A Novel Prediction-based Spectrum Allocation Mechanism for Mobile Cognitive Radio Networks

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Abstract

The spectrum allocation is an attractive issue for mobile cognitive radio (CR) network. However, the time-varying characteristic of the spectrum allocation is not fully investigated. Thus, this paper originally deduces the probabilities of spectrum availability and interference constrain in theory under the mobile environment. Then, we propose a prediction mechanism of the time-varying available spectrum lists and the dynamic interference topologies. By considering the node mobility and primary users' (PUs') activity, the mechanism is capable of overcoming the static shortcomings of traditional model. Based on the mechanism, two prediction-based spectrum allocation algorithms, prediction greedy algorithm (PGA) and prediction fairness algorithm (PFA), are presented to enhance the spectrum utilization and improve the fairness. Moreover, new utility functions are redefined to measure the effectiveness of different schemes in the mobile CR network. Simulation results show that PGA gets more average effective spectrums than the traditional schemes, when the mean idle time of PUs is high. And PFA could achieve good system fairness performance, especially when the speeds of cognitive nodes are high.

Keywords: Cognitive radio, spectrum allocation, prediction, mobility, graph theory, PUs' activity

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1. Introduction

Cognitive radio (CR) is considered as a feasible intelligent technology for 4G wireless networks or self-organization networks [1][2]. Secondary users (SUs) can opportunistically access the licensed spectrum without causing interferences to the PUs [3]. Thus, it is necessary to have an optimal MAC layer schedule. Graph coloring model, as a tool for spectrum allocation, has been widely investigated these days [4][5]. The optimal coloring problem of a graph is known to be NP-hard. Thus, recent works focus on heuristic approaches to close to the optimal spectrum allocation solutions. Ref. [6] presented greedy algorithm (GA) achieving close to optimal spectrum utilization and fairness algorithm (FA) getting better allocation fairness. Peng and Zheng first considered color sensitive graph coloring (CSGC) algorithm for the heterogeneity in the spectrum rewards in Ref. [7], in which a graph-theoretical model was developed to characterize the spectrum access problem under a number of different functions of optimizing utilization and fairness. To reduce the allocation duration of CSGC, paper [8] presented a kind of parallel algorithm that divided bidirectional graph in CSGC into many simple subgraphs; however the parallel algorithm cannot work under constraint of fairness rules. While, a maximal independent set (MIS) spectrum allocation algorithm based on graph theory was presented with the goal of enhancing fairness [9].

However, most of the existing graph-based spectrum allocation schemes for the CR network are based on the network snapshot model, which means these schemes focus on a static spectrum environment. Actually, the static spectrum allocation is based on the assumptions that both the PUs and the SUs are fixed during simulations, however, this assumption is impractical for a mobile situation.

In practice, the spectrum availability is time-varying due to the random variations of the arrivals and departures of PUs. Therefore, some works have focused on the impact of PUs' on-off behaviors [10][11][12]. In [13], a continuous-time Markov chain model was proposed to model the interactions between PUs and SUs. Paper [14] presented a prediction approach for call arrival rate and call holding time of PUs. By the traffic pattern forecast of PUs, SUs can estimate the utilization of frequency bands, thus reduces the frequency hopping rate. The spectrum prediction is more effective for throughput optimization by a new definition of channel availability vector that characterized the licensed channels state information [15].

On the other hand, mobility is an important factor in mobile wireless communications [16]. However, the mobility of nodes is not fully investigated for spectrum allocation in CR network. In [17], a cluster-based spectrum and interference aware routing protocol is proposed to repair the route considering PUs' activity for mobile CR networks. Moreover, the routing protocol can increase throughput and reduce data delivery latency. The author proposed a topology control and routing scheme to improve end-to-end network performance, i.e., throughput and delay [18].

In fact, a reactive CR system without prediction will degrade system performance because spectrum sensing may be delayed or take a long time [19][20]. Thus, a CR network should be forward looking rather than reactive [21]. In this paper, we focus on prediction spectrum allocation mechanism in mobile cognitive radio networks. Our main contributions can be summarized as follows: 1) we extend the traditional static graph-based model [4][5][6][7][8][9] to dynamic mobile model. Based on deducing the probabilities of spectrum availability and interference constrain in theory under the mobile model, a prediction mechanism considering node mobility and PUs' states is presented. 2) Two novel prediction-based spectrum assignment algorithms (PGA and PFA) aiming at maximizing spectrum utilization and

fairness are respectively proposed on the basis of the predictions mechanism. 3) New utility functions which investigate spectrum utilization and fairness are redefined in order to evaluate the performance of different algorithms under the mobile CR environment. 4) Finally, we conduct some simulations to confirm the accuracy of the prediction mechanism and the utilities of the prediction-based spectrum allocation algorithms. Compared with the conventional GA an FA, the proposed schemes achieve high spectrum utilization and fairness utilities respectively when the prediction performance is accurate relatively.

The rest of the paper is organized as follows. The system model is described in Section 2, and the predictions of spectrum availability and interference constrains for cognitive nodes are discussed in Section 3. In Section 4, two novel prediction-based spectrum allocation algorithms are proposed. We will show the simulation results along with a discussion in Section 5. And Section 6 concludes the paper.

2. System Model and Utility Function

2.1 System Model

Consider a mobile CR network deployment scenario where N SUs coexist with M PUs depicted in **Fig. 1**. Each primary user (PU) is composed of a primary base station (PBS) and a group of primary receivers. Suppose each PU has a coverage area, and PBS determines the PU's coverage area. In the model, PU is allowed to use the associated licensed channel, while SUs can use the licensed channels opportunistically. In other words, SUs within the coverage area of one PU are not allowed to use the corresponding licensed channel when the PU is active. Additionally, we assume that CR network assigns spectrums periodically, and the spectrum allocation duration is very short which can be neglected. And set the spectrum allocation time interval is T_c. The activity of each PU is modeled as an active/inactive (on/off) scheme independently. The time intervals of the active and inactive states follow exponential distributions with means $1/\lambda_p$ and $1/\mu_p$, respectively [22][23][24]. So the active and inactive probability density function can be written respectively as

$$f_{\mathrm{ON}}(t)=\begin{cases}\lambda_p \mathrm{e}^{-\lambda_p t} & t\geq 0\\ 0 & t<0\end{cases}. \tag{1}$$

$$f_{\mathrm{OFF}}(t)=\begin{cases}\mu_p \mathrm{e}^{-\mu_p t} & t\geq 0\\ 0 & t<0\end{cases}. \tag{2}$$

