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Prediction-Based Spectrum Management in Cognitive Radio Networks

Yanxiao Zhao, Zhiming Hong, Yu Luo, Guodong Wang, and Lina Pu

***Abstract*—Cognitive radio networks (CRNs) have been widely studied to improve spectrum utilization through a dynamic spectrum allocation scheme. However, many challenges remain and one big issue is how to provide an efficient spectrum management in a mobile environment. In this paper, we propose a new prediction-based spectrum management strategy to tackle this challenge. Both spectrum prediction and users' mobility prediction are fully considered in the proposed strategy. Combining the prediction information and cooperative sensing, a CR base station can obtain the sensing information for future location of each secondary user, so as to prearrange high-quality channels for secondary users ahead of time. In addition, we propose a new channel selection scheme when multiple channels are available simultaneously. Besides traditional decision factors, the new channel selection algorithm takes the channel's future availability obtained from spectrum prediction into account. By properly integrating the spectrum prediction, user mobility prediction, and channel selection, the new spectrum management strategy is capable of allocating the spectrum resource more efficiently. Extensive simulations are conducted and results verify that the proposed spectrum management strategy significantly improves the system performance in terms of reducing handoff times and improving user satisfactory, connection reliability, and channel utilization.**

***Index Terms*—Channel selection, cognitive radio network (CRN), high-order hidden bivariate Markov model (H^{2}BMM), spectrum prediction, user mobility prediction.**

I. Introduction

RADIO spectrum is the most valuable resource to implement wireless communications. With evergrowing new applications in wireless communications, the traditional static spectrum allocation scheme reveals its inherent limitation. On one hand, the limited amount of available radio spectrum can no longer meet new demands, which leads to the issue of spectrum scarcity [1]–[4]. On the other hand, according to the study of Federal Communications Commission, the utilization of allocated spectrum is relatively low, from 15% to 85% [5]. Therefore, novel paradigms are called for to improve spectrum efficiency, among which cognitive radio networks (CRN) is one promising solution that adopts the dynamic spectrum allocation strategy [6]–[9].

A CRN typically consists of two types of users: Primary users (PUs) and secondary users (SUs). PUs are licensed users and they are authorized to use the designated channels whenever as needed. In contrast, SUs are unlicensed users and they are only allowed to access channels opportunistically without interfering PUs. In this way, the spectrum utilization can be significantly improved. However, several grand challenges remain to successfully implement CRNs. One of the most challenging problems is how to efficiently manage or allocate spectrum in a mobile CRN environment [10]. In the literature, some existing works can be found to manage the spectrum from different perspectives. In [11], Song and Xie mainly focus on the problem of channel selection. In [12], spectrum uncertainty and user mobility are jointly applied to design a mobility management scheme for CR cellular networks, but no channel selection is considered. Few of existing work handles the mobility issue of SUs while considering the challenge of spectrum uncertainty and channel selection.

In this paper, we propose a novel and comprehensive spectrum management strategy, termed prediction-based spectrum management (PBSM). PBSM is composed of three processes: spectrum prediction, user mobility prediction, and channel selection. Spectrum prediction refers to the process of analyzing and predicting channel behaviors [13], [14]. It can foresee future statuses (e.g., idle or busy) for channels. User mobility prediction refers to the process of analyzing and predicting users' motion [15]. Based on the predicted information of spectrum and user mobility, a base station can obtain the available channels at future locations for each SU via cooperative sensing, so that the SU can be equipped with knowledge of channel availability at the next potential place ahead of time. This will provide longer accessing time for SUs to perform data communication on selected channel and eventually enhance the spectrum utilization. In addition, it is very likely that multiple channels are available for communications and these channels possess different characteristics [16]. An SU may need to select the most desired one to achieve the best performance. Therefore, a well-designed channel selection algorithm is required.

With regard to the spectrum prediction in PBSM, we improve the high-order hidden bivariate Markov model (H^{2}BMM) by considering the discontinuous sensing behaviors of mobile SUs. Besides the high-order and the bivariate features in the hidden Markov model, this advanced H^{2}BMM also considers

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the mobility of SUs and achieves better prediction accuracy[1] in a mobile CRN. For user mobility prediction, we implement a high-order Markov model-based predictor in our paper to forecast SUs' motion. The high-order Markov predictor is reported to have higher prediction accuracy than moving average or static neighbor graph (SNG) predictors according to [17]. In terms of channel selection, a hybrid of multiple analytic hierarchy process (M-AHP) and gray relational analysis (GRA)-based weighted algorithm is further developed for a multichannel environment. Besides consideration of quality of service (QoS) and received signal strength (RSS), we also consider the channel's future availability. With the proposed channel selection algorithm, we can significantly reduce the ping-pang effect, a phenomenon of frequent spectrum handoffs occurred between two cells on the edge [18].

