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Reinforcement Learning-Based Channel Hopping for Efficient Rendezvous in Asymmetric Cognitive Radio Networks

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Abstract:
This paper tackles the rendezvous challenge in asymmetric cognitive radio networks (CRNs) by introducing a novel reinforcement learning (RL)-based channel-hopping strategy. Traditional approaches, such as the jump-stay (JS) algorithm, often face limitations in asymmetric scenarios where secondary users (SUs) experience diverse channel availabilities, resulting in prolonged time-to-rendezvous (TTR). The proposed RL-based algorithm utilizes the actor-critic policy gradient method to dynamically adapt channel selection strategies to environmental variations, thereby minimizing TTR. Comprehensive simulations reveal that the RL-based method outperforms the JS algorithm by significantly reducing the expected TTR (ETTR), especially in asymmetric conditions where conventional M-sequence-based strategies are less efficient. These findings highlight the potential of RL-based solutions to enhance robustness and efficiency in both asymmetric and predictable network settings.
Keywords: Cognitive radio networks; channel-hopping; expected time-to-rendezvous; reinforcement learning; actor-critic policy gradient

1. Introduction

The rapid expansion of wireless communication technology has led to an unprecedented increase in the demand for the finite and valuable resource of radio spectrum [1]. Traditional spectrum allocation policies, in which spectrum bands are statically assigned to licensed users (primary users, PUs), have resulted in significant inefficiencies. Some portions of the spectrum remain unused, while other parts become congested, preventing optimal utilization of this critical resource. To address these issues, cognitive radio networks (CRNs) have emerged as a promising solution, enabling secondary users (SUs) to dynamically access underutilized spectrum without causing interference to PUs [2–8].

A critical challenge in CRNs is the rendezvous problem, which involves ensuring that two or more SUs find a common communication channel to exchange data. Successful rendezvous is a prerequisite for establishing a communication link and is a fundamental operation in CRNs. The rendezvous problem becomes especially complex in asynchronous environments, where SUs operate without global time synchronization, leading to mismatches in channel availability [2–4]. To overcome these challenges, various channel-hopping (CH) schemes have been developed, allowing SUs to rendezvous efficiently and reliably by periodically hopping across different channels according to predefined sequences [3,4,8,9].

However, many existing CH schemes assume that all SUs share a common set of available channels, a situation that is rare in real-world scenarios. In practice, the set of available channels can vary among SUs due to factors such as geographic location, interference patterns, and differing regulatory constraints [5,9,10]. This heterogeneity in channel availability complicates the rendezvous process, making it difficult for SUs to find a common channel. A notable early solution is the jump-stay (JS) algorithm, designed to facilitate rendezvous even when the set of shared channels differs among SUs. While the JS algorithm represents significant progress, it has the drawback of requiring a large number of attempts to achieve successful rendezvous, resulting in increased time-to-rendezvous (TTR) and making it less suitable for real-time applications [9].

To address the limitations of traditional CH schemes, recent research has explored the application of reinforcement learning (RL) techniques to the rendezvous problem in CRNs [5]. RL is well-suited for dynamic environments where agents must learn optimal strategies through interaction. For instance, [5] models the rendezvous problem as a multi-armed bandit (MAB) problem, where each SU independently learns to select the optimal channel based on past experiences. This approach leverages RL's adaptability, allowing SUs to improve their channel selection strategies over time. However, the MAB approach has a limitation in that it does not consider state, which can be problematic when trying to learn the optimal policy in reinforcement learning.

In this paper, we propose a novel RL-based approach that designs the state using the experience of the SUs' previous attempts to learn the optimal policy. Additionally, we modify the existing method by applying a negative reward for each failed attempt, aiming to achieve rendezvous with the fewest possible attempts. We also propose an architecture that embeds and learns each state to allow the use of deep learning-based reinforcement learning, which we train using the actor-critic policy gradient technique.

In summary, the key contributions of this paper are as follows:

- We propose an RL-based rendezvous algorithm that effectively handles scenarios where SUs have different sets of available channels, addressing a significant limitation of existing methods [2–4,9]. An actor-critic-based algorithm is used to train the agent, with the state and reward designed specifically for the rendezvous scenario in a cognitive radio environment.
- The proposed approach reduces TTR and improves rendezvous success rates compared to existing algorithms, making it more suitable for real-time applications [8,10,11].
- We provide a comprehensive performance analysis, demonstrating that the proposed method consistently achieves faster and more reliable rendezvous compared to the JS algorithm and the RL-based approach in [5,8,10].