A random walk-based mobility model is proposed in paper [25]. Suppose mobility of cognitive nodes is uncorrelated, and each node's movement consists of a sequence of random length intervals called mobility epochs, during which a node moves in a constant direction at a constant speed. Therefore, the mobility of a given node n is based on epoch lengths, speed, and direction. Epoch lengths are exponentially distributed with mean $1/\lambda$ [25][26], denoted as

$$B(x)=\mathrm{P}(T\leq x)=1-e^{-\lambda x}. \tag{3}$$

The speed of node n is a uniform distributed over $(0,v_{\max})$ and the direction is an IID uniformly distributed over $(0,2\pi)$. It is reasonable to assume the speed, direction and epoch lengths of node n are uncorrelated. **Fig. 1** is an instantaneous snapshot of a CR network, in which 20 mobile cognitive nodes are uniform distributed in the deployment area. The movement characteristics (speed, direction and epoch lengths) of any two different nodes are also uncorrelated. And the interference radius of each cognitive node is r. In the mobile CR

network deployment area, 2 PUs (PU1 and PU2) are located. The coverage radius of each PU is R.

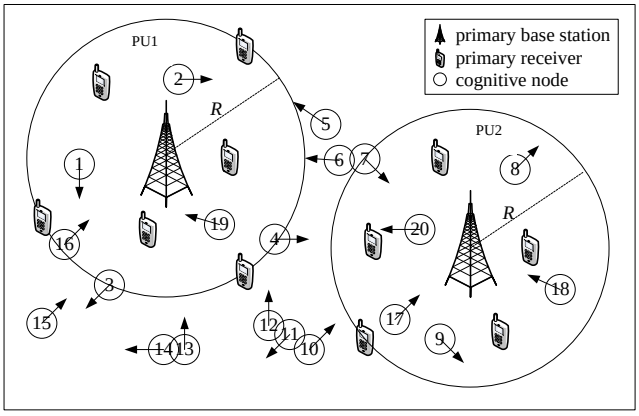

Fig. 1. System model of cognitive network

Based on the proposed mobile model, two kinds of issues need to be investigated. One is the available spectrum lists of the cognitive nodes. The other is the interference constrains of the cognitive nodes. First, each cognitive node has an available spectrum list, and it is obvious that the available spectrum list is time-varying due to the mobility of the cognitive nodes and the changing activities of PUs. So, one cognitive node n can use the licensed channel m at t only if $l_{m,n}(t)=1$ with $l_{m,n}(t)$ given as

$$l_{m,n}(t)=\begin{cases}1 & D_{\mathrm{PU}m,\mathrm{SU}n}(t)\geq R+r\\ 1 & D_{\mathrm{PU}m,\mathrm{SU}n}(t)<R+r\cap(\alpha_m(t)=1)\\ 0 & D_{\mathrm{PU}m,\mathrm{SU}n}(t)<R+r\cap(\alpha_m(t)=0)\end{cases}, \tag{4}$$

where $D_{\mathrm{PU}m,\mathrm{SU}n}(t)$ is the distance between PU_m and cognitive node n at t, and $\alpha_m(t)$ represents the activity state of PU_m, given as

$$\alpha_m(t)=\begin{cases}1 & \mathrm{PU}_m \text{ is idle at } t\\ 0 & \mathrm{PU}_m \text{ is busy at } t\end{cases}. \tag{5}$$

In practice, $l_{m,n}(t)$ is mainly depended on the position of node n and the state of PU_m. (4) reflects the instantaneous spectrum availability. $l_{m,n}(t)=1$ denotes licensed spectrum m is available to cognitive node n at t. $l_{m,n}(t)=0$ denotes licensed spectrum m is not available to cognitive node n at t. Next, we need to state interference constrain. Instantaneous interference constrain $e_{i,j}(t)$ for any two different cognitive nodes i and j at t can be expressed as

$$e_{i,j}(t)=\begin{cases}1 & D_{\mathrm{SU}i,\mathrm{SU}j}(t)<2r\cap(i\neq j)\\ 0 & D_{\mathrm{SU}i,\mathrm{SU}j}(t)\geq 2r\cap(i\neq j)\end{cases}. \tag{6}$$

$D_{\mathrm{SU}i,\mathrm{SU}j}(t)$ is the distance between node i and node j at t. $e_{i,j}(t)=1$ represents that node i and node j have interference constrain if they use the same licensed spectrum at t. $e_{i,j}(t)=0$ represents that node i and node j don't have interference constrain if they use the same licensed spectrum at t. Therefore, interference constrain reflects that any two different cognitive nodes will impact each other if they use the same licensed channel simultaneously. Note that both available spectrum lists and interference constrains mentioned above are instantaneous.

2.2 Utility Functions

In order to measure the accuracy of the proposed prediction mechanism, two evaluation parameters are given first. Available spectrum prediction error rate ρ_s is given as

$$\rho_s = \frac{\sum_{n=1}^{N}\left(M_n^{\text{alarm}} + M_n^{\text{dismissal}}\right)}{\sum_{n=1}^{N} M_n^{\text{total}}}, \tag{7}$$

where M_n^{total} is the total number of available spectrums for node n. $M_n^{\text{dismissal}}$ is the total number of spectrums for node n which are not counted by the prediction mechanism while these spectrums should be included in the real available spectrum set. M_n^{alarm} is the total number of spectrums for node n which are counted by the prediction mechanism while these spectrums should not be included in the real available spectrum set. Actually, $M_n^{\text{dismissal}}$ represents the number of available spectrums for false dismissal and M_n^{alarm} represents the number of available spectrums for false alarm. The bigger ρ_s is, the worse the accuracy of available spectrum prediction mechanism is. Similar to the definition of ρ_s, interference constrain prediction error rate ρ_I is given as

$$\rho_I = \frac{N_{\text{alarm}} + N_{\text{dismissal}}}{N_{\text{total}}}, \tag{8}$$

where N_{total} is the total number of interference constrains for the mobile CR network. N_{alarm} represents the number of interference constrains for false alarm. And $N_{\text{dismissal}}$ represents the number of interference constrains for false dismissal.

In addition, we need to redefine the utility functions of spectrum allocation owing to the mobile CR model. Traditionally, the objective of the spectrum allocation problem can be defined as utility functions [27]:

Max-Sum-Bandwidth (MSB): it aims to maximize the total spectrum utilization regardless of fairness for the CR network. The utility function is defined as

$$U_{\text{sum}} = \frac{1}{N}\sum_{n=1}^{N}\sum_{m=1}^{M} a_{n,m}\cdot b_{n,m}, \tag{9}$$

where $a_{n,m}=1$ represents that spectrum m is assigned to node n, and $b_{n,m}$ means the reward that node n can get if spectrum m is assigned to node n.

