GHAR: Graph-based Hybrid Adaptive Routing for Cognitive Radio Based Disaster Response Networks

---

Citation:

Thuan Ngo, Hiroki Nishiyama, Nei Kato, Satoshi Kotabe, and Hiroshi Tohjo, "GHAR: Graph-based Hybrid Adaptive Routing for Cognitive Radio Based Disaster Response Networks," IEEE International Conference on Communications (ICC 2016), Kuala Lumpur, Malaysia,May.2016.

GHAR: Graph-based Hybrid Adaptive Routing for Cognitive Radio Based Disaster Response Networks

Thuan Ngo[1§], Hiroki Nishiyama[1†], Nei Kato[1⊥], Satoshi Kotabe[2‡], and Hiroshi Tohjo[2⊤]
[1]Graduate School of Information Sciences, Tohoku University, Sendai, Japan
[2]NTT Network Innovation Laboratories, NTT Corporation, Yokosuka, Japan
[§]thuan.ngo@it.is.tohoku.ac.jp, [†]hiroki.nishiyama.1983@ieee.org, [⊥]kato@it.is.tohoku.ac.jp,
[‡]kotabe.satoshi@lab.ntt.co.jp, and [⊤]tohjo.hiroshi@lab.ntt.co.jp

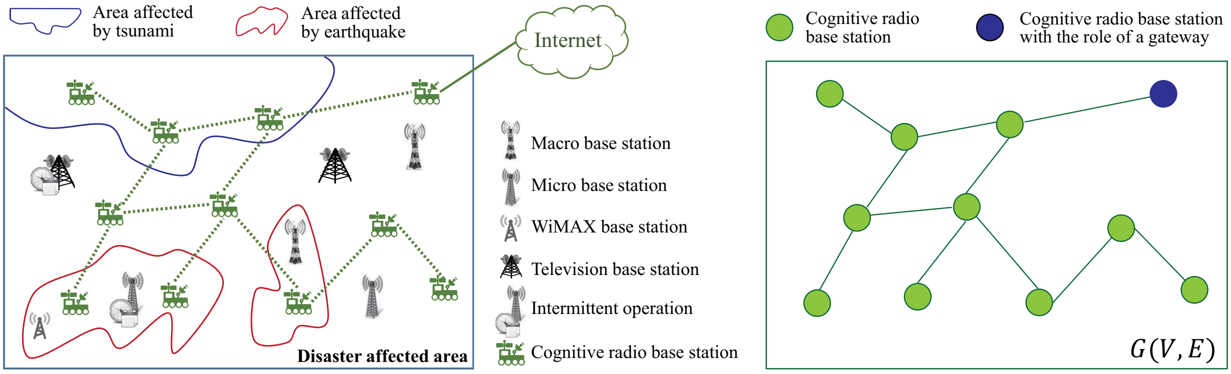
***Abstract*—Although the importance of Disaster Response Networks (DRNs) has been highlighted in many researches, the requirement of spectrum agility has not been well addressed. In this paper, we focus on using all-spectrum cognitive radio for DRNs to fulfill this requirement. We consider a DRN constructed by Cognitive Radio Base Stations (CRBSs), which are deployed in the disaster affected area. Each CRBS is equipped with multiple antennas to support different frequency bands available in the area. Based on the considered DRN, we propose a Graph-based Hybrid Adaptive Routing scheme, which we refer to as GHAR. There are two phases in GHAR, centralized phase for topology formation and distributed phase for adaptive routing. In the centralized phase, we propose an algorithm that unites k non-overlapping minimum spanning trees to construct the topology for the next phase. We provide an analysis on the relationship between k and the adaptability with cognitive radio as well as the complexity of routing process. We also provide an analysis on the optimality of k. Furthermore, extensive simulations are conducted to validate our analysis. Simulation results confirm the effectiveness of our proposal and the existence of the optimal value of k.**