The remainder of this paper is organized as follows. Section 2 reviews related work on CH schemes and RL approaches to the rendezvous problem, providing a detailed discussion of the strengths and weaknesses of existing methods [3,5,8–10]. Section 3 introduces the proposed RL-based rendezvous algorithm, including the integration of M-sequences and the learning framework used to optimize hopping patterns [10]. In Section 4, we evaluate the performance of our method through extensive simulations, comparing it with both traditional and RL-based CH schemes [5,8]. Finally, Section 5 concludes the paper and outlines potential future research directions, including the exploration of more advanced RL techniques and the application of our approach to other types of dynamic spectrum access problems [9,10].

2. System Model and Related Works

2.1. System Model

In this study, we analyze a cognitive radio network (CRN) where a limited number of secondary users (SUs) and primary users (PUs) operate within a single contention area. The available spectrum is divided into NNN non-overlapping orthogonal channels, numbered 1,2,…,N1, 2, \dots, N1,2,…,N, with these channel numbers known to all SUs. Each SU, equipped with a half-duplex transceiver, can switch between channels, but can only operate on one channel at a time.

We consider a self-configuring network model, where SUs can communicate with one another if they are within range. In this framework, PUs are the licensed owners of the spectrum bands and access the channels in a synchronized time-slot manner. All channels have identical bandwidth and are identified by their central frequency. The channels are spaced with equal bandwidth separation from neighboring channels, as is typical in many wireless systems (e.g., IEEE 802.11). A channel is available to an SU if no interference is present during its transmission. SUs use a suitable sensing technique to detect available channels from the NNN available options before beginning the rendezvous process. The model is asymmetric, meaning that the set of channels available to each SU differs, although there is always an overlap between these sets, ensuring that rendezvous is possible. In contrast, PUs select channels randomly for data transmission on a slot-by-slot basis, potentially leading to situations where multiple PUs use the same channel simultaneously. Consequently, some channels may be unavailable for rendezvous during certain time slots, making them inaccessible.

We assume an asynchronous network model, meaning there is no global time synchronization among SUs. However, the time-slot duration is assumed to be long enough to complete the rendezvous process. For simplification in analysis, we assume that the clock difference between two SUs is a random integer number of mini-slots. In this study, we explore reliable active scanning (RAS), which is an effective and simple method for detecting lost probe requests and quickly retransmitting or switching to another channel. However, the successful transmission of a probe request is uncertain due to the possibility of collisions and the lack of acknowledgment. In this active scanning approach, an SU broadcasts a probe request and expects to receive a response from any nearby SU.

The fundamental structure of the rendezvous process is illustrated in Figure 1. At time t=1, both SUs A and B are on channel 1 and are within communication range of each other. As a result, A and B discover each other at time t=1t = 1t=1 on channel 1. These two SUs become time-synchronized and proceed to rendezvous with other nodes in such a way that neither of them attempts rendezvous in the same time-slot. At time t=2, when A tries to rendezvous on channel 2, B holds its attempt. Similarly, at time t=3, B attempts to rendezvous on channel 3, while A holds its attempt. At time t=5, B and

C successfully rendezvous on channel 4. From this point, all three SUs follow the same procedure to rendezvous with additional nodes.

In the cognitive radio environment, when a connection is desired, channels that are in use by other users are considered unavailable to avoid interference. Therefore, we generalize the scenario to a two-user case, where each user has access to a different set of channels. This approach allows us to address the problem in the context of a two-user scenario, where the number of channels available to each user may not be identical Figure 1. Structure of Rendezvous Process** Illustrates the interactions of SUs during the rendezvous process, with channel usage over time for SUA,SUB, and SU C.

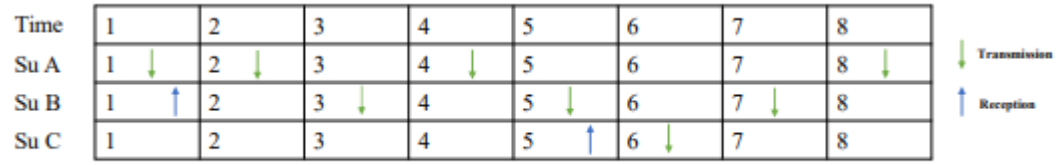


Figure 1. Structure of rendezvous.