Max-Proportional-Fair (MPF): it focuses on the proportional fairness for the CR network. The utility function is expressed as

$$U_{\text{fair}} = \sum_{n=1}^{N}\lg\left(\sum_{m=1}^{M} a_{n,m}\cdot b_{n,m}\right). \tag{10}$$

MSB rule is relatively selfish and non-collaborative, while MPF rule characterizes fairness and collaboration. Owing to the mobile CR model, the utility function U_{sum} is redefined as

$$U_1 = \frac{1}{N}\sum_{n=1}^{N}\sum_{m=1}^{M} a_{n,m}\cdot b_{n,m} \qquad (n,m)\in S, \tag{11}$$

where $(n,m)\in S$ denotes the licensed spectrum m is available to cognitive node n from t_0 to t_0+T_c. It means that spectrum m is available to cognitive node n not only at t_0 but also at any time between t_0 and t_0+T_c.

$$S=\left\{(n,m)\,|\,l_{n,m}(t)=1 \text{ from } t_0 \text{ to } t_0+T_c\right\}. \tag{12}$$

In fact, U_1 reflects the 'effective' spectrums one cognitive node can get during T_c on average. Nevertheless, U_1 cannot measure the fairness among different nodes. U_{fair} is redefined as

$$U_2 = \frac{1}{N}\sum_{n=1}^{N}\lg\left(\sum_{m=1}^{M} a_{n,m}\cdot b_{n,m} + \Delta\right) \quad (n,m) \in S . \tag{13}$$

Δ ($0<\Delta<<1$)is very small positive number to prevent the antilogarithm from being equal to zero. U_2 reflects the difference of 'effective' spectrums that different cognitive nodes can get during T_c. The bigger U_2 is, the higher the CR network fairness performance is. U_1 and U_2 are defined to reflect time-varying features.

3. Prediction of Spectrum Availability and Interference Constrains

Actually, spectrum availability and interference constrain varies with the time t due to the mobility of the CR networks. This paper mainly considers the continuous states of spectrum availability and interference constrain for a period such as T_c, and then presents prediction spectrum allocation schemes. First, the probabilities of spectrum availability and interference constrain will be deduced under the mobile CR model in the following sub-sections.

3.1 Prediction of Spectrum Availability for Cognitive Nodes

The spectrum availability of one cognitive node varies because of the node's mobility and PUs' arrivals/departures with the time t. Thus, the spectrum availability prediction of one cognitive node includes two parts. One is the prediction of busy/idle activities for PUs. The other is the prediction of relative positions between PUs and cognitive nodes. Moreover, it is obvious that the two parts need to be considered together. First, we state spectrum availability which is different from(4), denoted by $A_n^m(T)$

$$A_n^m(T) = \{\text{The availability of spectrum } m \text{ for cognitive node } n \text{ lasts from } t_0 \text{ to } t_0+T\}. \tag{14}$$

$A_n^m(T)$ means that spectrum m is available to cognitive node n for a continuous time period T. It is noted that we focus only on two kinds of the cognitive nodes based on the mobile model. The first kind is the nodes which are not in the coverage area of PU_m at t_0. The second kind is the nodes which are in the coverage area of PU_m while PU_m is idle at t_0. In other words, it is not necessary to predict the spectrum availability of one node if the node is in the interference region of a busy PU_m at t_0. It is because the spectrum availability can be directly detected by spectrum sensing.

First, we investigate the situation that cognitive node n is not in the coverage area of PU_m at t_0. The main idea is to let node n predict a continuous time period T_p that spectrum m being available to node n will last its availability during T_p. Our goal is to get spectrum availability $A_n^m(T_c)$ during T_c by calculating $A_n^m(T_p)$. In practice, $A_n^m(T_p)$ mainly includes two parts: $A_1(T_p)$ and $A_2(T_p)$. $A_1(T_p)$ indicates the probability that node n does not move into the coverage area of PU_m from t_0 to t_0+T_p. $A_2(T_p)$ indicates the probability that node n moves into the coverage area of PU_m at t_0+T_x ($0 \le T_x \le T_p$)while PU_m is idle from t_0+T_x to t_0+T_p. Actually, $A_n^m(T_p)$ also contains other complicated situations.

However, $A_1(T_p)$ and $A_2(T_p)$ dominate the main parts considering the short allocation interval time. The calculation of $A_1(T_p)$ also consists of two parts: P_{out1} and P_{out2}.

$$A_1(T_p)=P_{\text{out1}}+P_{\text{out2}}, \tag{15}$$

where P_{out1} represents the situation that the velocity of the node n remains unchanged between t_0 to t_0+T_p and P_{out2} represents the other situations. According to(3), P_{out1} is easy to get as

$$P_{\text{out1}}=1-B(T_p)=e^{-\lambda T_p}. \tag{16}$$

However, the accurate calculation of P_{out2} is complicated because it is difficult to know the spectrum availability caused by the changes of velocity for node n. Next, we try to get the approximate value $\mathrm{E}(P_{\text{out2}})$ by estimating P_{out2}. Denote a random variable $\Phi<T_p$ for a time interval between t_0 and t_0+T_p during which node n changes its velocity. Then, $P(\phi\le\Phi<T_p)$ indicates the probability that node n keeps its velocity unchanged from t_0 to $t_0+\phi$ while node n changes its velocity after $t_0+\phi$. And $P(\phi\le\Phi<T_p)$ is easy to get as

$$p(\phi\le\Phi<T_p)=B(T_p)-B(\phi)=\left(1-e^{-\lambda T_p}\right)-\left(1-e^{-\lambda\phi}\right)=e^{-\lambda\phi}-e^{-\lambda T_p}. \tag{17}$$

The approximate value $\mathrm{E}(P_{\text{out2}})$ is defined as

$$\mathrm{E}(P_{\text{out2}})=\int_0^{T_p} l_2(\phi)f(\phi)\mathrm{d}\phi, \tag{18}$$

where $l_2(\phi)$ is a function of ϕ. In order to get $l_2(\phi)$, we first calculate the continuous total time T_t that node n will not move into the coverage area of PU_m if velocity changes happen between t_0 to t_0+T_p. After the first change happens at $t_0+\phi$, node n still has a great probability of staying out of the coverage area of PU_m. And the probability of the velocity keeping unchanged for node n from $t_0+\phi$ to t_0+T_p is $e^{-\lambda(T_p-\phi)}$ by(3). Thus, the total time T_t that node n will not move into the coverage area of PU_m can be written as

$$T_t=\phi+(T_p-\phi)p_a e^{-\lambda(T_p-\phi)}+\varepsilon_a, \tag{19}$$

where p_a is the probability for node n moving far away from PU_m after the first velocity change. $\varepsilon_a\ge 0$ is used to include all the situations that are not calculated by $\phi+(T_p-\phi)p_a e^{-\lambda(T_p-\phi)}$. Therefore, we can get $l_2(\phi)$ as

$$l_2(\phi)=\frac{\phi+(T_p-\phi)p_a e^{-\lambda(T_p-\phi)}}{T_p}+\varepsilon_a, \tag{20}$$