***Index Terms*—Cognitive radio, adaptive routing, graph-based algorithm, disaster response network.**

I. Introduction

The significant impact of disasters on human life has drawn a great deal of research attention on disaster responses. After a disaster occurs, the network infrastructure in the disaster affected area can be damaged or completely destroyed. If some remaining cellular base stations are still operating, the critical situation can be relaxed by using device-to-device (D2D) communication approaches such as in [1], which introduces a novel D2D local area network (D2D-LAN) framework for improving network capacity. If all base stations are completely destroyed, a totally new network needs to be deployed. In order to deal with both situations, building a new disaster response network (DRN) for the disaster area is the most suitable choice. Many research works have been conducted in the field of DRNs [2]–[5], which highlight the key requirements of DRNs including quality of service (QoS), robustness and reliability, coverage and mobility, rapid deployment, interoperability, spectrum agility, self-organization, and cost effectiveness. In order to fulfill the requirements of DRNs, especially in terms of spectrum agility, which has not been well addressed in the existing works, cognitive radio should be considered because of its advantages including heterogeneity, reconfigurability, self-organization, and interoperability with existing networks [6]–[8]. Particularly, due to the effect of the disaster, the infrastructure could be completely destroyed or partially damaged, or might be able to operate intermittently, resulting in a significant availability of spectrum for use by cognitive radio. The availability of spectrum depends on locations and time periods due to different degrees of disaster effects and the situations of recovery process, respectively. Therefore, a method that effectively and adaptively utilizes the available spectrum in the disaster affected area is required. In order to design such a method, we focus on the following research issues. First, all-spectrum cognitive radio should be considered for utilizing any available spectrum in the area. Second, the differences in time, location, and operator might lead to the difference in the availability of spectrum. Furthermore, only some locations in the disaster area can have connectivity to the outside world, and thus, the method to route traffic in the area to such locations needs to be taken into account. To effectively address these research issues, we consider a cognitive radio based DRN as shown in Fig. 1(a). After a disaster occurs, many mobile base stations, which we refer to as Cognitive Radio Base Stations (CRBSs), are deployed to the area to provide network communication services. Each CRBS is equipped with multiple antennas to support different frequency bands, such as cellular networks, WiMAX, television, and so forth. Traffic from all CRBSs will be routed to the gateway, i.e., the CRBS having connectivity to the outside area. We assume that the CRBSs are agile and cost-efficient enough to be deployed with a relatively large amount in the disaster affected area. However, the trade-off relationship between the adaptability with cognitive radio and the routing complexity needs to be solved. If each CRBS has too many direct connections to other CRBSs in the area, the routing process will have a high complexity, causing high delay in routing traffic. On the other hand, if each CRBS has too few neighbors, when the neighboring nodes cannot use the spectrum, the CRBS is unable to find the next hop to route its traffic, and thus, fails to adapt with the changing environment.

Motivated by this crucial trade-off problem, we propose a routing scheme called the Graph-based Hybrid Adaptive Routing (GHAR). Our proposed scheme includes two phases: centralized and distributed phases. In the centralized phase, a central CRBS eliminates unnecessary neighbors of each node in the network. The objective of this phase is to form a topology and reduce the complexity of routing process. Our proposed algorithm for the centralized phase aims to find



(a) (b)

Fig. 1. Considered disaster response network using cognitive radio base stations. (a) Considered scenario. (b) Corresponding modeled network.

k non-overlapping minimum spanning trees (MSTs) on the original network. The combination of the resulted MSTs forms the topology for the next phase. In the distributed phase, a distributed adaptive routing algorithm is carried out on the constructed topology. Distributed adaptive routing is employed to guarantee the adaptability of the network with the change of available spectrum in the area. Furthermore, we provide an analysis on the relationship between k and the adaptability with cognitive radio as well as the complexity of routing process. An analysis on the optimality of k is also provided. In addition, extensive simulations are conducted to validate the analytical findings. The simulation results confirm that there is a value of k that optimally solves the trade-off relationship between cognitive radio adaptability and network complexity.

The remainder of this paper is organized as follows. Section II outlines the motivation and challenges of the cognitive radio based DRNs. In Section III, we introduce our assumptions, the network model, and the metrics for evaluating the considered network. In Section IV, we describe our proposed scheme called GHAR, which includes both centralized and distributed phases. The analysis on the trade-off relationship between complexity of routing process and the adaptability with the changing environment is presented in Section V. We present the performance evaluation in Section VI and conclude the paper in Section VII.