By integrating the above three processes (i.e., spectrum prediction, user mobility prediction, and channel selection), the proposed spectrum management strategy (i.e., PBSM) can utilize the spectrum more efficiently due to the following benefits. PBSM improves communication quality, including link stability, bandwidth utilization, and users satisfaction. SUs are able to occupy the vacant channel quickly even if only a portion of frequency band is sensed by each SU in a single sensing period. As far as we know, it is the first attempt to investigate a comprehensive spectrum management scheme by considering three critical processes in CRNs.

Our main contributions are briefly summarized below.

- A novel PBSM is proposed to enhance both the spectrum efficiency and user satisfaction.
- Both spectrum prediction and user mobility prediction are applied in PBSM, so that the system could predict future spectrum status at the future locations of SUs in a mobile CRN environment.
- Extensive simulations are conducted to assess the performance of PBSM and results verify that the proposed PBSM significantly improves the system performance by reducing handoff times and improving user satisfactory, connection reliability and channel utilization.

The rest of the paper is organized as follows. Section II introduces the related work. Section III presents the main idea of the proposed PBSM scheme. User mobility prediction and spectrum prediction approaches are summarized in Section IV. Section V presents the detailed description of the proposed channel selection algorithm. Prediction cost of the proposed scheme is analyzed in Section VI. Simulation results are described in Section VII and conclusions are drawn in Section VIII.

II. Related Work

In CRNs, the dynamics in spectrum occupancy status are generally resulted from the activities of PUs, the position changes of SUs and the spectrum sharing among them. The spectrum prediction, user mobility prediction, and the channel selection become critical techniques to improve the spectrum utilization while mitigating the harmful interference to PUs. In this section, we briefly introduce the advantages and limitations of existing algorithms in spectrum prediction, user mobility prediction, and channel selection.

A. *Spectrum Prediction*

To achieve a seamless handoff in CRNs, many spectrum prediction approaches have been proposed in the last decade [19]. Here, we briefly introduce representative prediction algorithms in different categories.

1) Markov Model Based: In the Markov model-based spectrum prediction, the channel status is commonly represented by "0" or "1" indicating the channel being *idle* or *busy*, respectively. In real applications, due to the noise and interference during spectrum sensing, the actual channel state is typically hidden from SUs. Therefore, the spectrum prediction algorithms in this category are generally based on the hidden Markov model (HMM) [20], where a hidden state space is constructed to describe the relationship between the true channel state and sensing results. The goal of HMM is to calculate future states by training the state transition probability matrix and emission probability matrix.

Although widely used in forecasting the activities of PUs, HMM has inherent weaknesses. First, the geometric distribution characteristic of HMM determines that it could not accurately describe the dwell time of channel state. Second, in HMM, one state is solely determined by its immediate previous state, which may not be accurate in a real scenario. To improve the performance of HMM, several algorithms, such as high-order HMM [21] and hidden bivariate Markov model (HBMM) [22] are introduced. In our prior work, the proposed H^2BMM leverages the advantages of both high-order and bivariate features and achieves superior performance in this category [23]. Therefore, in this paper, we choose H^2BMM as a prototype and propose the advanced H^2BMM, which integrates the mobility features of SUs.

2) Moving Average Model Based: When the sequence to predict has seasonal and trend features, the future value can be estimated based on the historical observations using moving average model (MAM). A k-order MAM takes k historical observations as input and produces the average as the predict to the next value. To enhance the influence of the most recent data on the prediction result, an exponential MAM is proposed, where the weights to older observations exponentially decrease. In [24], the exponential MAM is used to predict the energy level of channels in CRNs. The spectrum sensing time can be saved by only sensing the channels whose predicted energy level is lower than a preset threshold (considered as unoccupied by PUs). However, the false predictive rate of MAM-based predictor will significantly increase if the values of sequence have no obvious seasonal feature or are highly dynamic.

3) Neural Network Based: Neural network typically consists of multiple layers in a directed graph, where the input layer takes historical observations as input data, the output layer predicts the future status, and one or more hidden layers in-between. Each node (e.g., neuron) in a layer connects with a certain weight to nodes in the next layer. The prediction proceeds by training

[1] Prediction accuracy is defined as the percentage of correct prediction on the channel status (i.e., idle or busy).

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the model and calculating the weights of the graph. Tumuluru *et al.* in [25] applied a neural network-based spectrum prediction to assist the spectrum sensing in CRNs. Channels predicted to be idle will not be sensed by SUs to save time and energy. The performance of neural network-based prediction, however, depends on the appropriate selection of network model (e.g., number of layers and neurons).

B. User Mobility Prediction

In a CRN, the mobility of SU may cause additional handoff delay when it moves from one place to another. To handle such a problem, predicting the movement of SUs is advocated as a promising solution. By analyzing the historical records of SUs' locations, we can discover each SU's motion pattern and predict their future locations. In [12], a mobility management framework is proposed to mitigate heterogeneous spectrum availability.