2.2. Related Works

In cognitive radio networks (CRNs), achieving efficient and reliable rendezvous among secondary users (SUs) is a critical challenge. Several channel-hopping sequences have been proposed to address this issue, each offering distinct advantages and drawbacks.

The **Jump-Stay (JS)** hopping sequence is one of the most widely studied methods for facilitating rendezvous in asynchronous CRNs [6,7]. This approach involves SUs periodically "jumping" to different channels based on a predefined sequence, followed by a "stay" phase on these channels for a certain duration to increase the likelihood of successful rendezvous. Figure 2 illustrates an example of the JS algorithm's operation. Here, MMM represents the total number of channels, and PPP denotes the smallest prime number greater than MMM. In this scenario, the two SUs successfully attempt a rendezvous on channel 1 during the second trial. The JS hopping sequence proceeds with "hopping" up to the 10th step, followed by a "stay" phase. The deterministic nature of the JS sequence ensures predictable channel coverage, making it easy to implement in scenarios lacking global time synchronization. However, its fixed hopping pattern can lead to inefficiencies in dynamic environments where channel availability frequently changes. Additionally, the potential for increased rendezvous time and collisions in dense networks limits its scalability and adaptability.

M-sequences (maximum-length sequences) provide an alternative approach, leveraging pseudorandom properties to reduce the predictability of channel-hopping and minimize collisions [13]. Generated using linear feedback shift registers (LFSRs), M-sequences ensure balanced channel usage and guarantee that all channels will eventually be covered within a fixed period. While M-sequences offer robust collision avoidance and pseudorandomness, they introduce additional complexity in generation and implementation compared to simpler methods like JS sequences. Moreover, the fixed length of M-sequences, determined by the LFSR configuration, may not always align well with the number of available channels, leading to inefficiencies in certain scenarios [8,11].

While the JS hopping sequence offers simplicity and deterministic channel coverage, it struggles with adaptability in dynamic environments and faces scalability issues in larger networks. On the other hand, M-sequence-based hopping provides improved pseudorandomness and balanced channel usage, making it more suitable for environments where collision avoidance is paramount. However, its complexity and fixed sequence length can create challenges. **Prime number-based sequences** offer a balance between simplicity and collision avoidance, though they require careful tuning to ensure even channel coverage and avoid periodic collisions [10]. The choice of hopping sequence should therefore be determined by the specific requirements of the network, such as flexibility, computational efficiency, and robustness against collisions.

Recent advances in CRNs have explored the application of **reinforcement learning (RL)** techniques to solve the rendezvous problem [5]. RL is particularly useful in asymmetric models and situations where it is difficult to define a rendezvous sequence mathematically. Through interaction, agents can autonomously discover optimal strategies. Most prior research has focused on **adversarial bandit-based approaches**, where channel selection probabilities are dynamically adjusted based on past experiences to improve the likelihood of successful rendezvous. While these methods adapt well to changing environments and optimize channel selection, they often fail in their reward settings. Specifically, they may not sufficiently minimize unnecessary attempts or reduce excessive channel exploration. Furthermore, since these methods assume changing channel states and require channel state information, they cannot be applied to the blind rendezvous system model considered in this study.

To overcome these limitations, this paper proposes an advanced RL-based approach that goes beyond previous methods by incorporating both state and policy learning. By designing the reward structure to prioritize fewer attempts and configuring states based on prior actions, the proposed method enables the agent to learn optimal policies. This improvement leads to higher rendezvous success rates and reduced **time-to-rendezvous (TTR)**, ultimately enhancing network performance.

Finally, some recent algorithms have explored the use of **multiple radios** to speed up channel exploration [14]. However, this paper focuses on solutions using a single radio, without the addition of multiple wireless interfaces.

3	1	4	2	5	3	1	4	2	5	3	3	3	3	3
2	1	5	4	3	2	1	5	4	3	4	4	4	4	4

Figure 2. JS hopping sequence for $M = 4$, $P = 5$ in [6].