II. Cognitive Radio Based Disaster Response Networks: Motivation and Challenges

In this section, we provide a discussion on the necessity of having all-spectrum cognitive radio based DRNs and the challenges to make those DRNs possible.

A. Motivation of Disaster Response Networks Based on All-Spectrum Cognitive Radio

Among the approaches to fulfill the requirements of DRNs, cognitive radio is considered as the most suitable candidate of DRNs because of its two noticeable features. First, cognitive radio can utilize the available spectrum in the area when the primary user of the spectrum does not use it. In fact, the spectrum resource will be widely available in the disaster areas due to the damages of infrastructure after disasters. Second, cognitive radio can adaptively change with the change of available spectrum. Especially in disaster areas, the change of available spectrum is expected to happen more frequently. However, according to the survey results presented in [2], none of the conducted works can satisfy the requirement of spectrum agility, which is the capability of operating in a wide range of different frequency bands. Therefore, in this paper, we focus on using all-spectrum cognitive radio for DRNs to utilize any available spectrum in disaster affected areas. By making DRNs support multiple frequency bands, the networks can be adapted to local variations in spectrum use and regulation.

B. Challenges for Cognitive Radio Based Disaster Response Networks

In order to apply cognitive radio for DRNs, there are many challenges that need to be resolved. Here, we outline three main challenges for cognitive radio based DRNs.

- *Routing*: unlike other type of networks, DRNs have to face more difficulties due to the situation in disaster affected area. Following a disaster, many places in the area might be isolated. Only few locations can have connectivity to outside world, which are the locations located closely to non-affected area, or the locations having facilities to connect to a network with very large coverage such as satellite network [9], [10]. Therefore, even though we can deploy network equipment to isolated locations, routing is very important to bring network connectivity to the whole isolated area.
- *Adaptability*: this is always a challenge for cognitive radio networks. However, in the DRNs scenarios, the challenge becomes even more critical due to the frequent change of available spectrum. In disaster areas, base stations and infrastructure can be inactive because of many reasons: power outage, damage, safety shutdown, and so forth. It is not easy to predict when and how the infrastructure will recover, because the situation is different for each disaster. Therefore, adaptability is one of the major challenges for designing a cognitive radio based DRN that can adapt with different scenarios of disasters.
- *Complexity*: the demand of using network service in disaster areas is always much higher than normal because

the disaster victims will try to use the Internet to confirm safety of their family, relatives, and friends, while the network infrastructure is usually damaged or destroyed. However, as mentioned above, only a few places in the area can have connectivity to outside area. Therefore, after DRN is deployed in the area, the complexity of the routing process needs to be minimized, in order to provide acceptable Internet connection to users in the disaster affected area.

III. System Assumptions and Definitions

In this section, we first summarize the assumptions for our considered network, and then present how the network is modeled. Furthermore, the metrics to evaluate the effectiveness of the proposed scheme are introduced.

A. System Assumptions

As shown in Fig. 1(a), the considered DRN is constructed by multiple CRBSs. Each CRBS is equipped with multiple antennas to support multiple frequency bands. The CRBSs are assumed to have the ability to switch between different antennas to adapt with the change in available spectrum in the area. Additionally, we assume that at a certain time, a central CRBS can be selected to carry out the centralized phase, which is for forming the topology.

B. Network Model

For a cognitive radio based DRN constructed by CRBSs, we define a graph $G(V, E)$, as shown in Fig. 1(b), where V is the set of nodes, i.e., CRBSs, and E is the set of links connecting the CRBSs. In this paper, we use index number i to represent CRBS i and a pair (i, j) to represent the link connecting CRBS i and CRBS j. The Euclidean distance between CRBS i and CRBS j is represented by d_{ij}.

1) Spectrum availability at a node: In the considered network, the central CRBS periodically senses the spectrum availability status and select the best frequency band for the DRN to use for the next time period. Since the availability of the selected frequency band in each locations is different, we define ρ_i as the probability that the CRBS i can use the selected frequency band in its local area during the next time period.