1) Markov Family Based: In a k-order Markov predictor, the prediction to the next position is made based on the latest k observations, which are also referred to the current state of the Markov predictor. In [26], a mobility prediction method is proposed for mobile phone users based on the enhanced Markov algorithm. The Markov process in the proposed algorithm has two components: the global prediction algorithm (GPA) and the local prediction algorithm (LPA). GPA is used when the user's data exist in the training database and LPA is adopted when GPA fails. The prediction accuracy of Markov predictor highly depends on the correct estimation on the transition probability matrix M as any errors in the estimate of M will accumulate in predicting future steps.

2) SNG Based: The SNG method [17] predicts the future position of mobile users by constructing an empirical probabilistic transition graph of users' mobility. The graph is built as follows: If a movement from i to j is observed, a directed edge (i, j) is added to the graph if the edge does not exist or the weight of (i, j) is added by 1. Normalized weight of edges from the same point can be considered as the probability of moving to the corresponding positions. The future position of PU is thus predicted as the location that has the highest weight. The SNG predictor can have a good estimation on the users' mobility if the network topology does not change quickly over time and PUs move around in a bounded area. Otherwise, the predictor may not collect enough topology information for prediction.

In [17], Butun *et al.* compare several different mobility prediction mechanisms and simulation results indicate that the Markov family-based predictor has the best achievable prediction accuracy, followed by cumulative distribution function (CDF) and SNF predictor. Therefore, in this paper, we adopt high-order Markov model to forecast the position changes of PUs.

C. Channel Selection

It is very likely that multichannels are available for communications and SUs need to select the best channel. Many approaches for the spectrum decision have been proposed to improve the performance of the network.

1) Fuzzy Logic System (FLS) Based: FLS is a nonlinear mapping system between its input and output, where the input attributes (e.g., RSS, delay, packet loss rate, and cost) are not precisely defined. In [27] and [28], a hierarchical model with two FLSs is presented to solve the issue of channel selection. In that model, one of the FLSs is used to control the transmission power and another to determine whether or not it is performing the frequency handover. The main advantage of such strategy is that it can decrease transmit power consumption and achieve a small number of spectrum handovers.

2) Analytic Hierarchy Process Based: The principle of AHP is to decompose complex problem into a hierarchy of decision factors, each of which can be solved independently. AHP consists of three steps: decomposition, importance assignment, and weight calculation. In the first step, the channel selection problem is divided based on the performance criteria. Then importance values on a scale of 1 to 9 are assigned based on users' intuition. Weights are calculated in the last using the eigenvector method. In [29], an AHP-based channel selection strategy is proposed for heterogeneous wireless networks. An experiment is conducted to assess the performance of AHP-based strategy, demonstrating that AHP is highly affected by human factors because it is a kind of subjective decision-making method. In [30], the M-AHP is proposed to extend the AHP reflecting multiple users' preferences rather than the single user of AHP.

3) GRA Based: Gray system theory is a superior mathematical system to deal with uncertainties. It uses colors from black through gray to white to represent information from total unknown to fully known. The gray area indicates the existence of uncertainties. GRA builds gray relationships between channel candidates and an ideal channel of best quality. The similarity between them is described as the gray relational coefficient (GRC). The selected channel is the one with the highest GRC. GRA and AHP usually work together in the channel selection[31]–[33]. AHP is used to decompose channel selection problem into subproblems and calculate the weights factor, while GRP ranks the channel candidates and makes the selection. It shows that this hybrid approach can mitigate the unnecessary handovers caused by the ranking abnormality problem and brings better network performance than traditional methods. Hence, in PBSM, we implement the hybrid M-AHP and GRA for channel selection, which integrates the spectrum prediction and user mobility prediction.

III. Prediction-Based Spectrum Management

In this section, we develop a PBSM scheme, which integrates the H^{2}BMM-based spectrum predictor, high-order Markov model-based user mobility predictor, and the hybrid channel selection based on M-AHP and GRA. The goal of the new scheme is to utilize the spectrum resource efficiently in a mobile CRN. Note that user mobility prediction and spectrum prediction approaches will be introduced in Section IV. Details about channel selection approach will be presented in Section V.

A typical scenario of a multichannel CRN with mobile SUs is demonstrated in Fig. 1. As shown in the figure, the network consists of three PUs, the coverage of which are denoted by three large circles, and several SUs are represented by purple dots. Each PU possesses several authorized channels and SUs are allowed to access all channels that are unoccupied. We adopt the

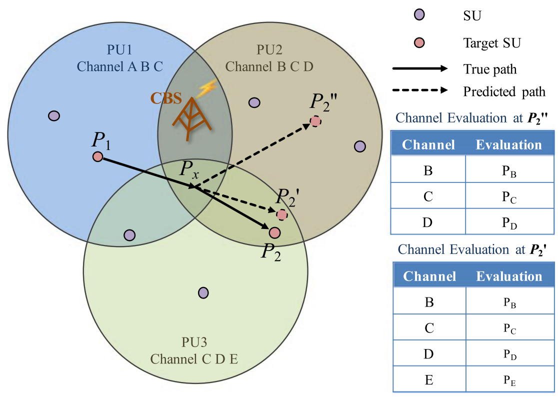

Fig. 1. Scenario of multichannel CRN with mobile SUs.

