# Bayesian Contextual Opportunistic Channel Accessibility Modeling in Railway Cognitive Radio

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## Abstract

This paper aims at solving the optimization problem of global channels opportunistic accessibility in railway cognitive radio environment. Especially, we propose an efficient cooperative model for multiple wayside base stations, which consists of *bayesian inference* to calculate the probability of success transmission on single station and team collaboration to maximize network performance within a group of base stations. Instead of only performing the traditional sensing and assigning, the base stations have an ability to learn from the interactions with the others and environment to get prior knowledge. The base station agents further analyze prior knowledge and perform optimal channel assignment for global network performance. Our cooperative model of channels opportunistic accessibility is then formulated, and an example in railway communication revealed that the model can also reduce the computational complexity in the high-mobility communication environment.

## 1 Introduction

With the rapid growth of wireless network users, spectrum bands nowadays have become a costly resources ["Wang *et al.*, 2015; Akyildiz *et al.*, 2006]. However, some of the spectrum, which is licensed by the government several decades ago, is sporadically used because of the development of the science and technology. The current fixed spectrum allocation policy adopted by the government agencies becomes unable to handle the spectrum scarcity problem due to the growing demand of the spectrum resources [Ma *et al.*, 2015]. To address this critical issue, Federal Communication Commission already gave the permission to unlicensed users(a.k.a. secondary users) to utilize the licensed spectrum when the licensed users(a.k.a. Primary users) are not in use, known as dynamic spectrum access [fcc, 2002]. This concept is not only proposed to solve the spectrum inefficiency problem, but also driving a new research area: *cognitive radio*.

Cognitive Radio was first proposed by Joseph Mitola in 1999 [Mitola and Maguire, 1999]. Its basic idea is that unlicensed users can use a software-defined radio, in which they learn from the environment and apply its reconfigurability to adaptively adjust its parameters to achieve a high efficiency and robust network [Haykin, 2006]. However, considering the factors of the environment, serious unpredictability of the system is one of the critical issue of cognitive radio [Zeng *et al.*, 2010; Akyildiz *et al.*, 2008; Wang *et al.*, 2011]. When performing spectrum management, base stations in the cognitive radio environment have to face a spectrum decision problem as the behavior of choosing a busy licensed spectrum for the unlicensed users to communicate will seriously affect the performance of unlicensed users.

Applying cognitive radio technique in railway has attracted much interest in the research community and governmental agencies. Federal Railroad Adminstration proposed a cognitive radio method to improve the performance of positive train control systems in order to gain train safety and efficiency [Amanna *et al.*, 2010]. The French Urbanisme des Radio Communications project was one of the first projects in France and in Europe to raise the problem of the optimization of spectral resources in the Paris region, taking into account the transport field and particularly the urban guided systems [Berbineau *et al.*, 2014]. Specifically, we focus on the high-speed railway environment in this paper to solve the train communication problem. When the train rides at a very high speed, such the problems as Doppler shifts, fast cell switching and the penetration loss are difficult to avoid, consequently causing the frequent spectrum handoff and further lowering global performance of network communication [Kalil *et al.*, 2010; Kumar *et al.*, 2015; Ai *et al.*, 2014]. Under this circumstance, the base stations in the network need an ability to act individually, typically “assign and handoff”, and work together for global optimization, which possesses huge computational complexity.

The decentralized nature of multi-agent system allows us to model a complex railway communication system, in which each base station is considered as an interacting intelligent agent. Each agent can coordinate with the adjacent agents by exchanging information to achieve global performance of the system. But the decision process of each agent has to be performed independent of the system due to the inherent characteristics of base station.

