CLUSTERING AND REINFORCEMENT-LEARNING-BASED ROUTING FOR COGNITIVE RADIO NETWORKS

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ABSTRACT

The CRN is a future generation wireless communication system that allows SUs to use the underutilized or unused spectrum, known as white spaces, in licensed spectrum with minimum interference to PUs. However, the dynamic conditions of CRNs (e.g., PUs' activities and channel availability) make routing more challenging compared to traditional wireless networks. In this tutorial, we focus on solving the routing problem in CRNs with the help of a clustering mechanism. Cluster-based routing in CRNs enhances network scalability by reducing the flooding of routing overheads, as well as network stability by reducing the effects of dynamicity of channel availability. Additionally, RL, an artificial intelligence approach, is applied as a tool to further enhance network performance. We present SMART, which is a cluster-based routing scheme designed for the CRN, and evaluate its performance via simulations in order to show the effectiveness of cluster-based routing in CRNs using RL.

INTRODUCTION

The cognitive radio network (CRN) is a future generation wireless communication system that solves the problem of spectrum scarcity caused by static channel assignment policy in the past. The CRN solves this problem by allowing secondary users (SUs) or unlicensed users to explore and exploit underutilized licensed channels, known as white spaces, which are owned by primary users (PUs) or licensed users for improving overall channel utilization. Whenever a PU re-appears on the operating channel of an SU, the SU must switch to another available channel or wait for the PU's transmission to cease.

With the emergence of CRN applications such as cognitive radio sensor networks and cognitive vehicular networks, multihop routing for wide area coverage is becoming essential. Multihop routing in CRNs is challenging due to several factors. First, a CRN is characterized by the dynamicity of channel availability (or white spaces) due to different levels of PUs' activities. Second, the broadcasting of routing control messages over the distinctive available channels causes higher routing overhead and limits network scalability. Third, the dynamicity of channel availability can cause lack of a common control channel (CCC) for exchanging control information in routing.

Routing protocols for traditional wireless networks that maintain end-to-end paths, for example, ad hoc on-demand distance vector (AODV) routing protocol, are not preferable for CRNs because they do not consider the challenges of multihop routing in CRNs and highly increase the network overhead by constantly flooding the routing messages. Hence, such protocols cannot be directly applied in CRNs. Therefore, routing protocols for CRNs must address the challenges of CRNs by considering spectrum awareness in order to establish stable routes so that SUs can perform data communication for long durations without having much disruption from PUs, as well as with minimal interference to PUs. Furthermore, there are only limited cluster-based routing schemes proposed in the literature in the context of CRNs.

In this article, we solve the routing problem in CRNs with the help of a clustering mechanism and reinforcement learning (RL), an artificial intelligence approach, which is our main contribution. Cluster-based routing for CRNs enhances network scalability by reducing the flooding of routing overheads as well as network stability by reducing the effects of the dynamicity of channel availability. RL is a tool that further enhances network performance through observing and learning the environment. We have proposed a cluster-based routing scheme using RL, which is known as SMART and is designed for CRNs, in order to fulfill the requirement on the minimum number of common channels in a cluster through cluster maintenance (i.e., cluster merging and splitting), which enhances network stability as well as network performance. Since cluster-based routing has not been well investigated before in the context of CRNs, this is the focus of our article.

The organization of this article is as follows. In the following two sections, we present an overview of clustering and cluster-based routing for CRNs, respectively, by highlighting their advantages and importance for solving the problem of multihop routing in CRNs. Then we present an overview of RL. Subsequently, we present Spec-

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trum-Aware Cluster-Based Routing (SMART), which is a cluster-based routing scheme that applies RL to CRNs. Following that, we evaluate the performance of SMART. Finally, we conclude in the last section.

