the MAS. The PUs first gets channel resources assigned by the BSs. The PUs then uses a portion of the resources and provide the rest to the SUs. SUs must compete for channel resources that are idle. As a result, a resource allocation mechanism among PUs should be devised to ensure that their benefits are maximized.

SU-to-SU: The SU agent first collects the channel resource utilization state, which includes the number of active channels, as well as the number of PUs and SUs. There are two types of relationships between CR users: rivalry and neutrality. We can assume that the number of channel resources, PUs, and SUs is C, M, and N, respectively. SUs is in a neutral relationship when $C–M \geq N$. As a result, the various idle channel resources can be occupied by SUs negotiating among themselves. There is a competitive relationship among SUs when $C–M<N$, and there are C–M subchannels. In the C–M sub-channels, these SUs compete for spectrum resources. As a result, each SU must adopt an acceptable policy.

PU-to-SU: In CRNs, PUs and SUs can interact and learn. PUs preferentially employ the spectrum resources allocated by the BSs during the encounter. Idle resources can then be allocated to the SUs. As previously stated, N SUs compete for spectrum resources, with $S=\{s_1, s_2, ... s_n\}$ defining their data demands. Both PUs and SUs aim to maximize resource consumption in a dynamic multi-agent context. To do so, the PUs must be able to recognize SUs and their data needs. Each PU's strategy is: allocation, request, and wait. When a PU's idle resources are adequate to be assigned for SUs to use, each PU chooses to wait, however when a PU does not have $R_L=1$ (where, R_L is the long-term reward among all the rewards of PUs given by $R=\{r_1, r_2, ... r_m\}$), it shows that the PUs' resources are sufficient to meet SU demands. If R is less than one, the PUs must request information from other PUs with R equal to one. Then, in a dynamic environment, PUs execute continual online learning by interacting with SUs to determine the best resource allocation approach. An SU's goal, like that of PUs, is to maximize the amount of resources available to suit their demands. The selection policy of the SUs is dynamically updated, and there are $M^{N–1}$ options to pick the resources of the PUs. Policies are created in distributed agents (PUs and SUs) to coordinate their behaviors so that they can fulfil their common aim of maximizing resource consumption as efficiently as possible.

Intelligent BS Control Mechanism

The MARL model of an intelligent BS control system is also shown in Figure 3. As the network's core infrastructure, BSs provide basic signal coverage and channel resources for existing cells, ensuring that customers have as many available channel resources as possible and a high data transmission rate. As a result, we represent this BS control mechanism as a MAS in the BS layer and CR user layer. Our BS control technique is designed to increase channel resource usage and transmission rate.

In general, the BS covers the cellular region, and the number of resources controlled by each BS, the number of BSs, and so on affect the communication quality of the total cellular system. Switching between BSs can also make full use of channel spectrum resources. The BSs intelligently obtain the ideal approximation estimation of the probability distribution of channel resources based on online learning and trial and error. As previously stated, BSs are MAS agents, and we suppose that there are N-BSs ($B=b_1, b_2, ... b_n$) that manage N cells.

CHALLENGES AND OPEN ISSUES

Despite the fact that several concerns connected to AI technologies and resource allocation in CRNs have been widely explored, the suggested hierarchical distributed networking framework offers a novel viewpoint and research area. However, there are other obstacles and outstanding topics in this study area that can be addressed.