Actually, modeling channel accessibility in railway for quantitative analysis is still a challenge. There are four explanations:

(1) As we all known, the licensed spectrum has been assigned to the Primary users(PUs) already. Although we intend to share the licensed spectrum with the secondary users(SUs), it is difficult to forecast the spectrum holes, as the PU activity is intangible and has certain randomness. But through long-term observation, the recorded history may show the statistical information of PU occurrence, and the corresponding distribution of occupancy duration [Saleem and Rehmani, 2014; Sung *et al.*, 2010];

(2) When the train is communicating using a licensed channel, it may suffer a collision with another concurrent SU such as wayside devices. Collisions among the concurrent SUs would lower the quality of service [Wu *et al.*, 2010; Hong-Jiang and Qi, 2009];

(3) The channel quality may induce error during the train transmission due to the inherent unreliability of the wireless channel. A receiver on the train may receive unnecessary duplicate copies of the same signal in a short period because of multi-path reflections. Instead, the background noise needs higher reception gain to avoid errors [Xing *et al.*, 2013];

(4) Frequent spectrum handoffs have a negative impact on link delay and link maintenance. Adjacent agents would coordinate to reduce the unnecessary spectrum handoffs [Kumar *et al.*, 2015].

Based on the above facts, it is necessary to provide an optimized inference model for improving the efficiency of opportunistic channel accessibility within entire railway radio network with multiple base stations. Many researchers have done great contributions to address this issue, such as spectrum sensing and management technique, PU activity prediction and so on[Kim and Kim, 2010; Niyato *et al.*, 2008; Canberk *et al.*, 2011]. However, many methods about modeling channel accessibility or radio resource allocation consider only the performance of single base station such as [Xie *et al.*, 2012; Liu *et al.*, 2001]. And see [Liu *et al.*, 2001], multi-user opportunistic transmission scheduling is modeled, at each time slot, the user chooses the best weighted channel. The weight of the channel reflects the long term system fairness. By only considering the time varying property of the channel, the investigation seems not comprehensive. And location information is considered in [Choi *et al.*, 2014] to perform optimal sensing and power allocation. There is a lack of comprehensive research about multiple base stations collaboration for global network performance. Also, Bayesian Nash equilibrium model is given in [Krishnamurthy, 2009], to provide the competitively optimal behavior for cognitive radio. And [Başaran *et al.*, 2016] provides the bayesian method in spectrum sensing. [Xing *et al.*, 2013] shows the bayesian way in PU prediction. Based on these investigations, this paper aims at providing a better communication network for the locomotive and the access points for urban scenarios in a railway cognitive radio environment by establishing a comprehensive multi-agent collaboration model for bayesian opportunistic channel accessibility using priori context features.

The decision about channel access of a base station agent must change the performance of railway radio communication. Through measuring the quality of service of the SUs within entire network, the base station agent can easily evaluate the effect of its previous decisions. By recording these bypass feedbacks about decisions and performances, the agent can learn from past experience and promote further actions so as to achieve the optimal selection.

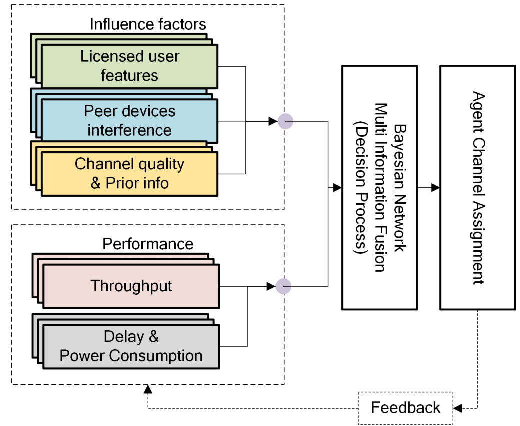


Figure 1: Proposed bayesian network model using causes and effects.

The rest of the paper is organized as follows. Section 2 presents a formulation of our problem in details, in which a mathematic model for the channel opportunistic access is given. In section 3, the basic principle of bayesian network is summarized, with the bayesian network based channel accessibility model using multiple cues and quality of service subsequently, in addition the leverage of the inference in agent making decision under uncertainty. In section 4, an example of the railway cognitive radio is given to illustrate the inference of the proposed model. Section 5 concludes the paper.

## 2 Problem Formulation

As we discussed above, channel accessibility should be inferred from available context cues. Just lacking of sufficient clues would cause highly uncertainty in such an inferring process. To address this issue, as more clues as possible should be introduced in this inferring process to avoid uncertainty. We pay our attention to the causes of the channel accessibility, and the effects that channel accessibility brings to the communication performance between the trains and base station agents. Standing on the impacts on channel accessibility, we divide these causes into four categories: PU activity types, peer devices interference, physical factors, priori information from neighboring agents.