Clustering in CRNs

Clustering, a topology management mechanism, provides network stability and scalability by organizing nodes into logical groups called clusters. The cluster structure provides a suitable network model to support cooperative tasks, which are very important for CR operations (e.g., routing and channel sensing). Figure 1 shows a cluster structure in which nodes are grouped into three clusters. Each cluster consists of four types of nodes: clusterhead, member node, relay node, and gateway node. The clusterhead is the central processor for cooperative tasks within the cluster. Each member node is associated with a clusterhead. The clusterhead and member nodes communicate between themselves using a common channel known as an operating channel. This communication is known as intra-cluster communications. The operating channel is available to all nodes in a cluster. A relay node is a member node that provides connection to another member node which is located out of the transmission range of the clusterhead. A gateway is also a member node that can hear from neighboring cluster(s). It provides two-hop, or even more hops, inter-cluster communications and is located at the boundary of a cluster.

Cluster size represents the number of nodes in a cluster, and it affects various performance metrics. Larger cluster size minimizes routing overhead since the flooding of routing overheads only involves clusterheads and gateway nodes along a backbone, and also reduces error probability in the final decision of channel availability since it is based on channel sensing outcomes collected from the higher number of nodes in a cluster. Smaller cluster size (or a higher number of clusters in a network) maximizes the number of common channels, and hence connectivity among nodes in a cluster, because physically close nodes are more likely to have a similar list of available channels. Since clusters may use different operating channels, the contention and interference levels in the network can be reduced, and this subsequently improves routing and network performance. The higher number of common channels in a cluster minimizes the occurrence of re-clustering due to improved connectivity between nodes within a cluster. While achieving larger cluster size may seem to be more favorable in traditional wireless networks in order to improve scalability, the same cannot be said for CRNs. Since smaller cluster size maximizes the number of common channels in a cluster, it enhances the connectivity among member nodes and the clusterhead in a cluster. This improves stability and addresses the challenge of dynamicity of channel availability in CRNs [1].

Cluster-Based Routing in CRNs

Routing protocols can be cluster-based, running over the clustered network. In the literature, there have been a larger number of separate investigations into clustering [2, 3] and routing [4, 5], but there is only a perfunctory attempt to investigate

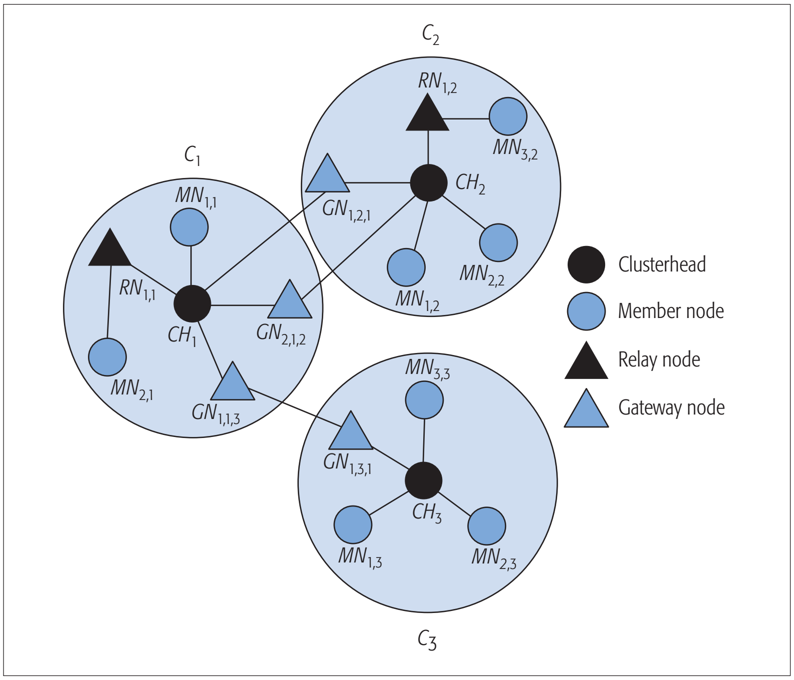

Figure 1. Cluster structure.

cluster-based routing schemes for CRNs. Readers are referred to surveys on clustering [6, 7] and routing algorithms [8] in CRNs for a comprehensive review of the literature.