$f(\phi)$ is given by

$$f(\phi)=\lim_{\Delta\phi\to 0}\frac{P(\phi\le\Phi<T_p)-P(\phi+\Delta\phi\le\Phi<T_p)}{\Delta\phi}=\lambda e^{-\lambda\phi}. \tag{21}$$

When $T_p<T_c$ is satisfied, node n should change its velocity (speed or direction) before t_0+T_p, which makes node n moving far away from PU_m. According to(18),(20),and(21), the spectrum availability $A_n^m(T_c)$ for node n is derived as

$$A_n^m(T_c)\approx\mathrm{E}(P_{\text{out}2})=\frac{1}{\lambda T_p}+\varepsilon_a+e^{-\lambda T_p}\left(\frac{1}{2}p_a\lambda T_p-\frac{1}{\lambda T_p}-\varepsilon_a-1\right). \tag{22}$$

When $T_p \geq T_c$ is satisfied, the spectrum availability $A_n^m(T_c)$ for node n is derived as

$$A_n^m(T_c) \approx A_1(T_c) + \mathrm{E}(P_{\mathrm{out2}}) = \frac{1}{\lambda T_c} + \varepsilon_a + e^{-\lambda T_c}\left(\frac{1}{2}p_a \lambda T_c - \frac{1}{\lambda T_c} - \varepsilon_a\right). \tag{23}$$

It is noted that ε_a includes other situations which could happen as small probability events. For instance, node n changes its velocity for more than two times, which makes node n still not moves into the coverage area of PU_m during T_c.

Next, we investigate the situation that cognitive node n is in the coverage area of PU_m while PU_m is inactive at t_0. We need to investigate not only the movement of node n but also the duration of the idle state for PU_m from t_0. Furthermore, we believe that the prediction of the idle state for PU_m is more important unlike the first situation, which is because of the initial position of node n. Similar to the analysis method of the first situation mentioned above, the main idea is to let node n predict a continuous time period T_p^{out} that node n will not move out of the coverage area of PU_m during T_p^{out}. Note that T_p^{out} is different from T_p.

When $T_p^{\mathrm{out}} < T_c$ is satisfied, $A_n^m(T_c)$ for node n is derived as

$$A_n^m(T_c) = P_{\mathrm{in}} \cdot \int_{t_0}^{t_0+T_p^{\mathrm{out}}} f_{\mathrm{OFF}}(t)\,\mathrm{d}t + \varepsilon_{\mathrm{in}}, \tag{24}$$

where $\int_{t_0}^{t_0+T_p^{\mathrm{out}}} f_{\mathrm{OFF}}(t)\,\mathrm{d}t$ denotes the idle probability of spectrum m from t_0 to $t_0+T_p^{\mathrm{out}}$. $\varepsilon_{\mathrm{in}}$ tries to include all the other spectrum availability situations. P_{in} denotes the probability that node n moves out of the coverage area of PU_m before $t_0+T_p^{\mathrm{out}}$. P_{in} also includes two parts. P_{in1} represents the situation that the velocity of the node n remains unchanged between t_0 to $t_0+T_p^{\mathrm{out}}$. P_{in2} represents the other situations. P_{in} can be written as

$$P_{\mathrm{in}} = \frac{1}{\lambda T_p^{\mathrm{out}}} + \varepsilon_b + e^{-\lambda T_p}\left(\frac{1}{2}p_b \lambda T_p^{\mathrm{out}} - \frac{1}{\lambda T_p^{\mathrm{out}}} - \varepsilon_b\right), \tag{25}$$

where p_b denotes the probability for node n moving far away from PU_m after the first velocity change in order to differentiate from the first situation. $\varepsilon_b \geq 0$ is used to include all the situations that are not calculated by $\phi + \left(T_p^{\mathrm{out}} - \phi\right) p_b e^{-\lambda\left(T_p^{\mathrm{out}} - \phi\right)}$. According to(2),(24)and(25), the spectrum availability $A_n^m(T_c)$ for node n is derived as

$$A_n^m(T_c) = \left(\frac{1}{\lambda T_p^{\mathrm{out}}} + \varepsilon_b + e^{-\lambda T_p^{\mathrm{out}}}\left(\frac{1}{2}p_b \lambda T_p^{\mathrm{out}} - \frac{1}{\lambda T_p^{\mathrm{out}}} - \varepsilon_b\right)\right)\left(\mathrm{e}^{-\mu_p t_0} - \mathrm{e}^{-\mu_p\left(t_0+T_p^{\mathrm{out}}\right)}\right) + \varepsilon_{\mathrm{in}}. \tag{26}$$

When $T_p^{\mathrm{out}} \geq T_c$ is satisfied, the spectrum availability is mainly determined by the working state of PU_m. Therefore, the spectrum availability $A_n^m(T_c)$ for node n is derived as

$$A_n^m(T_c) = \int_{t_0}^{t_0+T_c} f_{\mathrm{OFF}}(t)\mathrm{d}t + \varepsilon_c = \mathrm{e}^{-\mu_p t_0} - \mathrm{e}^{-\mu_p(t_0+T_c)} + \varepsilon_c, \tag{27}$$

where ε_c denotes all the other spectrum availability situations.

3.2 Prediction of Interference Constrains for Cognitive Nodes

The instantaneous interference constrain between two different cognitive nodes is determined by the relative positions in the mobile CR network denoted by(6). The prediction of interference constrain principally investigates whether there is interference

constrain $\chi_i^j(T_c)$ between cognitive nodes i and j from t_0 to t_0+T_c while there is no interference constrain at t_0. Those nodes, which have interference constrain at t_0, are not included. It is due to that the interference constrain of these nodes can be obtained by spectrum sensing technology.