(1) *PU activity:* When a SU and a PU have a collision on using a same channel in a CR network, the spectrum shared by the SU would seriously affect date transmission of the PU. The kind of concurrent spectrum occurrence with the PU goes against the principle of the protection of licensed devices[Haykin, 2006]. Hence, for channel accessibility of SUs, the activities of PUs must be considered, which can be seen as the primary cause of the fluctuation of the railway cognitive radio network.

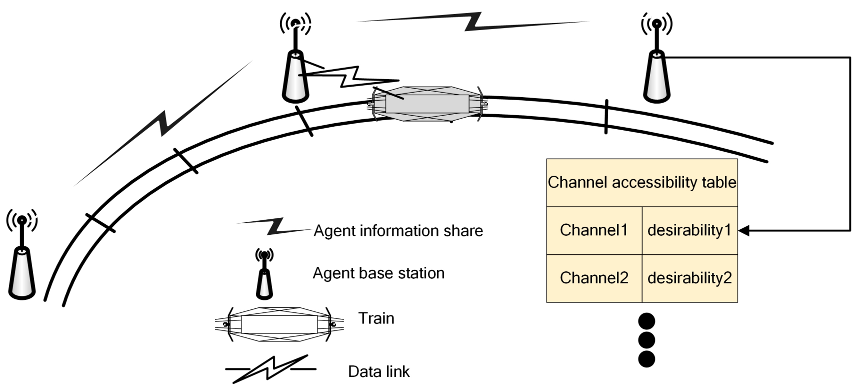


Figure 2: The overall structure of multi-agent collaborative railway cognitive radio channel accessibility framework.

(2) *Peer devices interference:* Some wayside equipment such as bluetooth devices, wireless sensor networks, and Ad-Hoc networks along the railway are another interference to the network. We permit the collision between these peer devices by considering the cooperation and competition in cognitive radio network, which is also a research area to which a lot of attention has been paid[Tragos *et al.*, 2013].

(3) *Physical factor:* Some physical factors, such as multipath reflections, channel gain, thermal noise, propagation loss, transmission power and reception gain, often cause a unpredictable transmission failure. We can not ignore these physical factors.

(4) *Neighbors information:* Through interaction with neighboring base stations, a base station can get its neighboring channel-related information and know the working channel of the train. Once taking it into consideration, the base station would obviously reduce the negative spectrum handoffs.

A large amount of prior knowledge constitute the causes of spectrum decision for a base station. A value function is used to distinguish the accessibility of each channel. Correspondingly, the effects after choosing a channel can be also used to validate the choice whether to be optimal or not. We often employ the metric about quality of service as the indicators.

(1) *Throughput:* After assigning the channel, either locomotive or the access point for urban scenarios will start to transmit data over the channel. By calculating the throughput of the SUs, we can easily judge whether this assignment is good or bad.

(2) *Power consumption:* The transmitter and receiver of the train or the base station will consume more power if the assignment is not good enough [He *et al.*, 2008; 2009]. For example, if some of the packets are dropped during receiving or the receiver find out that there are occasional bit flips in the data stream, transmitter and receiver may consume unnecessary power to retransmit.

(3) *Pocket Delay:* End-to-end delay or one-way delay refers to the time taken for a packet to be transmitted across a network from source to destination. Such as waiting for the PU to leave, or in a peer devices transmission queue would cause packet delay. It is also another significant indicator to measure network performance [Lin, 2013].

With the definition about the causes and effects of channel accessibility, we can explicitly infer the channel accessibility. Bayesian network is an effective approach to deal with such the uncertainty. It offers reasoning semantics for representing the relation of “cause and effect” via an intuitive graphical representation. The proposed model is shown in Figure 1. We can see from the figure that, the agents can get information from the environment, through analyzing and reasoning these information, the agent can assign channel to the train.

## 3 Bayesian Opportunistic Channel Accessibility

The Bayesian Network is a probabilistic graphical model that represents a set of random valuables and their conditional dependencies via a directed acyclic graph. By leveraging the bayesian network we can inferring high-level hypothesis from some observable quantities, latent variables or unknown parameters [Friedman *et al.*, 1997; Heckerman, 1999]. The overall structure of our proposed model along a railway can be see in Figure 2.