Cluster-based routing is preferred in CRNs for the following reasons. First, it provides network stability by reducing the effects of dynamic channel availability since any changes to channel availability affect the network at the cluster level, so only local updates are required instead of reconfiguration of the entire network. Second, it provides network scalability as routing control messages, such as route request (RREQ) and route reply (RREP), are only exchanged among some nodes, specifically clusterheads and gateway nodes. Clusterheads and gateway nodes share a similar operating channel, and gateway nodes are aware of the operating channels of neighboring clusters; this facilitates broadcasting using a single transceiver as it is no longer required to broadcast in the distinctive available channels used by neighboring nodes in non-clustered networks. Third, it reduces the need for a common control channel to exchange control information in routing since an operating channel is used that is available to all nodes in a cluster. Fourth, it supports cooperative tasks and improves channel sensing outcomes. For example, a clusterhead collects channel sensing outcomes from its member nodes and subsequently makes a final decision on channel availability. This improves the accuracy of channel availability decisions compared to decisions made based on the outcome of a single node.

Reinforcement Learning: A Tool to Enhance Network Performance

RL [9] is an artificial intelligence approach that enables an agent or decision maker to observe its state and reward, learn, and then perform an action in order to improve the state and reward in

Since CRN is characterized by the dynamicity of channel availability due to PUs' activities, cluster maintenance is imperative in CRNs to adapt the cluster structure and cluster size. RL reduces the effects of dynamic channel availabilities by observing, learning and taking the optimal or near-optimal actions that minimizes cluster maintenance.

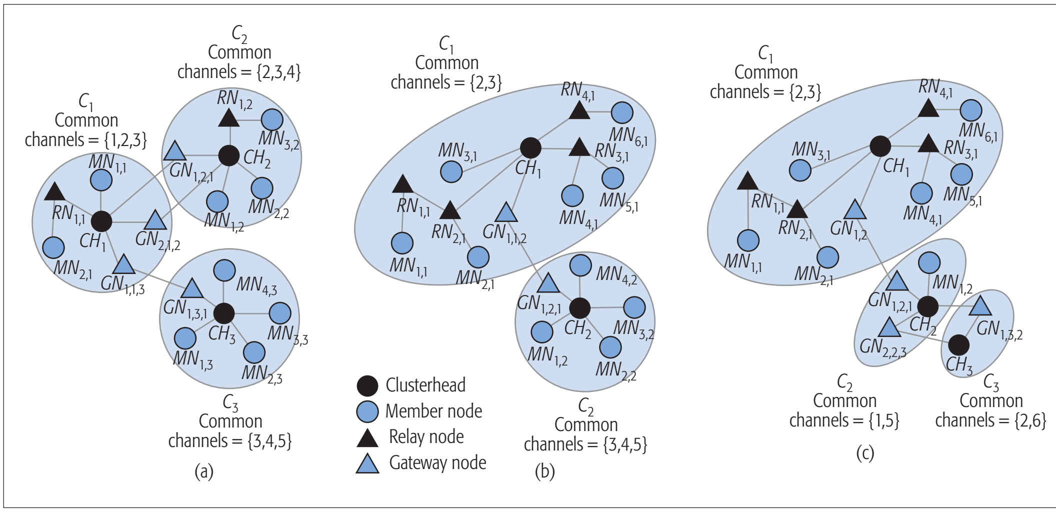

Figure 2. An illustration of cluster maintenance: a) initial clusters formed after cluster formation; b) new clusters after cluster merging is performed on clusters 1 and 2 in initial clusters; c) new clusters after cluster splitting is performed on cluster 2 due to re-appearance of PUs on common channels 3 and 4 of cluster 2 in b).

the next time instant. In the RL model, the action affects (improves or deteriorates) the state and reward, which affects the next choice of action by an agent. With the passage of time, an agent estimates the reward for each state-action pair, which constitutes knowledge, and subsequently carries out a proper action at the next time instant given a particular state to maximize accumulated rewards. The important representations for the agent in the RL model include state, action, and reward.