TABLE I
TASKS OF CBS AND SU

CBS	SU
Instruct SUs in local sensing Collect sensing data Update spectrum prediction model Predict channel status Update mobility prediction model Predict SUs' future location Provide channel status enquiry service	Sense channel Upload sensing results to CBS Select from channel candidates

TABLE II
DATA FORMAT FOR SENSING RESULT UPLOAD

User location (GPS coordinate)	Sensed Channel	Sensing Time	Sensing result

centralized architecture, where a CR base station (CBS) controls the handoff and other behaviors of SUs through a separated control channel. There is no direct communication among SUs for sensing information exchange, as the cooperative sensing is achieved through the coordination of CBS on the sensing assignment and sensing result fusion.

Among the three components in the proposed spectrum management scheme, the prediction of spectrum availability and user mobility is performed on the CBS and the channel selection is made by SUs. To be specific, the responsibilities of CBS include instructing SUs in local sensing, fusing the sensing data collected from SUs, updating the prediction model, performing spectrum and mobility prediction, and distributing channel status information to SUs as listed in Table I. The tasks of SUs cover sensing channel according to the assignment of CBS, uploading sensing results to CBS, and conducting channel selection based on the channel status provided by CBS. The sensing result uploaded by SUs follows the structure shown in Table II.

The flow chart of the proposed spectrum management scheme is depicted in Fig. 2. By instructing SUs to only sense the channels that are predicted to be idle at a high probability, both the sensing time and energy can be significantly saved on SUs. The CBS collects sensing result and location information from SUs to update matrix and train prediction models. By considering where SUs will move to and the future channel status at

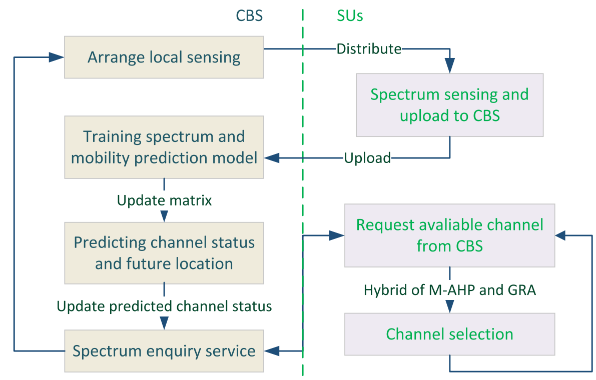

Fig. 2. Flow-chart of the spectrum management scheme.

that place, the CBS provides spectrum enquiry service for SUs to recommend several most likely available channels resulting from the prediction result. Leveraging the hybrid of M-AHP and GRA algorithm, SUs select a suitable one from these candidate channels and then determine whether a handoff is necessary. If necessary, a handoff process will be conducted after receiving a CBS's permission. To summarize, the CBS plays the role of spectrum manager in CRNs to guide the sensing and handoff behaviors of SUs. SUs need to follow the CBS's instruction to sense specified channels and upload sensing information.

The solid arrows in Fig. 1 indicate the moving path of the target SU. Due to the potential errors in the user mobility prediction, the predicted path may differ from the true path of SUs as depicted by the dashed arrow in Fig. 1. The availability of the channel will depend on both the activity of PUs and the location of SUs. Thereby, both the prediction errors in spectrum prediction and mobility prediction will lead to the inaccurate estimation on the channel status. Taking Fig. 1 as an example, an SU moves from location P_1 to location P_x. The CBS predicts that the SU will move to location P_2' and recommends available channels in P_2' to SUs accordingly. The SU calculates an evaluated value P_i for each channel i and decides the necessity of handoff. Before the SU moves to the actual location P_2, which is close to the predicted location, the corresponding reaction such as handoff has been completed. That is the situation of a successful mobility prediction. However, if the CBS fails to predict SU's future location, for example, the location point P_2'' in Fig. 1, channels recommended by the CBS may not be suitable for accessing location P_2 and additional cost may happen to the SU. In the latter situation with wrong predictions, we will analyze the prediction cost, which will be presented in Section VI.

IV. PREDICTION OF USER MOBILITY AND SPECTRUM

Prediction of the future position of SUs and the activity of PUs is the key technique assisting CBS to make wise recommendations to SUs on the channel selection. In this section, we present the techniques that PBSM adopted for user mobility and spectrum prediction.

A. *User Mobility Prediction*

Since the status of wireless channel changes with not only time but also space, the mobility of an SU thus may cause

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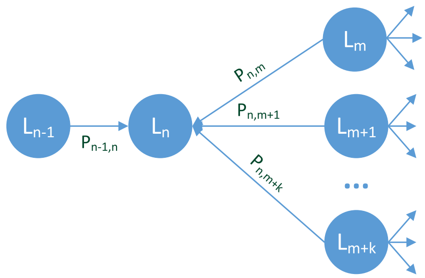

Fig. 3. Mobility prediction with high-order Markov model.

an additional handoff delay when it moves from one place to another [34]. To handle such a problem, predicting the movement of SUs is viewed as a promising solution. Many prediction models have been proposed to predict the user mobility, such as Markov family predictor, moving average predictor, CDF predictor, and SNG predictor. In [17], these four mobility models are evaluated and simulation results indicate that Markov Family predictor has the highest prediction accuracy. Therefore, in our proposed spectrum management scheme, high-order Markov model is employed for movement prediction.