2) Link cost: The cost of the link (i, j), c_{ij}, is calculated base on ρ_i, ρ_j, and d_{ij} as follows:

$$c_{ij} = (1 - \rho_i \rho_j) d_{ij}. \tag{1}$$

$(1 - \rho_i \rho_j)$ is the probability that at least one of the two CRBSs, i and j, cannot use the frequency band. In other words, $(1 - \rho_i \rho_j)$ is the probability that the link (i, j) will be disconnected during the next time period. d_{ij} is the distance between i and j. A longer distance leads to a weaker link between the two CRBSs. Therefore, the reason behind the equation (1) is that by choosing the link, we accept the risk of having the link that might be broken or weaken due to the effect of spectrum availability and link distance. Large values of ρ_i and ρ_j and small value of d_{ij} lead to low link cost, and vice versa.

3) Neighbor set: The set of neighbors of a CRBS i, $\mathcal{N}_i$, is defined as follows:

$$\mathcal{N}_i = \{j : j \in V, (i, j) \in E\}. \tag{2}$$

C. Metrics

In order to evaluate the performance of the considered DRN, we introduce the following metrics.

1) Cognitive Radio Adaptability Index (CRAI): We introduce CRAI of a CRBS as the index of the node's adaptability with the change of available spectrum. CRAI of a CRBS depends on the set of the CRBS's neighbor nodes and the probability that each neighbor can use the spectrum in its local area.

$$\mathcal{A}_i = \sum_{j \in \mathcal{N}_i} \rho_j, \tag{3}$$

where $\mathcal{A}_i$ is the CRAI of the CRBS i, and ρ_j is the probability that the CRBS j can use the spectrum at its local area.

2) Network complexity: This metric calculates the complexity that routing process might have when it is carried out on the topology constructed by the centralized phase. It is directly affected by the number of nodes and links of the network. The number of neighbors per CRBS can also be used to evaluate this metric.

3) Average node degree: In the graph modeling the considered network, degree of a node is calculated by the number of adjacent nodes. Therefore, the average node degree, D, is calculated by the average number of neighbors per CRBS as follows:

$$D = \frac{1}{|V|} \sum_{i \in V} |\mathcal{N}_i|. \tag{4}$$

4) Average number of hops to gateway: This metric is to estimate the number of hops from CRBSs in the disaster area to the gateway CRBS in the routing phase. After the topology is constructed, shortest paths from CRBSs to the gateway CRBS in terms of number of hops will be found. The average number of hops to gateway, H, is calculated by the average number of hops in the resulted paths as follows:

$$H = \frac{1}{|V|} \sum_{i \in V} h_i, \tag{5}$$

where h_i is the smallest number of hops needed to route traffic from CRBS i to the gateway.

5) Utility function: This metric can be considered as one of the most important metrics to evaluate the effectiveness of the network. We consider CRAI as the payoff we get after forming the topology in the centralized phase, and the production of the average node degree and the average number of hops to the gateway as the estimated cost for routing phase based on the resulted topology. The utility function, $\mathcal{U}$, can be calculated as follows:

$$\mathcal{U} = \frac{\sum_{i \in V} \mathcal{A}_i}{D \times H}. \tag{6}$$

IV. GHAR: The Proposed Graph-based Hybrid Adaptive Routing Scheme

Our proposed scheme, GHAR, includes two phases: centralized phase and distributed phase. In the centralized phase, a CRBS will be assigned as the central node to form the topology in which the redundant neighbors of each node, i.e., each CRBS, are removed before the next phase. In the distributed phase, a distributed adaptive routing will be carried out based on the topology formed in the previous phase. Note that the main contributions of this proposal are the hybrid approach and the algorithm inside the centralized phase. In the distributed phase, any distributed adaptive routing algorithm can be used. Selecting the algorithm for adaptive routing is not within the scope of this paper.