- State: represents the decision making factors observed in the operating environment by an agent. It can affect the reward (or network performance).
- Action: represents the action of an agent, which helps an agent learn about the optimal actions. It can affect the state (or operating environment) and reward (or network performance).
- Reward: represents the positive or negative consequence for the operating environment caused by the agent's action in the previous time instant in the form of network performance.

Q-routing has been applied in routing and is a prominent RL scheme. In the Q-routing model, *state* represents the destination node, *action* represents the next-hop neighbor node of the decision making node that relays data toward the destination node, and *reward* represents network performance (e.g., throughput). Each link of a route is associated with a cost (e.g., delay), and a node computes Q-value for each state-action pair (or destination and next-hop neighbor node pair) in order to estimate the cost required for transmitting the data toward the destination node along the route.

There are two main advantages of applying RL to routing in CRNs. First, rather than considering each factor that affects the network performance, RL models the network performance that covers various factors in the operating environment or network conditions affecting the network performance (i.e., the channel utilization level by PUs and channel quality); hence, it is a simple modeling approach. Second, prior knowledge of the operating environment or network conditions is not necessary, so an SU can learn about the operating environment on the fly as time goes by. Hence, the application of RL to cluster-based routing in CRNs can improve both routing and clustering performance, and it is very novel. Since a CRN is characterized by the dynamicity of channel availability due to PUs' activities, cluster maintenance is imperative in CRNs to adapt the cluster structure and cluster size. RL reduces the effects of dynamic channel availabilities by observing, learning, and taking the optimal or near-optimal actions that minimize cluster maintenance.

SMART

We present SMART for overcoming the challenges of multihop routing in CRNs through cluster-based routing and RL. In SMART, clustering aims to form clusters that fulfill the requirements on the number of common channels in a cluster and allow nodes to forward routing control messages efficiently without the need for broadcasting on all the available channels, while RL aims to find a route that increases the usage of white spaces for maximizing SUs' network performance. Moreover, in order to overcome the dynamicity of channel availability, SMART provides extension to clustering through cluster merging and splitting. Subsequently, SMART adjusts cluster size as time goes by so that a cluster fulfills the requirement on cluster size for improving scalability, as well as the number of common channels in a cluster for improving stability. SMART estimates the OFF-state probability of a channel at the next time instant [10], and uses this estimation to rank and select the operating channels in clustering and routes in routing.

Clustering

There is a significant amount of work on cluster formation and gateway node selection in CRNs; hence, readers are recommended to refer to the existing work [11–13] on cluster formation and gateway node selection. However, cluster maintenance (i.e., cluster merging and splitting) and cluster-based routing using RL are novel and have not been investigated before. Therefore, we mainly present them in this article, which is our main contribution.

Cluster maintenance adjusts the cluster size in order to reduce dynamic effects of the network, and it consists of cluster merging and splitting. These are best explained with illustrations as presented in Fig. 2. In this figure, the labels of the nodes are revised after each clustering event for better understanding. We assume that a threshold for a minimum number of common channels is two in both cluster merging and splitting. Cluster merging combines two clusters into one and is possible when two clusters satisfy the threshold for minimum number of common channels. Figure 2a presents initial clusters formed after cluster formation in which gateway node 1 in cluster 2 discovers that the set of common channels between clusters 1 and 2 is two, and it satisfies the threshold value. Thus, it informs both clusterheads in clusters 1 and 2 about the potential cluster merging. Suppose both clusterheads agree to merge and subsequently, gateway node 1 in cluster 2 becomes the new clusterhead as presented in Fig. 2b. The existing clusterheads in Fig. 2a relinquish their roles and become member nodes of the new clusterhead, and then inform their respective member nodes to join the new clusterhead. Member nodes that are in the transmission range of a new clusterhead in Fig. 2a join the new clusterhead. However, member nodes that are not in the transmission range of the new clusterhead request their previous clusterheads to provide connection to the new clusterhead, so the relinquished clusterheads become relay nodes for such member nodes as presented in Fig. 2b. Finally, the new clusterhead selects the operating channel of the new cluster, and subsequently, gateway nodes are selected to provide inter-cluster communication for the newly merged cluster.