SUs are required to record their locations periodically and upload the information to CBS along with the sensing result. Afterward, CBS predicts SUs' mobility by analyzing the uploaded location information using high-order Markov model. In the widely used standard Markov model, the current state solely depends on the previous one state. However, user movements are dramatically complex than the simplified model. To increase the dependences among location points of user mobility, we improve the standard Markov model to high-order Markov model, where one state depends on previous several states.

The diagram of high-order (second-order) Markov model-based mobility prediction is shown in Fig. 3. Assuming that an SU is reported to move from location L_{n-1} to L_n, CBS needs to search for L_{n-1} and L_n in historical data. The next possible location points are constructed to a sequence $X_n = \{L_m, L_{m+1}, ..., L_{m+k}\}$ in chronological order. Then, we can calculate the possibility of next movement $P(n-1, n) = \{P_{n-1,n,m}, P_{n-1,n,m+1}, ..., P_{n-1,n,m+k}\}$, where $P_{n-1,n,m} = P_{n-1,n}|P_{n,m}$ indicates the possibility that user moves from L_{n-1} to L_n and then to L_m. With the second-order possibility sequence $P(n-1, n)$, we are able to predict next possible location more accurately.

B. Spectrum Prediction

In this section, advanced H^{2}BMM spectrum prediction approach is introduced and adopted for our spectrum prediction process.

Advanced H^{2}BMM originates from H^{2}BMM-based spectrum prediction approach, which is proposed in [23]. The commonality and improvement between advanced H^{2}BMM and H^{2}BMM are summarized as follows.

The common features between advanced H^{2}BMM and H^{2}BMM include the following.

1) Both algorithms apply two-dimensional parameters, i.e., hidden process and underlying process, to accurately describe the channel behavior.
2) The channel state is divided into multiple substates, forming an underlying process, so that the channel substate dwell time follows a phase distribution, which is suggested from real-time CRNs.
3) Each state depends on multiple previous observations to improve the prediction accuracy.

In addition, both advanced H^{2}BMM and H^{2}BMM consist of three major steps. The first step is to generate a hidden channel state chain as well as observation chain. Second, a training process is conducted by using the widely used Baum–Welch algorithm. The last step involves the decision-making process about the channel future states.

The difference between advanced H^{2}BMM and H^{2}BMM is that the former takes the users' mobility into account, while H^{2}BMM was originally designed for a static CRN environment. In a mobile CRN, we cannot guarantee continuous sensing of the channel due to the mobility of SUs. Therefore, instead of a whole sensing sequence, the CBS is likely to receive many sensing pieces. Those sensing pieces are fully integrated into the training process in the advanced H^{2}BMM.

V. CHANNEL SELECTION ALGORITHM

After the prediction on SU's mobility and PU's activity, the CBS will be able to make a recommendation to the SU on channel candidates that are highly likely to be available. The SU is then able to select the best channel using the hybrid of M-AHP and GRA-based weighted algorithm. In this section, we introduce the channel selection algorithm adopted in PBSM. M-AHP is a subjective algorithm, while GRA is an objective algorithm. The integration of M-AHP and GRA [31] considers both objective fact and user preference. Compared with traditional weighted methods, our channel selection algorithm highlights the future channel availability and set it as the most important factor to evaluate the channel quality.

These influence factors are divided into two categories: positive factor and negative factor. Positive factor means that a high value of the factor is conducive to the final result. Negative factor means that a smaller value of the vector is more favorable to the final result. We use "+" and "−" to indicate positive and negative factor, respectively. The definitions of $f1(+), f2(+), f3(+), f4(-), f5(-), f6(-)$ are listed in Table III.

Both M-AHP and GRA are applied to evaluate each channel by considering all factors from $f1$ to $f6$. The final evaluation is the mean value of M-AHP and GRA since they have the same impact on the value of equivalent. The hierarchy diagram of hybrid M-AHP and GRA model is shown in Fig. 4.

In Fig. 4, $W_i^{'}$ and $W_i^{''}$ represent the weights of factor fi in M-AHP and GRA model, respectively. The weights in each model constitute their weight vector. The final weight vector is the linear weight of M-AHP and GRA weight vector with coefficient α which is set to be 0.5 in this paper. The following will present the weight derivation for M-AHP, GRA, and the hybrid of both.