### 3.1 Bayesian Inference of Channel Opportunistic Accessibility

Our main purpose of modeling the channel accessibility is to infer the unobservable hypothesis from available context cues. Our modeling for channel accessibility takes 3 steps.

(1) We first need to identify the target hypothesis variable and the corresponding information variable which have a robust random relation with the target variables.

(2) By building the topology of the directed acyclic graph, we need to divide the information variables node into two categories: “cause” nodes and “effect” nodes according to their casual hierarchical relations with the target node.

(3) Finally, we need to calculate conditional probabilities and infer the results that can help our base station agents make decision.

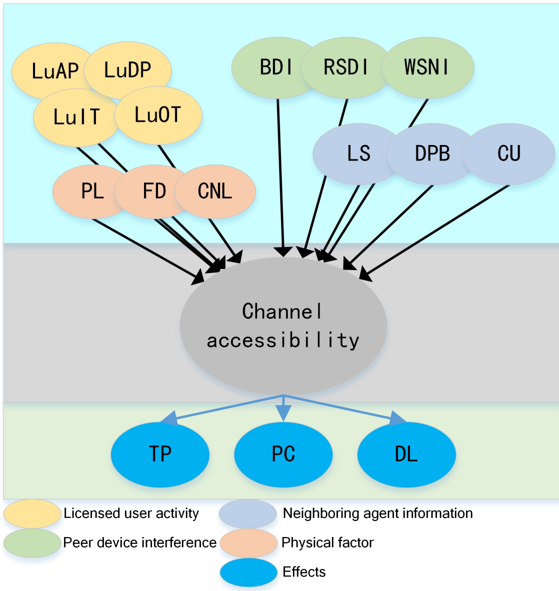


Figure 3: Bayesian Network Model for Channel Accessibility.

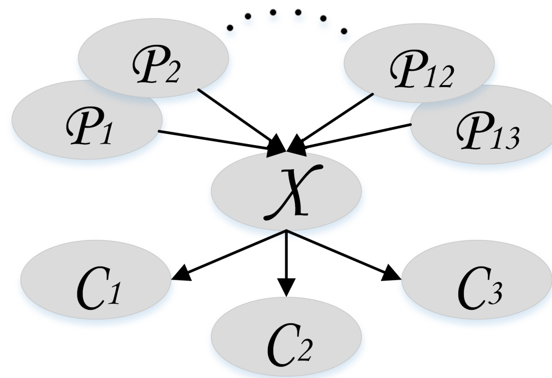


Figure 4: Mathematical Model of the Channel Accessibility.

We evaluate channel accessibility using the probability values over available channels. Now our target is to infer these probabilities. The influencing factors of channel accessibility and the effects that caused by the decision made by the base station agent are the information variables. As discussed in Section 2, the influencing factors include

(1) PU activity, that is, PU arrival probability (LuAP), PU departure probability (LuDP), PU occupancy time (LuOT), PU idle time (LuIT) [Saleem and Rehmani, 2014];

(2) Peer devices interference, that is, bluetooth devices interference (BDI), wireless sensor network interference (WSNI), railway side devices interference (RSDI);

(3) Physical factor, that is, channel noise level (CNL), propagation loss (PL), all kinds of fading (FD);

(4) Neighboring agent information, that is, the channel that the incoming train was using (CU), locomotive speed (LS), data packet remain in the buffer (DPB).

The effects include throughput (TP), power consumption (PC) and delay (DL)[Wu *et al.*, 2010]. Combining all the features, the bayesian network model is constructed as shown in Figure 3. Note that the abbreviations are created just to make the directed acyclic graph and the consequent tables clear and organized.

Next step is to define the states for each node in the direct acyclic graph. For simplicity but generality, in this paper we distinguish the channel accessibility into two different states, that is, *successful transmit* and *failed transmit* [Friedman *et al.*, 1997]. We denote $a$ as the positive state that the SU is highly possible to successfully transmit on the current channel, and $\overline{a}$ as the opposite side of $a$ as the channel status is not qualified for transmission. Once the intermediate node is set, the states of parent nodes and the child nodes can be determined, shown in Table 1 and Table 2 respectively.