A. Centralized Phase: Topology Formation

The most straightforward consideration of a redundant neighbor of a node is that the node will not choose that neighbor to be the next hop for transmission in any case. To come up with a scalable solution for removing redundant neighbors of each node, we design an algorithm to keep at least k neighbors while the chosen neighbors have high probability to be the next hop of the node in transmissions. k is a tuning factor that we can use to adjust the number of links in the topology. In order to keep the best neighbors of each node in terms of minimizing the total link cost, we extend the traditional MST algorithm [11] by using the equation (1) for calculating weights of links. Note that the traditional MST use only Euclidean distance between two nodes of a link as the link weight, we also consider the probability that each node can be used for transmissions. In order to guarantee that each node has at least k neighbors, we find k non-overlapping MSTs of the graph and combine them to construct the topology. As shown in Algorithm 1, in each iteration i, the ith MST of the graph, $MST_i(V_i, E_i)$ is found. After that, the links in MST_i, E_i, are removed from the original graph and added to the topology. By doing this process, the MSTs are guaranteed to be non-overlapped. MSTs are commonly found by using Prim's algorithm with the time complexity of $O(|E|\log|V|)$ [11]. Therefore, the complexity of the centralized phase, which is carried out only one time, is $O(k|E|\log|V|)$.

B. Distributed Phase: Adaptive Routing

After the topology formation phase, the resulted topology is used for routing the traffic in the DRN. In our proposed scheme, the topology formation phase is modularized and does not depend on the routing method that will be used in the next phase. Therefore, in the distributed phase of our proposal, any adaptive routing algorithm can be applied. Note that our main contributions are the hybrid approach and the highly modularized topology formation method, not the specific adaptive routing algorithm.

V. Optimality of k

In this section, we analyze the relationship between k and the metrics introduced in Section III-C. Base on the analysis, we discuss the existence of the optimal value of k that maximizes the performance of the proposal.

Algorithm 1 Topology Formation

Input: $G(V, E)$, k.
Output: Topology for the routing phase, $G^*(V^*, E^*)$.

```
Calculate the cost of each link by using (1).
G'(V', E') ← G(V, E)
V* ← V'
E* ← ∅
for i ← 1 to k do
    Find the ith MST of G'(V', E'), MST_i(V_i, E_i)
    E' ← E' \ E_i
    E* ← E* ∪ E_i
end for
return G*(V*, E*)
```

A. Cognitive Radio Adaptability Index versus k

Lemma 1: Given a network $G(V, E)$ and the value of k. $G^*(V^*, E^*)$ is the topology resulted by applying Algorithm 1 on $G(V, E)$. The average CRAI of the nodes in the topology $G^*(V^*, E^*)$ monotonically increases with the increase of k.

Proof: Based on (3), the average CRAI, $\mathcal{A}_{ave}$, of the nodes in the topology $G^*(V^*, E^*)$ is calculated as follows:

$$\mathcal{A}_{ave} = \frac{1}{|V^*|}\sum_{i\in V^*}\sum_{j\in\mathcal{N}_i}\rho_j. \quad (7)$$

As shown in Algorithm 1, when k increases, $|V^*|$ does not change and always equals to $|V|$. The change in the constructed topology is only in E^*. The increase of k leads to the increase in the neighbors of each node i, $\mathcal{N}_i$. Thus, $\sum_{j\in\mathcal{N}_i}\rho_j$ increases, and accordingly, $\mathcal{A}_{ave}$ increases. ■

B. Network Complexity versus k

Lemma 2: Given a network $G(V, E)$ and the value of k. $G^*(V^*, E^*)$ is the topology resulted by applying Algorithm 1 on $G(V, E)$. The complexity of routing phase using G^* monotonically increases with the increase of k.

Proof: In Algorithm 1, when k is increased by 1, the number of adjacent nodes for each node in the topology will be increased at least by 1. For routing based on the topology, each node needs to try with at least one more neighbor as the next hop. Hence, the complexity of routing phase will qualitatively increase with the increase of k. The increase in complexity depends on the routing algorithm used in the routing phase. For example, Dijkstra algorithm [12], the most well-known algorithm for finding shortest paths in graphs, has the complexity of $O(|E^*| + |V^*|\log|V^*|)$. In Algorithm 1, when k increases, more links are added to E^* while V^* is kept the same. Therefore, the complexity of $O(|E^*|+|V^*|\log|V^*|)$ will increases with the increase of k. ■