3. Methodology

The reinforcement learning (RL) framework is designed to model the system described in the previous section. Each secondary user (SU) is assumed to have access to MMM channels. Channels occupied by primary users (PUs) are considered unavailable, and the remaining channels are partially shared among different SUs. Within this RL framework, each SU selects a channel, which is interpreted as an action within the environment. For the purposes of this study, the environment is modeled with two SUs. The channels selected by each SU are then compared, and a corresponding reward is generated based on the comparison. Figure 3 illustrates the RL framework in simple terms. Each SU has its own agent, and the environment provides a reward based on whether a rendezvous has occurred between the two SUs. The state and reward received from the environment will be discussed in greater detail later.

Figure 3. Reinforcement learning framework for rendezvous.

3.1. Reinforcement Learning: Actor-Critic Algorithm

In this paper, the agents of the SUs are trained using the **actor-critic policy gradient algorithm** [15,16]. is given by:

$$\theta = \pi_\theta(s, a) \tag{1}$$

where s and a represent the state and action in the RL process. The critic function, $\hat{q}_w$, for the action value is given by:

$$w = \hat{q}_w(s, a) \tag{2}$$

The actor updates the policy parameter using the action value as follows:

$$\Delta\theta = \alpha\nabla_\theta \left(\log \pi_\theta(s, a)\right) \hat{q}_w(s, a) \tag{3}$$

where α represents the learning rate, typically chosen in the range $(0, 1)$.

The critic's parameter update is described by:

$$\Delta w = \beta \left(R(s, a) + \gamma\hat{q}_w(S_{t+1}, A_{t+1}) - \hat{q}_w(S_t, A_t)\right) \Delta w\hat{q}_w(S_t, A_t) \tag{4}$$

In this equation, the actor selects action A_{t+1} for state S_{t+1} at time $t + 1$, and then the critic updates its value parameters. Here, β, $R(s, a)$, and γ represent the learning rate, the reward function, and the discount factor, respectively. The term $(R(s, a) + \gamma\hat{q}_w(S_{t+1}, A_{t+1}) - \hat{q}_w(S_t, A_t))$ is the temporal difference error, and $\Delta w\hat{q}_w(S_t, A_t)$ is the gradient of the value function.

3.2. Action Space and State

In this study, the action space is divided into two types. The first is a **binary decision**, where selecting 111 corresponds to channel-hopping, and selecting 000 indicates no hopping. This aligns with the channel-hopping behavior of the JS algorithm. If the decision is to perform channel-hopping, the SU selects the next channel by adding 1 to the index of the previously chosen channel, which becomes the final channel for the rendezvous attempt. This approach introduces flexibility to the fixed sequential channel exploration defined by the JS algorithm, allowing the use of RL to optimize

channel selection. Furthermore, the action space can be expanded to include both the decision to hop and the extent of the hop when selecting a channel. To accommodate this, the actor network can be designed to split its outputs into two parts.

4. Simulation Results

4.1. Actor and Critic Networks

Figure 4 illustrates a simplified version of the policy and critic networks used in the experiments. In this setup, SN\text{SN}SN and Hdim\text{Hdim}Hdim represent the input and output dimensions of the fully connected network (FCN), respectively. The policy network takes the previously described states as inputs, specifically receiving two states—StateRt\text{StateRt}StateRt and StateWt\text{StateWt}StateWt—which are processed through separate FCN layers before being merged to infer the final output.

The critic network shares a similar structure with the policy network, but it differs by also including the action as an input in addition to the states. This action is combined with StateRt\text{StateRt}StateRt and StateWt\text{StateWt}StateWt, processed through individual FCN layers, and then merged to produce the final output.

Given that each model follows a sequential decision-making process where the next rendezvous channel is selected based on previously attempted channels, we incorporated transformers to enhance performance in handling sequential data. Transformers have demonstrated superior ability in representing sequential data, which is crucial for optimizing channel exploration. As a result, we designed an actor-critic network based on transformers, as depicted in Figure 5. The input and output of the transformer-based model are the same as those of the FCN model, with the difference being that the short-term state is input into the transformer, while the long-term state is embedded using an FCN network, and the two are then combined. For positional embedding, we use a learnable embedding matrix, as opposed to the sinusoidal method used in prior work.