Cluster splitting splits one cluster into two, and it is performed when a clusterhead realizes that its cluster cannot satisfy a threshold for a minimum number of common channels. Figure 2c shows clusters after cluster splitting is performed on Fig. 2b. Suppose common channels 3 and 4 of cluster 2 in Fig. 2b are re-occupied by PUs. Thus, the clusterhead of cluster 2 in Fig. 2b initiates cluster splitting. Since the clusterhead is aware of a list of available channels for all nodes in its cluster, it counts the number of nodes in each available channel and ranks these channels based on maximum node degree. Subsequently, the clusterhead selects the highest ranked channels and identifies nodes that have such channels available. In Fig. 2b, such channels are available to four nodes in cluster 2, so the clusterhead forms one cluster comprising these nodes as cluster 2, presented in Fig. 2c. For the remaining nodes, the clusterhead identifies the common channels among these nodes and creates another cluster consisting of them, which is presented as cluster 3 in Fig. 2c. Finally, clusterheads and gateway nodes for the newly split clusters are selected.

Cluster-Based Routing Using Reinforcement Learning

In this section, we present cluster-based routing based on Q-routing, an RL model, which is performed on the clustered network. A source clusterhead estimates the Q-value for each neighbor node to reach the destination node and subse-

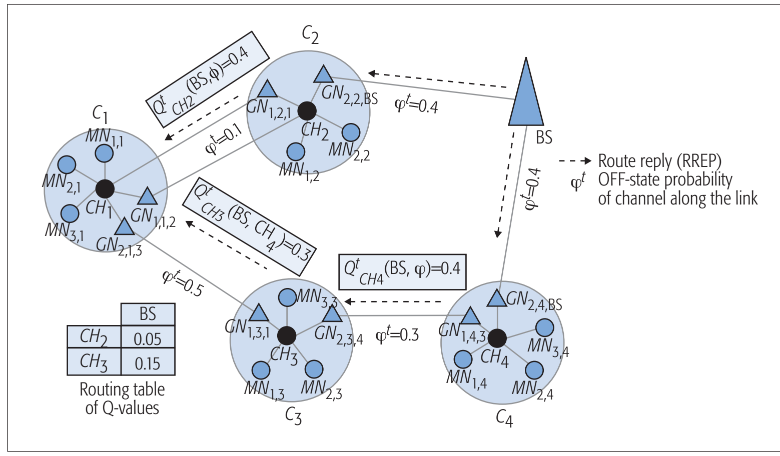

Figure 3. Cluster-based routing example.

quently updates the routing table of Q-values. The traditional Q-value equation [14] is modified to incorporate the OFF-state probability of the bottleneck channel along a route. The bottleneck channel is the channel having the least OFF-state probability for the next time instant along a route toward the destination node, connecting two clusters via an SU neighbor node. The Q-value equation can be generally described below:

$$Q_{src}^{next}(dst,nbr) \leftarrow \Big((1-\alpha)\times Q_{src}^{current}(dst,nbr)\Big) + \Big[\alpha \times \min\Big(chanProb_{src,nbr}^{current}, Q_{nbr,max}^{current}(dst)\Big)\Big]$$

where $0 \le \alpha \le 1$ is the learning rate, *src* is the source clusterhead, *nbr* is the SU neighbor node of the source clusterhead, *dst* is the destination node, $chanProb_{src,nbr}^{current}$ is the OFF-state probability of the operating channel between the source clusterhead and its SU neighbor node, and $Q_{src,nbr}^{current}(dst)$ is the OFF-state probability of the bottleneck channel along a route from an SU neighbor node of the source clusterhead's neighbor node to the SU destination node. The minimum value among $chanProb_{src,nbr}^{current}$ and $Q_{src,nbr}^{current}(dst)$ represents the channel availability probability of the bottleneck channel along the route.