In real railway environment, the probabilities of the parent nodes and child nodes can be easily recorded and adjusted by the agents in the long run. Consider that our main purpose is to propose the model in the paper, we here conduct these probabilities of all nodes by subjective estimation.

Now we can specify the probabilities of each node's states. Let $P = \{P_i | i = 1, 2, .., 13\}$ represents 13 parent nodes of the intermediate node. And let $C = \{C_j | j = 1, 2, 3\}$ represents the children nodes. Denote $x$ as the state variable of the intermediate node X. $p_i$ and $c_j$ are the state variable of the parent nodes $P_i$ and child nodes $C_j$ respectively. $P\{x|p_i\}$ and $P\{c_j|x\}$ represents the conditional probabilities. And the mathematical representation of our proposed model discussed above is shown in Figure 4.

When agent get the prior knowledge from the parent nodes and child nodes, denote $e_{pi}$ as the evidence provided by $P_i$, and $e_{cj}$ as the evidence provided by $C_j$. Then define the evidence set $e = (e_{pi}, e_{cj})$. The hypothesis of the channel accessibility belief is described by the conditional probabilities that $X$ will be in a certain stat after considering the evidence, denoted as $P(x|e)$. Considering only the parent nodes evidence, we can obtain:

$$P(x|e) \propto P(x|e_p) \cdot P(e_c|x) \tag{1}$$

According to bayesian formula:

$$\begin{aligned} P(x|e_p) &= P(x|e_{p_1}, e_{p_2}, .., e_{p_{13}}) \\ &= \sum_{all i,j,k} P(x|p_{1,i}, p_{2,j}, .., p_{13,k}) \cdot \\ &\quad P(p_{1,i}, p_{2,j}, .., p_{13,k}|e_{p_1}, e_{p_2}, .., e_{p_{13}}) \\ &= \sum_{all i,j,k} P(x|p_{1,i}, p_{2,j}, .., p_{13,k}) \cdot \\ &\quad P(p_{1,i}|e_{p_1}) \cdots P(p_{13,k}|e_{p_{13}}) \\ &= \sum_{all p_{m,n}} P(x|p_{m,n}) \prod_{M=1}^{13} P(p_M|e_{p_M}) \end{aligned} \tag{2}$$

Table 1: States of Parent Nodes

| Node property | Node | | | | |
|---|---|---|---|---|---|
| PU activity | Name | LuAP | LuDP | LuIT | LuOT |
| | State | High | High | Long | Long |
| | | Low | Low | Short | Short |
| Peer device interference | Name | BDI | RSDI | WSNI | |
| | State | Exist | Exist | Exist | |
| | | Inexist | Inexist | Inexist | |
| Physical factors | Name | PL | FD | CNL | |
| | State | High | High | High | |
| | | Low | Low | Low | |
| Neighboring agent information | Name | LS | DPB | CU | |
| | State | Fast | Many | Current channel | |
| | | Slow | Less | Not current channel | |

Table 2: States of Child Nodes

| **Node** | | **TP** | **PC** | **DL** |
|---|---|---|---|---|
| **State** | 1 | High | High | High |
| | 2 | Normal | Normal | Normal |
| | 3 | Low | Low | Low |

$$
\begin{aligned}
P(e_c|x) &= P(e_{c_1}, e_{c_2}, e_{c_3}|x) \\
&= P(e_{c_1}|x)P(e_{c_2}|x)P(e_{c_3}|x) \\
&= \prod_{N=1}^{3} P(e_{c_N}|x)
\end{aligned} \tag{3}
$$

where $i, j, k$ represent the index of the states of parent nodes, $M$ represents the index of parent nodes, $N$ represents the index of the child nodes, $p_{m,n}$ is the value of the $mth$ parent node in the $nth$ state.

By substituting equation (2) and (3) into (1):

$$
\begin{aligned}
P(x|e) \propto & \prod_{N=1}^{3} P(e_{c_N}|x) \cdot \\
& \left[ \sum_{all p_{m,n}} P(x|p_{m,n}) \prod_{M=1}^{13} P(p_M|e_{p_m}) \right]
\end{aligned} \tag{4}
$$

Using equation (4), we can calculate $P(\{x = a\}|e)$ and $P(\{x = \overline{a}\}|e)$ of the intermediate node state which we denoted above as $\{x = a\}$ and $\{x = \overline{a}\}$. With these inferring results, the agent can easily deduce the state of the current inferring channel by normalization $P(\{x = a\}|e)$ and $P(\{x = \overline{a}\}|e)$.