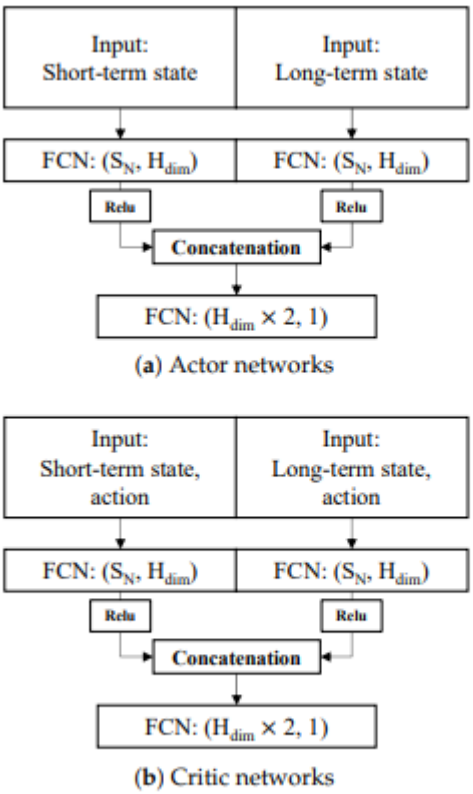


Figure 4. Actor and critic networks using fully connected layers.

To evaluate and compare the performance of the actor and critic models, we contrasted a simple FCN-based network with the more complex transformer-based model. This comparison offers insights into the optimization process, particularly considering the hardware limitations of the secondary user (SU) during channel exploration for rendezvous. In scenarios where the SU is not a smartphone-level device, hardware complexity is typically lower. Thus, if the performance of the two models is comparable, it may be feasible to design a reinforcement learning framework using a model similar to the FCN. Therefore, comparing the performance of these models is a critical aspect of future experiments.

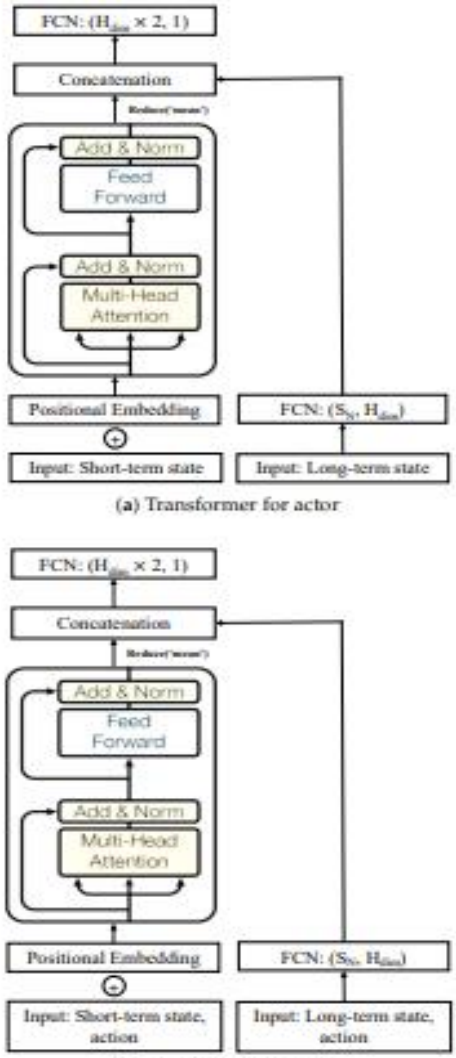


Figure 5. Actor and critic networks using transformer.

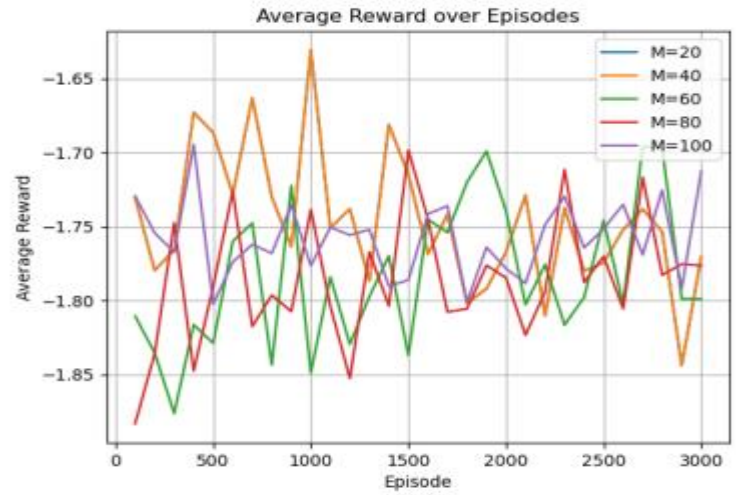
Figure 6 presents the trend of average reward during the training of each proposed model structure for the asymmetric cases. Each model was trained over 3000 episodes. A reward of -1 was assigned for each attempt, while a reward of 10 was given to the agent upon successful rendezvous. Consequently, if a rendezvous was not achieved within 10 channel explorations, the average reward would become negative. As the time-to-rendezvous (TTR) typically exceeds 10, the average reward across the entire experiment tended to remain negative. It was observed that the average reward converged after approximately 500 episodes. In the case of the simplified FCN model, oscillations in the average reward increased as the number of channels, MMM, increased.