Figure 3 presents an example of cluster-based routing using RL in which clusterhead 1 wants to send data packets to the SU destination node base station (BS). Initially, clusterhead 1 initiates an RREQ toward SU destination node BS in order to discover a route. The procedure of RREQ propagation is traditional, so we are not going into its details. When an SU destination node BS receives two RREQ messages from clustersheads 2 and 4, it generates RREP messages and sends them back to clusterhead 1 using the reverse route through which RREQ messages traversed. When clusterhead 4 receives an RREP message from SU destination node BS via its gateway node, it updates the Q-value with channel OFF-state probability of the link between cluster 4 and the SU destination node BS. Subsequently, clusterhead 4 embeds this Q-value in RREP and forwards it toward clusterhead 3. When clusterhead 3 receives RREP from clusterhead 4, it compares the OFF-state probability of a channel provided in the RREP with the OFF-state probability of a channel along the link between clusters 3 and 4, and finds that its link

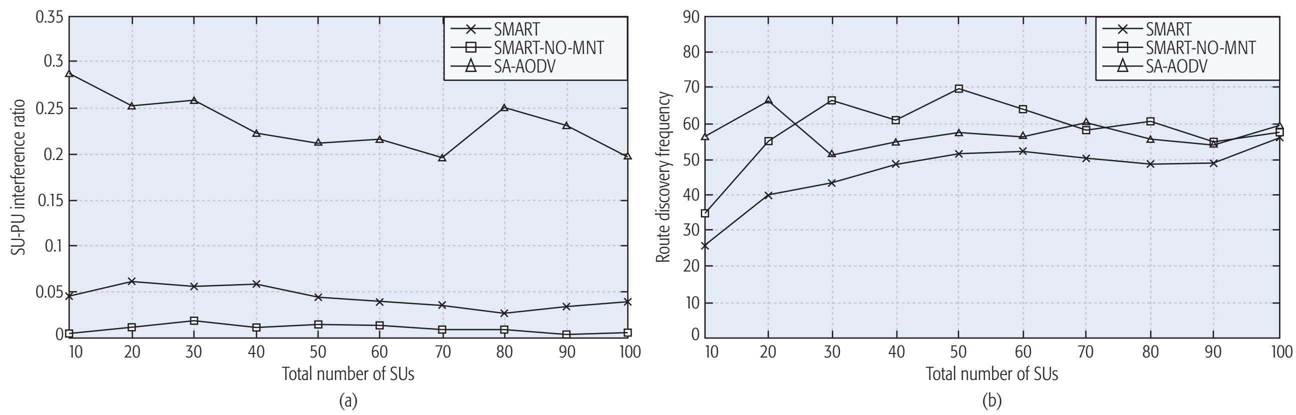

FIGURE 4. Evaluation results: a) SU-PU interference ratio; b) route discovery frequency.

channel has lower OFF-state probability. Therefore, it updates the Q-value and forwards it to the SU source node by embedding it in an RREP message. When the SU source node receives the RREP from clusterhead 3, it updates its routing table of Q-values. A similar procedure runs on clusterhead 2 to process the RREP. Finally, there are two entries in the routing table of Q-values at the SU source node. The SU source node selects clusterhead 3 as its next-hop SU node because it provides the highest Q-value for the route leading to the destination node BS. It is important to note that the lower route is selected because it is more stable, although it is longer compared to the alternative (upper) route.