TABLE III
INFLUENCE FACTORS IN CHANNEL SELECTION

Factor	Definition
$f_1(+)$	Estimated dwell time of *idle* state, ranges from 1 to 3 (three-step prediction).
$f_2(+)$	RSS of SUs, ranges from -60 to -110 dB.
$f_3(+)$	Bandwidth (10 Mb/s per user, 100 Mb/s in all), ranges from 0 to 100 Mb/s.
$f_4(-)$	Price of channel access, ranges from 0 to 1.
$f_5(-)$	Communication delay, ranges from 0 to 100 ms.
$f_6(-)$	Delay jitters, the difference in end-to-end one-way delay, ranges from 0 to 10 ms.

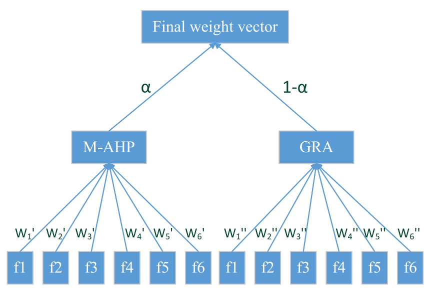

Fig. 4. Hierarchy diagram of hybrid M-AHP and GRA.

A. M-AHP Based Subjective Evaluation Method

In the first step of the channel selection algorithm, M-AHP is applied to obtain subjective weights. M-AHP is a subjective decision algorithm based on the relative weights of different factors. The importance of each factor is set according to the user's preference. The procedure of the M-AHP algorithm is described as follows. The number of decision makers is set to 5. For each decision maker m, an AHP judgment matrix is first defined, whose elements represent the relative importance of different factors. Then, the feature vector of the judgment matrix is solved to obtain the weight vector $w_m^{'T}$ of AHP. The final weight vector $w^{'T}$ of AHP is the geometric average of $w_m^{'T}(m = 1, 2, 3, 4, 5)$.

As mentioned previously, six influence factors are considered and the importance of each factor is reflected by the Santy ninth scale method. In Santy ninth scale, a larger scale means a higher importance. There are nine scales from integer 1 to 9, where 1 indicates equal importance, and 9 indicates extremely important. Similarly, the reciprocals of integers 1 to 9 are 1 to $1/9$, respectively, where $1/9$ indicates extremely least important. According to the user's preference, the judgment matrix of AHP, $\mathrm{JM}_{\mathrm{AHP}}$, is constructed as follows:

$$\mathrm{JM}_{\mathrm{AHP}} = \begin{array}{c} \begin{array}{cccccc} f1 & f2 & f3 & f4 & f5 & f6 \end{array} \\ \begin{bmatrix} C_{11} & C_{12} & C_{13} & C_{14} & C_{15} & C_{16} \\ C_{21} & C_{22} & C_{23} & C_{24} & C_{25} & C_{26} \\ C_{31} & C_{32} & C_{33} & C_{34} & C_{35} & C_{36} \\ C_{41} & C_{42} & C_{43} & C_{44} & C_{45} & C_{46} \\ C_{51} & C_{52} & C_{53} & C_{54} & C_{55} & C_{56} \\ C_{61} & C_{62} & C_{63} & C_{64} & C_{65} & C_{66} \end{bmatrix} \end{array} \begin{array}{c} f1 \\ f2 \\ f3 \\ f4 \\ f5 \\ f6 \end{array} \quad (1)$$

where C_{ji} indicates the importance scale of factor fi to factor fj.

According to the maximum eigenvalue of judgment matrix, the eigenvector could be calculated. Then, we normalize the eigenvector and assign it to the weight vector. Each element of the weight vector represents the weight of a factor

$$w_m^{'} = (w_{m1}^{'}, w_{m2}^{'}, w_{m3}^{'}, w_{m4}^{'}, w_{m5}^{'}, w_{m6}^{'})^T. \quad (2)$$

The final weight vector of M-AHP will be the geometric average of weight vectors of multiple AHPs

$$w^{'} = \sqrt[5]{\prod_{m=1}^{5} w_m^{'}}. \quad (3)$$

B. GRA-Based Objective Evaluation Method

In the second step of channel selection, GRA is applied to determine the objective weight. GRA is a multiattribute statistical analysis method. Compared with the other traditional multiattribute method, the gray correlation method does not require a large amount of data for computation and therefore it is easy-to-use. Gray relation means that the relation is existing but it is hard to formulate the relation. Gray relational degree is used to describe such a relation between any two factors. A high degree means a strong and linear relation.