The reward design stipulates a negative reward for failed rendezvous attempts. Therefore, significant oscillations in the average reward, especially toward the lower range, indicated high TTR during those episodes, which naturally led to a degradation in overall expected time-to-rendezvous (ETTR) performance. This underscores the importance of stabilizing the convergence of the average reward in reinforcement learning while maintaining a high reward level.

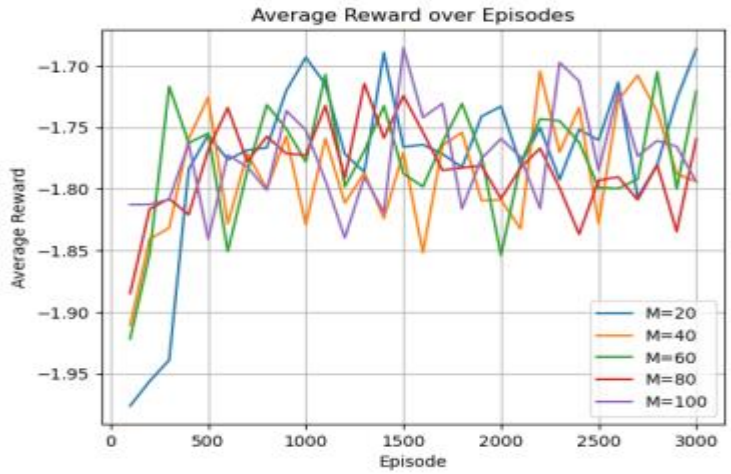
In the symmetric case, since all channels are shared channels, the important factor is the total number of channels. Therefore, we compare each algorithm when the number of channels is 20, 40, 60, 80, and 100. For each case, we independently conducted 15,000 tests (episodes) and compared the methodologies based on the average performance of each case. Initially, all entries for each state were set to zero. As a result, the first rendezvous attempt essentially selects actions randomly, following a uniform distribution. Additionally, since there is a method to apply the M-sequence in symmetric cases, the comparison will also include experiments using the M-sequence.

Figure 5 shows the performance comparison of each algorithm. In symmetric scenarios, the algorithm designed using M-sequence demonstrates the best ETTR performance. While the reinforcement learning-based algorithm shows slightly lower performance with about a 10% difference compared to the M-sequence algorithm, it achieves significantly better ETTR—about half that of the JS algorithm. Considering that the M-sequence-based algorithm is difficult to apply in asymmetric scenarios, the substantial performance gap between the reinforcement learning algorithm and the JS

algorithm suggests that the effectiveness of the reinforcement learning-based approach could become more pronounced in such environments.