Similar to the analysis method of the prediction for the spectrum availability, let one node predict a continuous time period $T_p^{'}$ that no interference constrain between the two nodes (i, j) will last from t_0 to $t_0+T_p^{'}$. In this case, the calculation of no interference constrain from t_0 to $t_0+T_p^{'}$ is divided into two parts: $L'_1(T_p^{'})+L'_2(T_p^{'})$. $L'_1(T_p^{'})$ indicates the velocities (speed or direction) of the two nodes remain unchanged between t_0 and $t_0+T_p^{'}$. $L'_2(T_p^{'})$ indicates the velocities for any of the two nodes (or both of them) changed between t_0 and $t_0+T_p^{'}$. According to(3), $L'_1(T_p^{'})$ is easy to be obtained as

$$L'_1(T_p^{'}) = \left(1-B(T_p^{'})\right)^2 = e^{-2\lambda T_p^{'}}. \tag{28}$$

The calculation of $L'_2(T_p^{'})$ is complicated. Thus, we can get the approximate value $\mathrm{E}(l'_2)$ by estimating $L'_2(T_p^{'})$. $\mathrm{E}(l'_2)$ is defined as

$$\mathrm{E}(l'_2) = \int_0^{T_p^{'}} l'_2(\varphi) f'(\varphi)\,\mathrm{d}\varphi. \tag{29}$$

where, $l'_2(\varphi)$ is a function of φ. In order to get $l'_2(\varphi)$, we calculate the total time of no interference constrain between i and j : $T_t^{'}$. Assume the first change (any of the two nodes) of velocities happens at $t_0+\varphi$. The probability of the velocities keeping unchanged from $t_0+\varphi$ to $t_0+T_p^{'}$ for the two nodes is $e^{-2\lambda(T_p^{'}-\varphi)}$ by(3). Thus, $T_t^{'}$ can be written as

$$T_t^{'} = \varphi + (T_p^{'}-\varphi)\, p_{\text{away}}\, \mathrm{e}^{-2\lambda(T_p^{'}-\varphi)} + \varepsilon_{\text{away}}. \tag{30}$$

p_{away} is the probability that the two nodes move far away from each other after the first change at $t_0+\varphi$ in velocity. In fact, $\varepsilon_{\text{away}} \geq 0$ tries to include all time periods that are not calculated by $\varphi+(T_p^{'}-\varphi)\, p_{\text{away}}\, \mathrm{e}^{-2\lambda(T_p^{'}-\varphi)}$. Therefore, we can get $l'_2(\varphi)$ as

$$l'_2(\varphi) = \frac{\varphi+(T_p^{'}-\varphi)\, p_{\text{away}} e^{-\lambda(T_p^{'}-\varphi)}}{T_p^{'}} + \varepsilon_{\text{away}}. \tag{31}$$

$f'(\varphi)$ is defined as

$$f'(\varphi) = \lim_{\Delta\varphi\to 0} \frac{P(\varphi \leq \Psi < T_p^{'}) - P(\varphi+\Delta\varphi \leq \Psi < T_p^{'})}{\Delta\varphi} = \lambda e^{-\lambda\varphi}, \tag{32}$$

where $P(\varphi \leq \Psi < T_p^{'})$ is easy to get as

$$P(\varphi \leq \Psi < T_p^{'}) = 2\left(1-B(T_p^{'})\right)\cdot\left(B(T_p^{'})-B(\varphi)\right)+\left(B(T_p^{'})-B(\varphi)\right)^2 = e^{-2\lambda\varphi}-e^{-2\lambda T_p^{'}}. \tag{33}$$

Thus, we have $\mathrm{E}(l'_2)$ according to(29),(31)and(32)

$$\mathrm{E}(l'_2) = \frac{1}{2\lambda T_p^{'}} + \varepsilon_{\text{away}} + e^{-2\lambda T_p^{'}}\left(p_{\text{away}}\lambda T_p^{'} - \frac{1}{2\lambda T_p^{'}} - \varepsilon_{\text{away}} - 1\right). \tag{34}$$

When $T_p^{'} < T_c$ is satisfied, any (or both) of nodes i and j should change its (their) velocity

(speed or direction) resulting in the two nodes moving far away from each other before $t_0+T_p^{'}$ if there is no interference constrain between them. Accordingly, the appearance probability of interference constrains for nodes i and j can be derived as

$$\chi_i^j(T_c)\approx 1-\mathrm{E}(l'_2)=1-\frac{1}{2\lambda T_p^{'}}-\varepsilon_{\text{away}}-e^{-2\lambda T_p^{'}}\left(p_{\text{away}}\lambda T_p^{'}-\frac{1}{2\lambda T_p^{'}}-\varepsilon_{\text{away}}-1\right). \tag{35}$$

When $T_p^{'}\geq T_c$ is satisfied, the interference constrain $\chi_i^j(T_c)$ for nodes i and j is derived as

$$\chi_i^j(T_c)\approx 1-L'_1(T_c)-\mathrm{E}(l'_2)=1-\frac{1}{2\lambda T_c}-\varepsilon_{\text{away}}-e^{-2\lambda T_c}\left(p_{\text{away}}\lambda T_c-\frac{1}{2\lambda T_c}-\varepsilon_{\text{away}}\right). \tag{36}$$

p_{away} represents the probability that the two nodes move away from each other after the first change at $t_0+\varphi$ in velocity, which makes no interference constrain between them during T_c.

4. Proposed Prediction-based Spectrum Allocation Algorithms

In this section, two novel prediction-based spectrum allocation algorithms, PFA and PGA, are proposed based on the analysis above.

The main steps of PFA are as follows.

Step1: Initialization. The initial coordinates of the cognitive nodes and the initial states of the PUs are randomly generated in the simulation area. The movements of the cognitive nodes are based on the random walk-based mobility model and the behaviors of PUs follow an exponential on/off traffic model according to (1) and (2). Suppose the probability thresholds of spectrum availability and interference constrains are respective α, β, which will be discussed later, and $v_{\max}$ is the maximum of the velocity for one cognitive node. Additionally, set T_c, $\varepsilon_{\text{away}}$, p_{away}, λ and μ_p.

Step2: Predict the working states of the PUs based on autoregressive moving average (ARMA) model, which is easy to implement with less computationally expensive [28][29][30].The ARMA model of order (p,q) is defined as

$$X_t=\sum_{i=1}^{p}a_iX_{t-i}+\sum_{j=1}^{q}\theta_j\xi_{t-j}+\xi_t \tag{37}$$

It is important to choose the order (p,q) of the model. In this paper, p and q are decided by AIC rule, which considers the fitting degree of data. In other words, ARMA(p,q) should achieve AIC minimum.