PERFORMANCE EVALUATION

The performance of SMART is evaluated in the network simulator QualNet 6.1, which is incorporated with CR functionality. The total number of SUs is 10 and of channels is 5. The SU learning rate α is set to 0.5 for maintaining a balance between the estimated and recent value. Since a cluster must have at least two common channels (i.e., master and backup channels), the threshold for the minimum number of common channels is set to 2. Whenever a master channel is re-occupied by PUs' activities, all member nodes and the clusterhead in a cluster switch to a backup channel. The simulation time for each run is 550 s, and a total of 100 simulation runs, each with random topology, were performed for each measurement. Each result shown in a graph is an average value for the values gathered in 100 runs. We assume perfect channel sensing because the main focus of our work is on the network layer. The ON-OFF transitions of PU activity follow a Poisson model with exponential distribution with rates $\lambda^k_{ON,j}$ and $\lambda^k_{OFF,j}$ for ON and OFF periods, respectively.

The network performance of SMART is compared to clustered and non-clustered schemes. The clustered scheme is known as SMART-NO-MNT (SMART no maintenance) that operates similar to SMART, but does not have the functionality of cluster maintenance (i.e., cluster merging and splitting). The non-clustered scheme, called SA-AODV (spectrum-aware AODV), is a variant of the AODV routing protocol designed for the CR environment that has been used for comparison in the literature [15]. SA-AODV is spectrum-aware and operates in a multi-channel environment. It selects a random channel from the list of available channels for operation. There are two performance metrics of SMART, specifically, SU-PU interference ratio and route discovery frequency. SU-PU interference ratio is the ratio of the total number of SU-PU interfered packets to the total number of transmitted packets by an SU source node. Route discovery frequency is the number of route discovery (or RREQ messages) initiated by SU source node.

Figure 4a presents SU-PU interference ratio. Figure 4b shows route discovery frequency. SMART achieves significantly lower SU-PU interference ratio as well as route discovery frequency. This is because SMART is a cluster-based routing that adopts cluster maintenance (i.e., cluster merging and splitting) and RL. The cluster maintenance mechanisms reduce the dynamic effects of network caused by PUs' activities, and RL helps in the right selection of SU next-hop node in routing by learning from the environment and previous actions. Therefore, the selected routes are stable, having fewer chances of PUs' re-appearance. SMART-NO-MNT causes higher route discovery frequency than SMART due to the lack of cluster maintenance mechanisms. Therefore, there is a higher chance that clusters lack inter-cluster connection with an increasing number of PUs, so the SU source node initiates a higher number of re-routings, and hence a higher number of RREQ messages are sent in order to discover a route. Additionally, SMART-NO-MNT drops a higher number of packets due to the lack of inter-cluster connection, and therefore, with a lower number of transmissions, the SU-PU interference is naturally lower. SA-AODV causes higher SU-PU interference and route discovery frequency due to the lack of stability achieved by clustering, as well as the benefit of RL for learning from the environment and previous actions. The results show the effectiveness and feasibility of cluster-based routing and the application of RL to routing for CRNs.

CONCLUSION

In this article, we focus on the routing problem in CRNs caused by an intrinsic characteristic of cognitive radio: dynamic channel availability. The problem is addressed by clustering mechanisms, particularly cluster merging and splitting, and an artificial intelligence approach, specifically RL. Clustering and RL solve the routing problem in

CRNs and improve network scalability and stability. We also propose SMART, which is a cluster-based routing scheme for CRNs, and evaluate it through simulations. One of the main goals of CRNs is to minimize SUs' interference to PUs. The simulation results confirm that cluster-based routing minimizes SUs' interference to PUs, and also selects more stable routes and achieves significantly lower route discovery frequency.

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Biographies

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Qiang Ni received his B.Sc., M.Sc., and Ph.D. degrees from Huazhong University of Science and Technology, Wuhan, China, all in engineering. He is a professor of communications and networking and the head of the Communication Systems Group at the School of Computing and Communications, Lancaster University. His main research interests are wireless communications and networking in which he has published more than 150 papers. He was an IEEE 802.11 Wireless Standard Working Group voting member and a contributor to IEEE wireless standards.

One of the main goals of CRN is to minimize SUs' interference to PUs. The simulation results confirm that cluster-based routing minimizes SUs' interference to PUs, as well as selects more stable routes and achieves significantly lower route discovery frequency.