In this GRA algorithm, an ideal vector is constructed as $C_{\mathrm{Ideal}}^T = [3\ -60\ 100\ 0\ 0\ 0]$, which indicates the most ideal values from the given ranges of six influence factors. Then, we construct the judgment matrix of GRA, $\mathrm{JM}_{\mathrm{GRA}}$, as below, where V_i^j indicates the value of factor f_i for channel C_j

$$\mathrm{JM}_{\mathrm{GRA}} = \begin{array}{c} \begin{array}{cccccc} C_{\mathrm{Ideal}} & C_A & C_B & C_C & C_D & C_E \end{array} \\ \begin{bmatrix} 3 & V_1^A & V_1^B & V_1^C & V_1^D & V_1^E \\ -60 & V_2^A & V_2^B & V_2^C & V_2^D & V_2^E \\ 100 & V_3^A & V_3^B & V_3^C & V_3^D & V_3^E \\ 0 & V_4^A & V_4^B & V_4^C & V_4^D & V_4^E \\ 0 & V_5^A & V_5^B & V_5^C & V_5^D & V_5^E \\ 0 & V_6^A & V_6^B & V_6^C & V_6^D & V_6^E \end{bmatrix} \end{array} \begin{array}{c} f1 \\ f2 \\ f3 \\ f4 \\ f5 \\ f6 \end{array}. \quad (4)$$

With the judgment matrix, the gray relational degree for each factor is calculated using the standard GRA formula. By normalizing the vector of the gray relational degree, the corresponding weight vector of GRA is obtained as follows:

$$w^{''} = (w_1^{''}, w_2^{''}, w_3^{''}, w_4^{''}, w_5^{''}, w_6^{''})^T. \quad (5)$$

C. Overall Weight Vector

In the last step of the channel selection algorithm, the overall weight vector can be determined from the above-mentioned M-AHP and GRA. Suppose the subjective and objective weight vectors obtained by M-AHP and GRA are $w^{'} = (w_1^{'}, w_2^{'}, w_3^{'}, w_4^{'}, w_5^{'}, w_6^{'})^T$ and $w^{''} = (w_1^{''}, w_2^{''}, w_3^{''}, w_4^{''}, w_5^{''}, w_6^{''})^T$, respectively. The comprehensive weight vector can be derived by a linear superposition

$$\begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ w_4 \\ w_5 \\ w_6 \end{bmatrix} = \alpha \begin{bmatrix} w_1^{'} \\ w_2^{'} \\ w_3^{'} \\ w_4^{'} \\ w_5^{'} \\ w_6^{'} \end{bmatrix} + (1-\alpha) \begin{bmatrix} w_1^{''} \\ w_2^{''} \\ w_3^{''} \\ w_4^{''} \\ w_5^{''} \\ w_6^{''} \end{bmatrix}. \tag{6}$$

Using the integrated weight $(w_1, w_2, w_3, w_4, w_5, w_6)^T$, and the normalized sequence of spectrum parameters for $(c_1, c_2, c_3, c_4, c_5, c_6)$, the overall performance of the network is

$$P = w_1 c_1 + w_2 c_2 + w_3 c_3 + w_4 c_4 + w_5 c_5 + w_6 c_6 \,. \tag{7}$$

By calculating the performance values of all of the spectrum, the channel with the highest value will be selected for data communication.

VI. Prediction Cost

In a mobile CRN, the proposed mobility management scheme can bring remarkable performance improvements, but it may result in an additional cost when wrong prediction occurs. In this section, we use the network scenario as described in Fig. 1 for an example to analyze the prediction cost when a successful or failed prediction occurs in PBSM.

A. Average Time Consumption on Spectrum Discovery

1) Successful Prediction: Recall that in Fig. 1, $P_1 \to P_x \to P_2$ is the actual moving path of the target SU. If $P_2^{'}$ is predicted to be the future position of the SU, marginal prediction errors exist but it will not incur failed spectrum access, which we call a successful prediction. We use $Ha_c^s(t)$ to indicate the probability that the CBS let the SU to sense channel c and the sensed state is s (0 for *idle* and 1 for *busy*) in tth slot, $c = 1, 2, 3, 4$, $s = 0, 1$ and $t = 1, 2, 3, 4$.

1) When $t = 1$

For channel 1,

$$Ha_1^0 (1) = (1 - P) A \tag{8}$$

$$Ha_1^1 (1) = P (1 - A) \tag{9}$$

$$Ha_1 (1) = Ha_1^0 (1) + Ha_1^1 (1) \,. \tag{10}$$

For channel $c = 2, 3, 4$,

$$Ha_c^0 (1) = (1 - Ha_{c-1} (1)) (1 - P) A \tag{11}$$

$$Ha_c^1 (1) = (1 - Ha_{c-1} (1)) P (1 - A) \tag{12}$$

$$Ha_c (1) = Ha_c^0 (1) + Ha_c^1 (1) \,. \tag{13}$$

2) When $t = 2, 3, 4$, for channel $c = t, \ldots, 4$,

$$Ha_c^0 (t) = \left(\sum_{i=t-1}^{c-1} Ha_i^1 (t-1) - \sum_{j=t}^{c-1} Ha_j (t) \right) (1 - P) A \tag{14}$$

$$Ha_c^1 (t) = \left(\sum_{i=t-1}^{c-1} Ha_i^1 (t-1) - \sum_{j=t}^{c-1} Ha_j (t) \right) P (1 - A) \tag{15}$$

$$Ha_c (t) = Ha_c^0 (t) + Ha_c^1 (t) \,. \tag{16}$$

3) Then, the average time consumption of spectrum discovery Ta is

$$Ta = \sum_{i=1}^{4} \left(i \cdot \left(\sum_{j=i}^{4} Ha_j^0 (i) \right) \right). \tag{17}$$

2) Failed Prediction: In this scenario, if an SU is predicted to move from P_x to $P_2^{''}$ instead of P_2. The bias between the predicted location and the real position may cause errors in the prediction of channel status, which we call a failed prediction. We use $Hb_c^s(t)$ to indicate the event that the CBS let the SU to sense channel c and the sensed state is s (0 for *idle* and 1 for *busy*) in the tth slot, $c = 1, 2, 3, 4$, $s = 0, 1$ and $t = 1, 2, 3, 4, 5$.