Step3: Predict available spectrums of all cognitive nodes. The available spectrum prediction mechanism for a given node n is shown in **Table 1**. Three situations are considered according to the different value of $D_{\text{PU}m,\text{SU}n}(t_0)$. When $D_{\text{PU}m,\text{SU}n}(t_0)\geq R+r+v_{\max}\cdot T_c$ is satisfied, spectrum m is available for node n. The other two situations have been discussed in section 3.1. Here, the corresponding prediction is done by the relationship between the prediction probability and the decision threshold α.

Step4: Predict interference constrains of cognitive nodes as shown in **Table 2**. Firstly, calculate the probability of interference constrains for any two different cognitive nodes by (35) when $T_p^{'}<T_c$ is satisfied and by (36) when $T_p^{'}\geq T_c$ is satisfied. Secondly, we assume that the interference constrain of two nodes exists when the probability of interference constrain is bigger than β. Otherwise, the interference constrain does not exist.

Table 1. Prediction mechanism of available spectrums for cognitive node n .

Prediction steps of available spectrums
if $D_{\mathrm{PU}m,\mathrm{SU}n}(t_0) \geq R+r+v_{\max}\cdot T_c$
Spectrum m is available for node n .
elseif $R+r \leq D_{\mathrm{PU}m,\mathrm{SU}n}(t_0) < R+r+v_{\max}\cdot T_c$
if $T_p < T_c$
Calculate $A_n^m(T_c)$ by (22).
else
Calculate $A_n^m(T_c)$ by (23).
end
if $A_n^m(T_c) > \alpha$
Spectrum m is available for node n .
end
elseif $D_{\mathrm{PU}m,\mathrm{SU}n}(t_0) < R+r$
if $T_p^{\mathrm{out}} < T_c$
Calculate $A_n^m(T_c)$ by (26).
else
Calculate $A_n^m(T_c)$ by (27).
end
if $A_n^m(T_c) > \alpha$
Spectrum m is available for node n .
end
end

Table 2. Prediction mechanism of interference constrain for cognitive node i and j .

Prediction steps of interference constrain
if $T_p^{'} < T_c$
Calculate $\chi_i^j(T_c)$ by (35).
else
Calculate $\chi_i^j(T_c)$ by (36).
end
if $\chi_i^j(T_c) > \beta$
Interference constrain exist.
else
Interference constrain does not exist.
end

Step5: All cognitive nodes exchange their link degrees and spectrum degrees. The edges are oriented from a higher spectrum degree to a lower one. When the number of spectrums for two nodes is same, the edge is oriented from a high link degree to a lower one. If a node is a sink node, it picks the spectrum that impact on the minimum number of neighbors. Then, all neighbors remove the spectrum from their spectrum availability lists. The spectrum selection performs from sink to source nodes. After a source node performs the process, the system resets and goes to assign the rest spectrums until all the available spectrums have been assigned.

The main differences between FGA and PFA are determined by the prediction of spectrum availability and interference constrains steps.

For simplicity, the main steps of PGA are given as following. Firstly, all cognitive nodes are ranked by the link degrees from low to high for each channel. Then the channel is assigned to the nodes by the link degrees from low to high. If two nodes have the same link degrees, the node with less assigned channels has higher priority to get a channel.

5. Simulation Results and Analysis

In this section, we investigate experimental results of our proposed PGA and PFA algorithms. Simulation parameters are shown in **Table 3**. The system utilities of the prediction algorithms and the traditional algorithms (GA and FA) are compared to evaluate the prediction performances. Note that, $\varepsilon_a=\varepsilon_b=\varepsilon_c=\varepsilon_{\text{in}}=\varepsilon_{\text{away}}$ is assumed during the simulation, since they are very small positive numbers in order to balance the according equations.

Table 3. Simulation parameters

Parameters	Variable
Total test numbers	5000
Simulation area	5km × 5km
Sample data length for primary spectrum prediction	500
R	1km
r	0.5km
T_c	1s and 5s
α	0.8
β	0.5~0.9
$p_a=p_b=p_{\text{away}}$	0.5
$\varepsilon_{\text{away}}$	0~0.3
$1/\lambda$	5s and 10s
$1/\mu_p$	0s~15s
Maximum speed of cognitive nodes	0m/s~50m/s
Total Number of PUs	5
Number N of cognitive nodes	10 and 15

According to **Fig. 2**, the fitting degree reaches about 87% when the sample data length is 500. The comparison results turn to be negative, since the original data based on ARMA is dealt with difference. In fact, if the on-off behavior of PUs is more cyclic and stochastic, the prediction result is more accurate. The on-off behavior prediction of PUs remains an open problem, which leaves as our future work.

As shown **Fig. 3**, it can be observed that ρ_s increases with the increasing of idle PUs, when $v_{\max}$ is a constant. When the number of idle PUs is fixed and less than 4.4, ρ_s increases with the increasing of $v_{\max}$. When the number of idle PUs is high (more than 4.4), ρ_s is not only depended on $v_{\max}$. Obviously, when the number of idle PUs is high (such as 5), almost each node needs to predict the available spectrum list, which increases the prediction uncertainty. In fact, the prediction uncertainty mainly increases the span of small probability events (ε_a, ε_b, ε_c, ε_{in}), which results in the uncertainty of $A_n^m(T_c)$ according to(22),(23) ,(26) and(27).

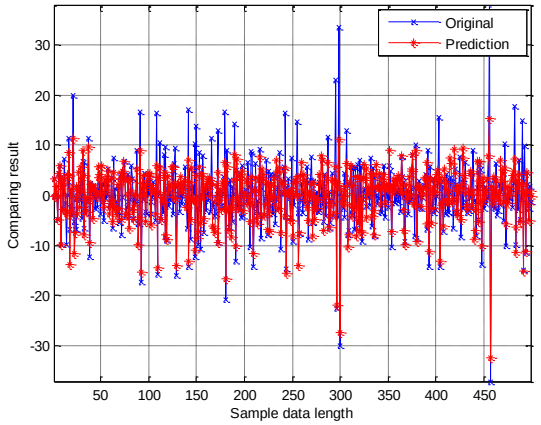

Fig. 2. Comparison between prediction data and original data for the working states of PUs.

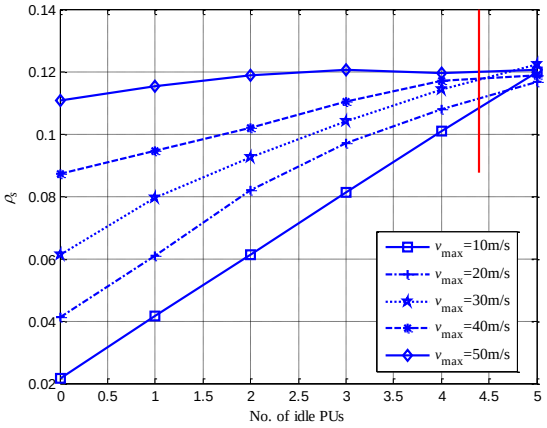

Fig. 3. Available spectrum prediction error rate ρ_s for cognitive nodes versus No. of idle PUs.