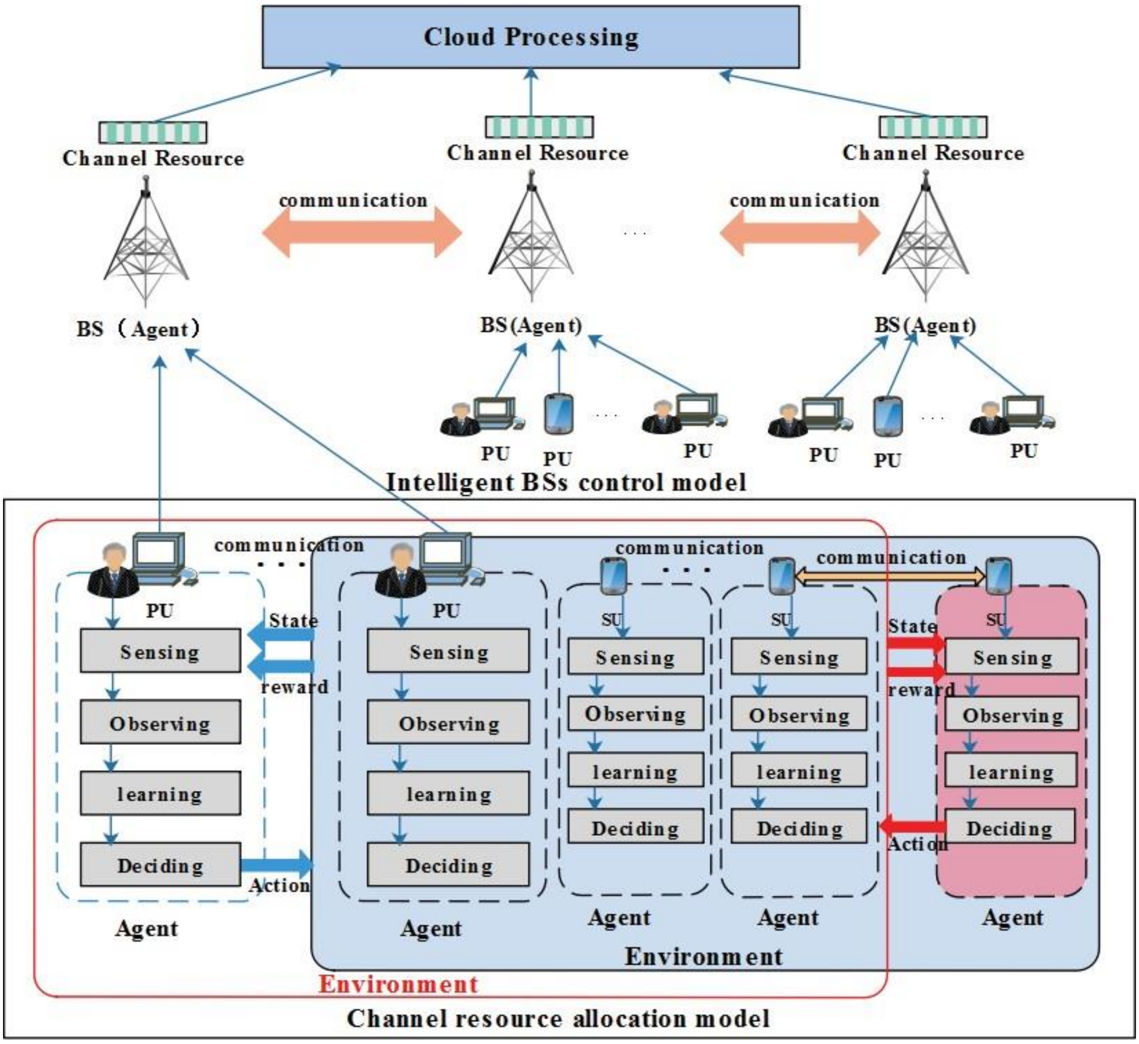

Figure 3. Intelligent BS control model and channel resource allocation model.

Complexity and Distributed Computing

The complexity of the suggested hierarchical network's network topology, as well as distributed computing, will be the key research problems in the future. The complexity of the proposed hierarchical distributed MAS is increased by the presence of numerous isomorphic agents in each layer. As a result, the MARL algorithm's efficiency should be increased further. At the isomorphic agents layer, for example, information can be transmitted not only among neighboring agents, but also among other agents, with the goal of accelerating agent learning convergence, obtaining the best joint action, and improving overall network performance. Furthermore, distributed computing comes at a high cost and takes a long time to complete. How to intelligently identify a far better allocation method in MAS, how to assign sub-tasks to each agent, and how to save settlement cost and time are all pressing issues that must be addressed.

Exploration-Exploitation

The MAS's environment in a communication network is typically dynamic due to the presence of various terminal users and devices. As a result, the trade-off between exploration and exploitation is the central issue in MARL [14]. When the network environment is unstable, the exploration aids the MARL strategy's convergence rate. Higher and more frequent exploration, on the other hand, may result in poor network performance, such as channel allocation issues and data loss. So, what is the best way to strike a balance? It is difficult to balance exploration with exploitation in order to discover new tactics and ensure the agents' long-term profitability.

Security and Trust

Agents from the same layer can communicate with each other in our proposed hierarchical MAS; and network nodes in CRNs are smart. The interplay of information among agents, on the other hand, causes security and trust issues [15]. In the meantime, the MARL method is being implemented in the CRN, and some vulnerabilities may be added to the MAS. A bad SU or an attacker, for example, may disrupt the MAS environment or offer misleading information, impairing the agent's ability to adopt the best strategy. As a result, the problem of a CR user attacking the agent may exist in CRNs, and more research into security and trust in the communication field is needed.

FUTURE RESEARCH TRENDS

User’s Mode

PUs and SUs are critical network components in CRNs, and their actions will inevitably have a substantial impact on network performance, including resource utilization and QoS. As a result, the relationship between CR users should be evaluated, followed by the user's behavioral mode and preferences analysis, which will aid agents in the MAS in automatically forming user patterns. The QoS of users can be improved by establishing user mode and mining user data. Agents can also build the best resource allocation technique during online learning to improve the overall performance of the communication network.

Network Characteristics

Only one layer of BSs is included in this study's proposed hierarchical network structure. However, as 5G technology develops, other cellular technologies, such as tiny cells, femtocells, and picocells, will emerge, in addition to MBSs. In addition, 5G cellular technologies have several problems. A high-density deployment of BSs, for example, will increase energy usage. As a result, resources should be wisely distributed among BSs in order to limit the number and concentration of BS setups. A multi-layer distributed MAS can also be explored in a hierarchical structure in the future, which can improve communication network performance and reduce energy usage.

Information Fusion

The 5G network, which is more sophisticated and dense, combines many types of existing or future wireless access transmission technologies and services.

Furthermore, the 5G network has a massive amount of device access and data. Also, because 5G will place a greater emphasis on the user experience, distributed awareness in the proposed hierarchical network should be made more intelligent, and information fusion technology at the cognitive node should be considered.

CONCLUSION

The four-layer distributed networking framework proposed in this study separates 5G mobile networks into four tiers. The author has proposed two resource allocation algorithms using MARL approaches in MASs to overcome the problem of strong user demands for resources and inappropriate resource allocation. To maximize resource usage, the author has first proposed the channel resource allocation mechanism to optimize resource distribution techniques across CR users. The intelligent BS control mechanism is then proposed, which allows BSs and PUs to be aware of available channel resources in order to intelligently modify the probability distribution of resources in BSs and learn resource allocation techniques in a dynamic environment. Overall, the hierarchical MARL method outperforms the dynamic MARL method in terms of intelligent resource allocation and communication network optimization in a dynamic context.

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