C. Average Number of Hops to Gateway versus k

Lemma 3: Given a network $G(V, E)$ and the value of k. $G^*(V^*, E^*)$ is the topology resulted by applying Algorithm 1 on $G(V, E)$. When the shortest paths in terms of hop count are considered, the average number of hops from nodes on the

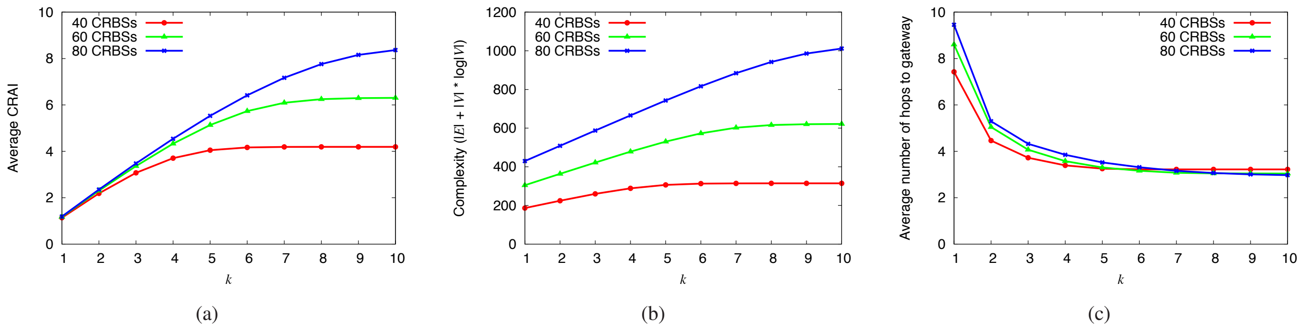


Fig. 2. k versus the average CRAI (a), the complexity (b), and the average number of hops to gateway (c).

TABLE I
SIMULATION SETTINGS

Parameter	Value
Simulation area	10 km × 10 km
Number of CRBSs	40, 60, 80
ρ_i of CRBS i	0.0 - 1.0
Transmission range of CRBSs	3 km
Number of different scenarios	300

topology $G^*(V^*, E^*)$ to the gateway monotonically decreases with the increase of k.

Proof: In Algorithm 1, when k increases, more links are added to E^* while V^* is kept the same. Therefore, there will be more possible paths from any node on the topology to the gateway. When we consider shortest paths in terms of hop count, with the increase of k, the new shortest paths will have less hop count than before, or at least keep the same number. Thus, the average number of hops from CRBSs to the gateway CRBS, monotonically decreases when k increases. ■

D. Optimality of k

As proven above, when k increases, the average CRAI increases, and thus, the total CRAI of the network, $\sum_{i \in V} \mathcal{A}_i$, also increases. Furthermore, the increase of k leads to the increase of the average node degree, D, and the decrease of the average number of hops to gateway, H. Therefore, according to (6), there will be a value of k that maximizes the utility, $\mathcal{U}$, of this proposal. Note that in every specific network scenario, the value of k has an upper bound, which is the largest node degree in the modeled graph. The optimal value of k can be any value between 1 and the upper bound, depending on the network scenario.

VI. Performance Evaluation

In order to validate the analytical findings and evaluate the performance of the proposed scheme, extensive simulations are conducted. In this section, the simulation setup and the evaluation results are presented.

A. Simulation Setup

Table I presents the details in settings of our simulations. In the area of 10 km × 10 km, the CRBSs are randomly deployed. The number of CRBSs is set to three different values, 40, 60, and 80, in order to evaluate the effect of CRBS density on the performance of the proposal. The probability that a CRBS i can cognitively use the spectrum in its local area, ρ_i, is randomly assigned from 0.0 to 1.0. The transmission range of CRBSs is set to 3 km. 300 different network scenarios are generated to find average results.