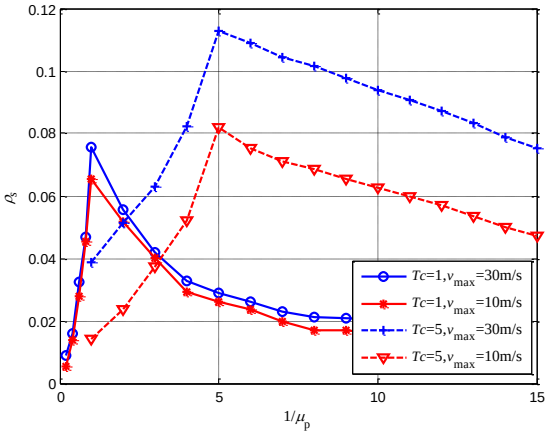

Fig. 4. Available spectrum prediction error rate ρ_s for cognitive nodes versus $1/\mu_p$.

In **Fig. 4**, the available spectrum prediction performance is studied versus $1/\mu_p$ and T_c. As expected, it can be seen from the figure that the prediction with short duration T_c shows better performance. However, the prediction performance is worse than that of the case $1/\mu_p$=1. In

addition, the worst prediction performance appears at $1/\mu_p$=1 and $1/\mu_p$=5 respectively. It is due to the fact that ρ_s is high under the given threshold when the mean idle time ($1/\mu_p$) of PUs is close to the duration T_c, which mainly impacts the prediction of spectrum availability for the second situation in section 3.1. Thus, any small deviation of the spectrum availability prediction would lead to a big influence on the decision result, when T_c is close to the mean idle time of PUs.

Fig. 5 and **Fig. 6** illustrate the interference constrain prediction error rates under different simulation parameters. In **Fig. 5**, the result was simulated under $\varepsilon_{\text{away}}$=0.1, T_c=5 and N=15, and β is the variable. When $1/\lambda$ and β are fixed, it can be seen that ρ_I degraded continually with the increasing of $v_{\max}$. When $1/\lambda$ and $v_{\max}$ are fixed, (such as $1/\lambda$=10, $v_{\max}$=30m/s), ρ_I has a minimum versus β, which is mainly depended on $1/\lambda$. According to (35) and (36), the existence probability of interference constrain is mainly determined by $1/\lambda$ when T_c, p_{away} and $\varepsilon_{\text{away}}$ are given. In fact, the existence of interference constrain is depended on the comparison between the probability and the threshold β based on interference constrain prediction algorithm (**Table 2**). From another point of view, $1/\lambda$ reflects mean epoch lengths with exponentially distributed. The bigger $1/\lambda$ is, the more accurate the existence prediction is. The larger $1/\lambda$ is, the larger $L'_1(T_p')$ is according to (28). Thus, false alarm of the interference constrain is decreasing with the threshold β increasing, which is the difference between $\beta = 0.7$ and $\beta = 0.75$.

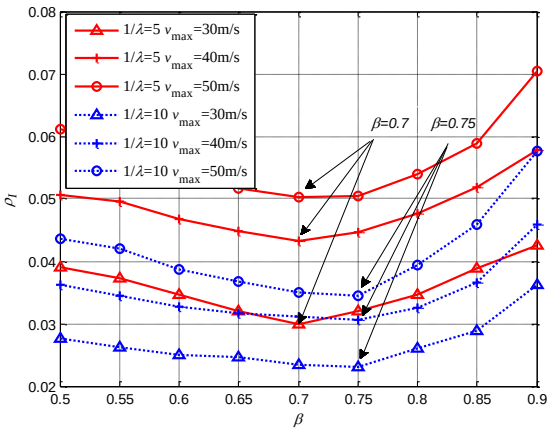

Fig. 5. Interference constrain prediction error rate ρ_I for cognitive nodes versus β.

Fig. 6 shows the impact of $\varepsilon_{\text{away}}$ on interference constrain error rate prediction ρ_I. The prediction performance achieves the best ρ_I when $\varepsilon_{\text{away}}$ is around 0.15~0.2 with $v_{\max}$ is a constant. When $\varepsilon_{\text{away}}$ is relatively larger, the "false alarm" is high. In contrast, when $\varepsilon_{\text{away}}$ is relatively small, the "false dismissal" would be high. In other words, $\varepsilon_{\text{away}}$ includes the entire small probability situations by (35) and (36). Thereby, $\varepsilon_{\text{away}}$ should be selected properly.

According to **Fig. 7**, as expected, U_{sum} is almost constant for GA and FA when $v_{\max}$ increases, since U_{sum} takes no consideration of time-varying for spectrum availabilities and interference constrains (regarding to (9)). However, U_{sum} decreases gradually for PGA and PFA with the

increasing of $v_{\max}$. In fact, the decreasing of available spectrums and the increasing of interference constrains directly lead to the decreasing of U_{sum} when $v_{\max}$ is high, because of the movements of cognitive nodes.

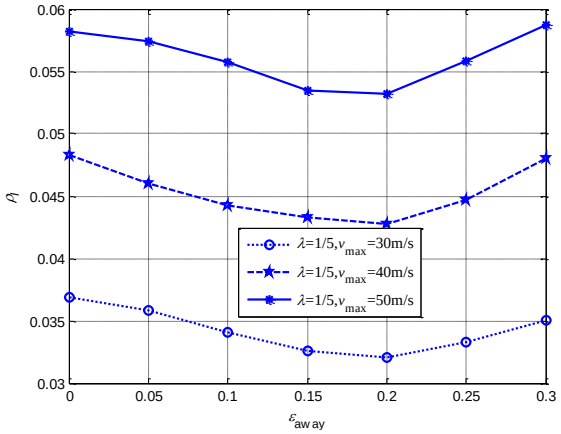

Fig. 6. Interference constrain prediction error rate ρ_I for cognitive nodes versus $\varepsilon_{\text{away}}$.