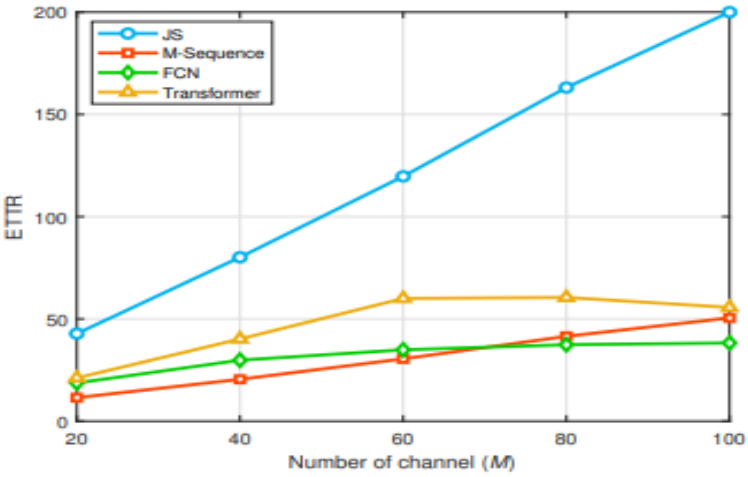


(a) Model using FCN

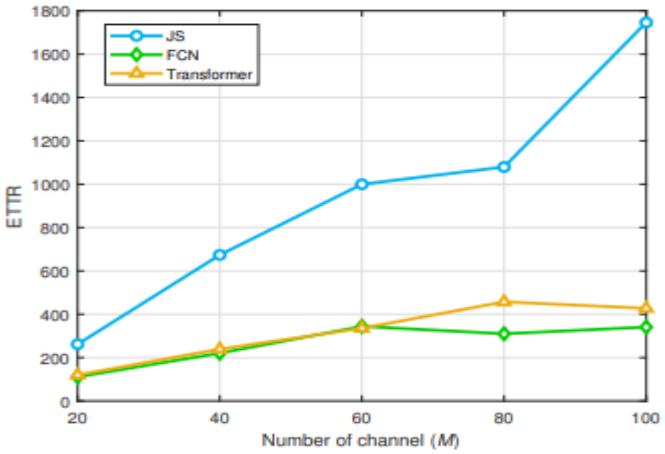


(b) Model using transformer

Figure 6. Average rewards over the number of episodes.



(a) Symmetric scenarios



(b) Asymmetric scenarios

Figure 7. ETTR for symmetric and asymmetric scenarios.

5. Conclusion

This paper proposes a novel reinforcement learning (RL)-based approach to address the rendezvous problem in cognitive radio networks (CRNs), particularly in environments where secondary users (SUs) have different sets of available channels. We introduced an actor-critic policy gradient algorithm to optimize channel selection strategies and reduce time-to-rendezvous (TTR), a crucial metric for improving the efficiency and reliability of dynamic spectrum access.The primary contributions of this study are:**RL-based Rendezvous Algorithm**: We developed a new RL-based algorithm that learns the optimal channel selection strategy, even in scenarios where SUs have heterogeneous channel availability. By incorporating past experiences into the learning process and modifying the reward structure to penalize failed attempts, our algorithm effectively reduces the number of rendezvous attempts needed. This leads to faster and more efficient rendezvous, making it more suitable for real-time CRN applications.

1. **Action Space and State Representation**: We innovated in defining the action space and states for the RL model. The action space consists of both binary decisions (whether to hop or stay on a channel) and the extent of the hop, which enables flexibility beyond the traditional channel-hopping sequences like the JS algorithm. The state representation includes both short-term and long-term action histories, enabling the agents to make informed decisions based on both recent experiences and cumulative attempts.
2. **Performance Improvements**: Our proposed approach outperforms traditional channel-hopping methods like the JS algorithm and other RL-based methods in terms of both rendezvous success rate and time-to-rendezvous. The actor-critic algorithm, with its ability to learn from the environment and adapt to changing conditions, leads to more reliable rendezvous and less redundant exploration of channels, which is especially beneficial in dynamic environments where channel availability fluctuates.
3. **Practical Considerations and Scalability**: While we limited the current study to a system with two SUs, the proposed method shows significant promise for scalability in larger networks. Future work could involve testing the algorithm in networks with multiple SUs and varying interference patterns. Additionally, while the current approach does not utilize multiple radios for faster exploration, it can be extended to such systems in future research. The method also adapts to networks where channel availability differs due to geographic location, regulatory constraints, or interference, making it highly relevant for real-world CRN applications.
4. **Future Research Directions**: Although the proposed approach significantly improves rendezvous performance, there are several potential avenues for future research. First, the integration of more advanced RL techniques, such as deep Q-networks (DQN) or multi-agent reinforcement learning (MARL), could further enhance the adaptability and performance of the algorithm. Second, exploring more sophisticated state representations that account for additional environmental factors (e.g., network congestion, channel state information) could further optimize the rendezvous process. Finally, extending this framework to other dynamic spectrum access problems, such as spectrum sensing or interference management, could broaden its application to a wider range of CRN use cases.

In conclusion, our RL-based approach addresses a key challenge in CRNs by enabling efficient and reliable rendezvous among SUs in the presence of heterogeneous channel availability. Through the use of actor-critic learning, the method improves rendezvous success rates and reduces the time required for rendezvous, thereby contributing to more efficient utilization of the radio spectrum in dynamic environments.

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