B. The Relationship between CRAI and k

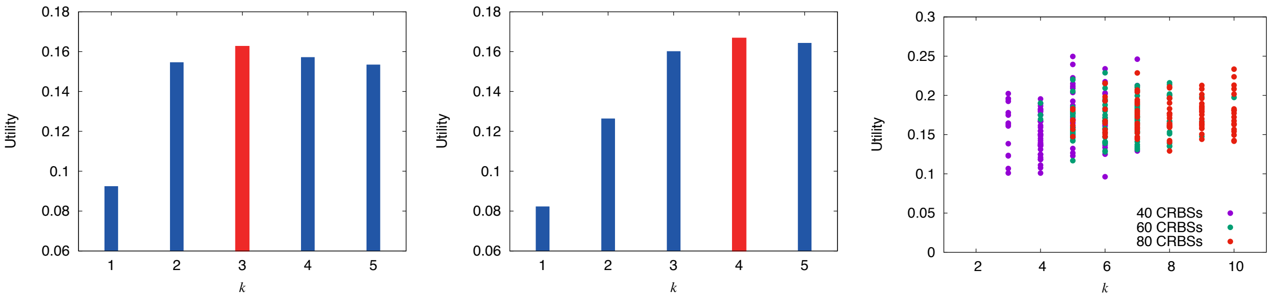
Fig. 2(a) demonstrates the relationship between the average CRAI and the value of k. The results show that when k increases, the average CRAI of the network also increases, which validates the conclusion of Lemma 1. The figure also shows the behavior of CRAI when the number of CRBSs changes. When k is small, e.g., k equals to 1 or 2, the change of the number of CRBSs does not make any significant change in the average CRAI. However, when k becomes larger, i.e., more than 3, the effect of the number of CRBSs on the value of CRAI becomes more noticeable. The larger number of CRBSs, the higher value of CRAI.

C. The Relationship between Complexity and k

In order to estimate the routing complexity with the resulted topology, we evaluate the complexity of finding shortest paths on the topology by using Dijkstra algorithm. Dijkstra algorithm on a graph $G(V, E)$ can be implemented with the computation time of $O(|E| + |V| \log |V|)$. Fig. 2(b) demonstrates the value of $|E| + |V| \log |V|$ with the topology resulted by using our simulations. The results show that when k increases, the complexity also increases. This proves the conclusion in Lemma 2. The figure also shows that the larger the number of CRBSs, the larger the complexity. It is reasonable because an increase in the density of network nodes will make the number of each node's neighbors increases.

D. The Relationship between the Average Number of Hops to Gateway and k

Fig. 2(c) validates the conclusion of Lemma 3 by showing that when k increases, the average number of hops to gateway, H, decreases. Furthermore, different numbers of CRBSs make different curves. A high density of CRBSs makes H decrease faster than a small density. In this figure, the lines intersect



(a) (b) (c)

Fig. 3. Different network scenarios lead to different optimal values of k, for example, optimal k equals to 3 in (a) and 4 in (b). (c) The distribution of optimal values of k with different network scenarios and different numbers of CRBSs.

when k equals to 7. When k is greater than 7, the increase in CRBSs' density even makes H decrease, which is contrary to the trend when k is less than 7. This is because if the density of CRBSs is small, a large value of k can not make more change in the topology. In contrast, if the density of CRBSs is large enough, more paths with less hop count will still be added to the topology. The paths with less hop count will make the average number of hops to the gateway, H, decrease.

E. The Existence of the Optimal k

The relationship between k and the utility, $\mathcal{U}$, is presented in Fig. 3, with different network scenarios. Figs. 3(a) and 3(b) demonstrate an example of having different optimal values of k for maximizing the utility when the network scenario is generated randomly with different seeds. It shows that the optimal value of k does exist but might be different depending on network scenarios. Fig. 3(c) illustrates the distribution of the optimal values of k and the optimal points when 300 different scenarios are simulated with different numbers of CRBSs. The figure shows that even with the same number of CRBSs, the optimal values of k can be also different with different generated scenarios. However, when the number of CRBSs becomes higher, the optimal values of k also tends to become larger.