## 4 Example of Railway Cognitive Radio Communication

In this section, we extract a simplified single agent single channel bayesian network model for railway channel accessibility. The simplified channel accessibility model and its mathematical model consists of 13 parent nodes and 3 child nodes, as shown in Figure 4.

As discussed above, the paper aims to propose the model, so we assume the conditional probability for each parent and child node as shown in Table 3 and Table 4.

We first consider the case without any evidence, we can calculate the probability of the state $P(\{x = a\})$ using the data shown in Table 3 as follows:

$$
\begin{aligned}
P(\{x = a\}) &= \sum_{all p_{m,n}} P(x|p_{m,n}) \prod_{M=1}^{13} P(p_M|e_{p_M}) \\
&= 0.5090
\end{aligned} \tag{5}
$$

and we have:

$$
P(\{x = \overline{a}\}) = 0.4910 \tag{6}
$$

We can see that the result of the good channel accessibility and bad channel accessibility is approximately equal. Without the evidence, the agent cannot determine whether the channel should be assigned to the train.

Assuming that the agent starts to record the railway communication information. After sensing every channel and invoking the history, the agent gathers all kinds of information from the environment. See the evidence information from the Table 3 in the probability format. After the train passed, we observe the train gained a fair throughput, cost low power consumption, and the delay of transmission is low. So we set the child nodes $C_1, C_2, C_3$ as $P(e_{c_1}|c_{1,1}) = 0.5, P(e_{c_1}|c_{1,2}) = 1.0, P(e_{c_1}|c_{1,3}) = 0$, and $P(e_{c_2}|c_{2,1}) = 0, P(e_{c_2}|c_{2,2}) = 0.5$ and $P(e_{c_2}|c_{2,3}) = 1$, and $P(e_{c_3}|c_{3,1}) = 0, P(e_{c_3}|c_{3,2}) = 0.5, P(e_{c_3}|c_{3,3}) = 1$, as shown in Table 4.

With the prior probability we can get from the parent nodes, the conditional probability of the $x = a$ and $x = \overline{a}$ can be calculated using equation (2). Using the data conducted

Table 3: Conditional [probabilities for parent nodes

| $P(x\|e_p)$ | $p_{1,1}$ | $p_{2,1}$ | $p_{3,1}$ | $p_{4,1}$ | $p_{5,1}$ | $p_{6,1}$ | $p_{7,1}$ | $p_{8,1}$ | $p_{9,1}$ | $p_{10,1}$ | $p_{11,1}$ | $p_{12,1}$ | $p_{13,1}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $a$ | 0.2 | 0.75 | 0.4 | 0.6 | 0.3 | 0.1 | 0.4 | 0.3 | 0.2 | 0.2 | 0.3 | 0.4 | 0.7 |
| $\overline{a}$ | 0.8 | 0.25 | 0.6 | 0.4 | 0.7 | 0.9 | 0.6 | 0.7 | 0.8 | 0.8 | 0.7 | 0.6 | 0.3 |
| $P(x\|e_p)$ | $p_{1,2}$ | $p_{2,2}$ | $p_{3,2}$ | $p_{4,2}$ | $p_{5,2}$ | $p_{6,2}$ | $p_{7,2}$ | $p_{8,2}$ | $p_{9,2}$ | $p_{10,2}$ | $p_{11,2}$ | $p_{12,2}$ | $p_{13,2}$ |
| $a$ | 0.7 | 0.65 | 0.6 | 0.4 | 0.7 | 0.9 | 0.6 | 0.7 | 0.8 | 0.8 | 0.7 | 0.6 | 0.3 |
| $\overline{a}$ | 0.3 | 0.35 | 0.4 | 0.6 | 0.3 | 0.1 | 0.4 | 0.3 | 0.2 | 0.2 | 0.3 | 0.4 | 0.7 |