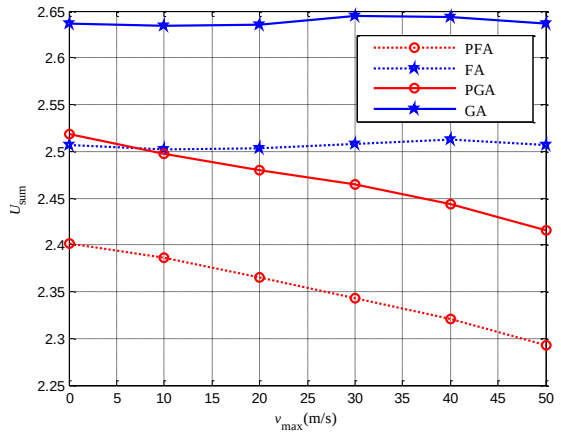

Fig. 7. Comparison of U_{sum} versus $v_{\max}$ for different algorithms.

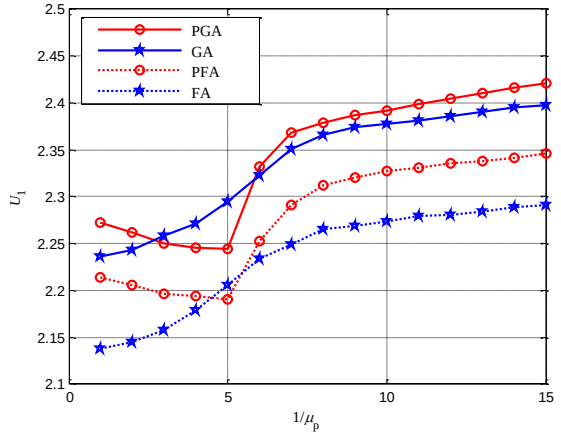

Fig. 8. Comparison of U_1 versus $1/\mu_p$ for different algorithms.

As shown in **Fig. 8**, PGA and PFA show good spectrum utilization performance U_1 compared with the traditional GA and FA, when $1/\mu_p>6$ is satisfied. It is because the prediction decision of spectrum availability is very strict when $1/\mu_p$ is close to T_c ($1/\mu_p=5$), which has been discussed in Fig.4. The deviation of the prediction result will happen easily according to the prediction mechanism in **Table 3**. Thus, the poor prediction of the spectrum availability leads to the decreasing of the effective spectrums U_1. Moreover, U_1 convergent gradually when $1/\mu_p$ becomes large, since the prediction of spectrum availability is almost correct at this time. Accordingly, there are no more gains with $1/\mu_p$ increasing.

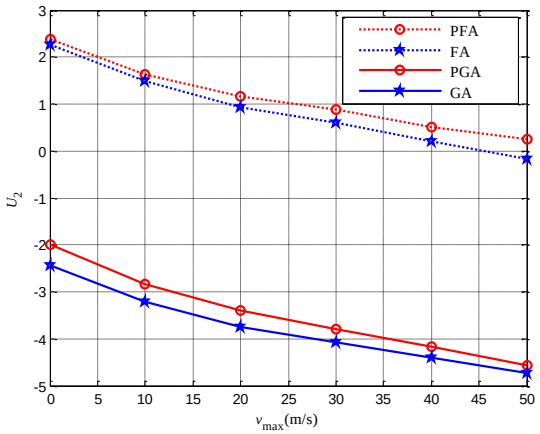

Fig. 9. Comparison of U_2 versus v_{max} for different algorithms.

As illustrated in **Fig. 9**, U_2 of our proposed PGA and PFA is higher than the conventional PA and FA respectively. The PFA has the best U_2 among all the four algorithms. When v_{max} is relatively small, such as "10m/s", the utility U_2 of PFA is higher than that of FA about 10.6%. When v_{max} is large enough, such as "40m/s", the utility U_2 of PFA is higher than that of FA about 143.7%. Actually, PFA shows its prediction profit when v_{max} is large. However, the utility U_2 of PGA is not so obvious improved compared with GA, when v_{max} is large relatively, i.e., "40m/s". The reason is that the goals of GA and PGA are in pursuit of spectrum utilization, not the fairness. In particular, the profits of U_2 for PFA and PGA are from the available spectrum prediction rather than from the interference constrain prediction when $v_{max}=0$.

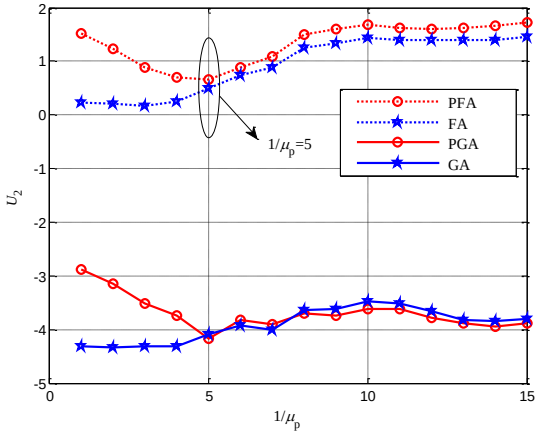

Fig. 10. Comparison of U_2 versus $1/\mu_p$ for different algorithms.

From **Fig. 10**, it is easy to find that the utility U_2 of PFA is always better than that of FA. The minimum gap between PFA and FA is about 32.2%, when $1/\mu_p$=5. It conformers that the prediction performance is worst when T_c is close to $1/\mu_p$ again, which we have discussed during **Fig. 4** and **Fig. 8**. The utility U_2 of PGA is better than that of GA when $1/\mu_p$ is relatively small, due to the prediction gains of PGA. Nevertheless, the utility U_2 of PGA is not better than that of GA when $1/\mu_p$ is large enough. The reason is that the goal of FGA is in pursuit of maximizing the spectrum utilization instead of the fairness, and the prediction of FGA is accurate when $1/\mu_p$ is large enough.

6. Conclusions

This paper proposed a prediction-based spectrum allocation mechanism in mobile CR network. By the derivation of the probabilities of spectrum availability and interference constrain, we obtained the prediction results of the dynamic available spectrum lists and interference topologies. Simulation results showed that the spectrum utilization of FGA is superior to the other algorithms when the mean idle time of PUs is high, with sacrificing fairness. Nevertheless, the spectrum utilization performance of FGA is worse than that of GA when the prediction decision is not accurate. In addition, PFA gets better fairness performance than the other supervised algorithms. Especially, when the mobile speeds of the cognitive nodes are relatively high, PFA shows its excellent fairness that is more effective and essential to the actual mobile CR network environment.

In future we will further analyze the on-off behavior prediction of PUs to obtain a general activity model and fully investigate the impact of $\varepsilon_{\text{away}}$ on prediction performance.

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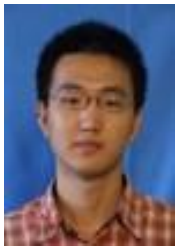

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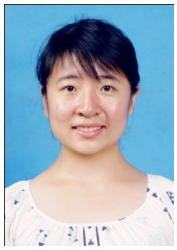

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