VII. Conclusion

In this paper, we focused on all-spectrum cognitive radio based DRNs to fulfill the spectrum agility requirement of DRNs. The considered DRN is constructed by CRBSs, deployed in the disaster affected area. Each CRBS is equipped with multiple antennas to support different frequency bands available in the area. All CRBSs in the network route their traffic to the CRBS having connectivity to the outside area. On the considered DRN, we proposed a Graph-based Hybrid Adaptive Routing scheme, which we referred to as GHAR. The proposed scheme includes two main phases, centralized phase for topology formation and distributed phase for adaptive routing. We proposed an algorithm that unites k non-overlapping MSTs on the original network to construct the topology in the centralized phase. An analysis on the relationship between k and the cognitive radio adaptability as well as the complexity of routing process was provided. Also, we proved that there is a value of k for a given network that optimally solves the trade-off relationship between cognitive radio adaptability and the network complexity. Additionally, extensive simulations were conducted to verify our analysis. The simulation results demonstrated the effectiveness of our proposal and confirmed the existence of the optimal value of k.

Acknowledgement

Part of this work was conducted under the national program, Cross-ministerial Strategic Innovation Promotion Program (SIP), supported by the Cabinet Office, Government of Japan.

References

[1] L. Song, D. Niyato, Z. Han, and E. Hossain, "Game-theoretic resource allocation methods for device-to-device communication," *Wireless Communications, IEEE*, vol. 21, pp. 136–144, Jun. 2014.

[2] S. Ghafoor, P. Sutton, C. Sreenan, and K. Brown, "Cognitive radio for disaster response networks: survey, potential, and challenges," *Wireless Communications, IEEE*, vol. 21, pp. 70–80, Oct. 2014.

[3] T. Sakano, Z. Fadlullah, T. Ngo, H. Nishiyama, M. Nakazawa, F. Adachi, N. Kato, A. Takahara, T. Kumagai, H. Kasahara, and S. Kurihara, "Disaster-resilient networking: a new vision based on movable and deployable resource units," *Network, IEEE*, vol. 27, pp. 40–46, Jul./Aug. 2013.

[4] L. Zhen, K. Wang, and H.-C. Liu, "Disaster relief facility network design in metropolises," *Systems, Man, and Cybernetics: Systems, IEEE Transactions on*, vol. 45, pp. 751–761, May 2015.

[5] T. Ngo, H. Nishiyama, N. Kato, T. Sakano, and A. Takahara, "A spectrum- and energy-efficient scheme for improving the utilization of mdru-based disaster resilient networks," *Vehicular Technology, IEEE Transactions on*, vol. 63, pp. 2027–2037, Jun. 2014.

[6] L. Ding, K. Gao, T. Melodia, S. N. Batalama, D. A. Pados, and J. D. Matyjas, "All-spectrum cognitive networking through joint distributed channelization and routing," *Wireless Communications, IEEE Transactions on*, vol. 12, pp. 5394–5405, Nov. 2013.

[7] T. Wang, L. Song, Z. Han, and W. Saad, "Distributed cooperative sensing in cognitive radio networks: An overlapping coalition formation approach," *Communications, IEEE Transactions on*, vol. 62, pp. 3144–3160, Sep. 2014.

[8] Z. Zhang, K. Long, and J. Wang, "Self-organization paradigms and optimization approaches for cognitive radio technologies: a survey," *Wireless Communications, IEEE*, vol. 20, pp. 36–42, Apr. 2013.

[9] I. Bisio and M. Marchese, "Performance evaluation of bandwidth allocation methods in a geostationary satellite channel in the presence of internet traffic," *Computer Networks*, vol. 52, pp. 275 – 291, Jan. 2008.

[10] I. Bisio and M. Marchese, "Satellite earth station (ses) selection method for satellite-based sensor networks," *Communications Letters, IEEE*, vol. 11, pp. 970–972, Dec. 2007.

[11] N. Li, J. Hou, and L. Sha, "Design and analysis of an mst-based topology control algorithm," *Wireless Communications, IEEE Transactions on*, vol. 4, pp. 1195–1206, May 2005.

[12] M. Barbehenn, "A note on the complexity of dijkstra's algorithm for graphs with weighted vertices," *Computers, IEEE Transactions on*, vol. 47, pp. 263–, Feb. 1998.