Table 4: Conditional probabilities of child nodes

| $P(e_c\|x)$ | | $a$ | $\overline{a}$ | $P(e_c\|x)$ | | $a$ | $\overline{a}$ | $P(e_c\|x)$ | | $a$ | $\overline{a}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $C_1$ | $c_{1,1}$ | 0.7 | 0.2 | $C_2$ | $c_{2,1}$ | 0.3 | 0.4 | $C_3$ | $c_{3,1}$ | 0.2 | 0.1 |
| | $c_{1,2}$ | 0.2 | 0.2 | | $c_{2,2}$ | 0.4 | 0.4 | | $c_{3,2}$ | 0.6 | 0.3 |
| | $c_{1,3}$ | 0.1 | 0.6 | | $c_{2,3}$ | 0.3 | 0.2 | | $c_{3,3}$ | 0.2 | 0.6 |

above, as:

$$\begin{aligned} P(\{x=a\}|e_p) &\propto \sum_{all p_{m,n}} P(x|p_{m,n}) \prod_{M=1}^{13} P(p_M|e_{p_M}) \\ &= 1.5353 \end{aligned} \tag{7}$$

$$P(\{x=\overline{a}\}|e_p) \propto 0.2713 \tag{8}$$

According to the equation (3), the conditional probability of $e_c$ can be calculated as:

$$\begin{aligned} P(e_c|\{x=a\}) &\propto P(e_{c_1}|x)P(e_{c_2}|x)P(e_{c_3}|x) \\ &= 1.85 \end{aligned} \tag{9}$$

$$P(e_c|\{x=\overline{a}\}) \propto 1.65 \tag{10}$$

Integrating equation (9), (10), (11), (12), the conditional probability $P(\{x=a\}|e)$ of node $X$ given all the occurrence of evidences can be calculated as:

$$\begin{aligned} &P(\{x=a\}|e) = \\ &\frac{P(\{x=a\}|e_p)P(e_c|\{x=a\})}{P(\{x=a\}|e_p)P(e_c|\{x=a\}) + P(\{x=\overline{a}\}|e_p)P(e_c|\{x=\overline{a}\})} \\ &= 0.8639 \end{aligned} \tag{11}$$

and the conditional probability of $P(\{x=\overline{a}\}|e)$ is :

$$\begin{aligned} &P(\{x=\overline{a}\}|e) = \\ &\frac{P(\{x=\overline{a}\}|e_p)P(e_c|\{x=\overline{a}\})}{P(\{x=a\}|e_p)P(e_c|\{x=a\}) + P(\{x=\overline{a}\}|e_p)P(e_c|\{x=\overline{a}\})} \\ &= 0.1361 \end{aligned} \tag{12}$$

Conducting the results of the equation (13) and (14), we can see that under the circumstance of the given information, agent can easily tell the channel accessibility. Although the given parts of evidences may be inaccurate, the status of channel accessibility can be clearly inferred in terms of likelihood probabilities. This proves that our proposed model can certainly give a precise inference when agent have comprehensive information. Note that if evidence is more precisely given, the more reliable our model will perform.

# 5 Simulation Results

In this section, we formulate some simulation in order to verify the effectiveness of our proposed BN scheme. Our overall aim is to best predict the channel accessibility for SU. The simulation is constructed as follows. For simplicity but generality, the CR network contains 1 agent base station and 1 SU. Within the cover range of the agent base station there are 10 channels which are allocated to 10 PUs respectively. All channels are assumed to have the same bandwidth. According to the assumption of the parent nodes above, we model 10 channels using different parameters in order to show the distinction between them. And the PU model is subject to continuous time markov process. Simulation lasts 2000 seconds. The spectrum sensing module of our proposed agent base station will notice the change of the environment and real-time update the channel accessibility, and use the QoS to adjust the channel accessibility. Through iteration, the agent base station will predict the channel accessibility more precisely. We separately simulate the BN network with and without the QoS of the cognitive to see if the prior knowledge works well. Also, we compare the result of our proposed scheme with the Reinforcement Learning method in [30] and opportunistic method. The probability of successful transmission plot is shown in figure 5. The performance curves are averages of over 500 Monte Carlo iterations. It is obvious that the RL method performs best which conducts its optimal policy during trial-and-error. This method works well but the learning process lasts long. And during the learning process, this method obtaine the optimal policy through an exhaustive search of all possible joint actions, which is not effective. As we can see from the BN2 curve, the curve depicts that our proposed BN network only with the prior knowledge learns faster than the RL method. However the eventual performance after the initial learning phase is worse than RL method. This gap shows the difference between prediction and the trial-and-error method. We sacrifice some QoS to greatly improve the effectiveness of our system. And at the end, the RL method reaches nearly 96%, the BN only with prior knowledge reaches 82%. When we add the QoS to help predict the channel accessibility, as shown by curve BN1, the performance of our proposed scheme rise to about 88%, which shows the necessity of the contextual

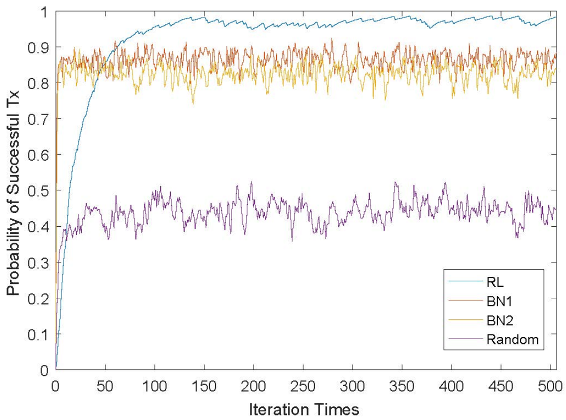


Figure 5: Probability of Successful Transmission of the 4 different methods in the cognitive network. The BN1 represents the proposed method. BN2 is the method without the QoS contextual inference. The RL represents the reinforcement learning proposed in [30]. The Random curve represents that the agent base station access the channel using opportunistic way.

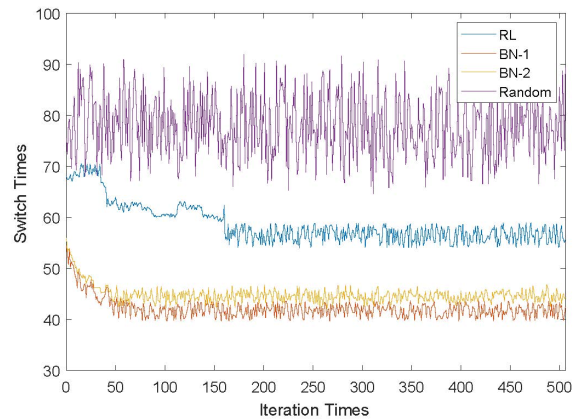


Figure 6: Channel Switch Times of the 4 different methods in the cognitive network. This QoS is different from the indicator in Figure 5. Channel switch will cause a lot harm to the communication quality, including switch delay, more power consuming during reconnection, even connection lost. Our proposed method can greatly reduce the channel switch times.

way of updating the channel accessibility. And the probability of successful transmission of opportunistic way of accessing the channel finds on average 46%. Figure 6 depicts the channel switch times of different methods. In figure 6, the proposed BN1 method shows the best performance amoung all the methods. We observe that the RL algorithm choose to trade off the channel switch times with the probability of successful transmission. The performance is roughly 55 times after the initial learning phase. Still the learning phase lasts more than 150 iterations, which shows that the RL method have a long learning phase to catch up with the BN method. And the BN2 method has slightly worse performance than the BN1 method. Moreover, the opportunistic method shows its unstablity, which shakes between 70 times to 90 times.

The simulation results shows that our proposed method has a short learning phase. BN method can fastly come into use with a good performance. The RL method shows the best probability of successful transmission, however performing a lot of channel switch which will cost the switch delay to affect the QoS of SU. And during the comparison between the BN1 and BN2, we can see that the QoS can help inference the channel accessibility. Hence, the BN channel accessibility inference method shows the effectiveness.

## 6 Conclusions

In this paper we propose a bayesian network based multi-agent railway communication modeling for channel accessibility, using a fusion of prior and validation information. The alternate approach for the agent base station can easily infer the channel accessibility for the train in railway cognitive radio environment. Due to its briefness, this approach can be easily deployed in the base station to ensure the communication quality for train control or for civil use. Future work can be directed to further investigation on machine learning paradigm in railway cognitive radio.

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