1) When $t = 1$, for channel $c = 1, \ldots, 4$,

$$Hb_c^0 (1) = \left(Ha_c^0 (1) \right)^2 . \tag{18}$$

2) When $t = 2$, for channel $c = 1, \ldots, 4$,

$$Hb_c^0 (2) = \left(1 - Ha_c^0 (1) \right) * Ha_c^0 (1) \,, \tag{19}$$

$$Hb_c^1 (2) = Ha_c^1 (1) \,, \tag{20}$$

$$Hb_c (2) = Hb_c^0 (2) + Hb_c^1 (2) \,. \tag{21}$$

3) When $t = 3, 4, 5$, for channel $c = t - 1, \ldots, 4$,

$$Hb_c^0 (t) = \left(\sum_{i=t-2}^{c-1} Hb_i^1 (t-1) - \sum_{j=t-1}^{c-1} Hb_j (t) \right) (1 - P) A \tag{22}$$

$$Hb_c^1 (t) = \left(\sum_{i=t-2}^{c-1} Hb_i^1 (t-1) - \sum_{j=t-1}^{c-1} Hb_j (t) \right) P (1 - A) \tag{23}$$

$$Hb_c (t) = Hb_c^0 (t) + Hb_c^1 (t) \,. \tag{24}$$

4) Then, the average time consumption of spectrum discovery Tb is

$$Tb = \sum_{i=1}^{5} \left(i \cdot \left(\sum_{j=i}^{5} Hb_j^0 (i) \right) \right). \tag{25}$$

Ta and Tb indicate the average time consumption in the period of spectrum discovery when the successful and failed prediction occur, respectively. Comparing (17) and (25), we come to a conclusion that failed prediction consumes more time to discover available spectrum.

B. Theoretical Analysis of Prediction Cost

In order to evaluate the influence of prediction failures on the spectrum management, the prediction cost is measured as follows. We define that cost comes from three sources as shown follows.

1) Mobility Prediction Failure: Cost + 1.
2) Spectrum Prediction Failure: Cost + 1.
3) No Connection: Cost + 1.

The theoretical analysis of the prediction cost is presented as follows. We use N to indicate the total slots number in the simulation. The average interval between two neighboring prediction is denoted by I and handoff delay is presented as D. A_s and A_m indicate the prediction accuracy of spectrum and user mobility, respectively. The estimation formula of prediction cost in different conditions is listed as follows.

1) Mobility Prediction is right AND Spectrum prediction is wrong,
   $\text{Cost}_1 = \alpha A_m(1 - A_s)ND/I$.
2) Mobility Prediction is wrong AND Spectrum prediction is right,
   $\text{Cost}_2 = \beta A_s(1 - A_m)ND/I$.
3) Mobility Prediction is wrong AND Spectrum prediction is wrong,
   $\text{Cost}_3 = \gamma(1 - A_s)(1 - A_m)ND/I$

where α, β, and γ are used to indicate the possibility of no connection in their corresponding condition. Overall prediction cost is the sum of Cost_1, Cost_2, and Cost_3. Please note that it is difficult to get a value of these weights using theoretical analysis. Therefore, in Section VII-D, simulation results on prediction cost will be presented and analyzed using these cost formulas.

VII. Simulation Results

In this section, we carry out extensive simulations to evaluate the proposed spectrum management scheme in terms of the accuracy of spectrum predictions, the efficiency of spectrum utilization, and prediction costs.

In the simulation, we consider the whole spectrum of 500 Mb/s, which is evenly divided into five subchannels for data communication. Note that the common control channel that is used for the coordination between CBS and SUs is separated from the data channel. In the network, we have three licensed PUs, the location and channel occupation of which are illustrated in Fig. 1. Each PU has 10% chance to utilize the channel in the unit of slot. In order to evaluate the performance of PBSM in networks of difference size, we vary the number of SUs from 2 to 10. The SUs randomly move in a 400 by 400 m area. The CBS locates in the center of the network and can cover all SUs in the whole region. We set the spectrum sensing interval of SUs as three slots and the handoff delay as one slot.

A. Performance Comparison on Spectrum Prediction

In this section, we first evaluate the accuracy of the advanced H^2BMM and H^2BMM on spectrum prediction and show the results in Fig. 5. Prediction accuracy is defined as the ratio of correct spectrum prediction.

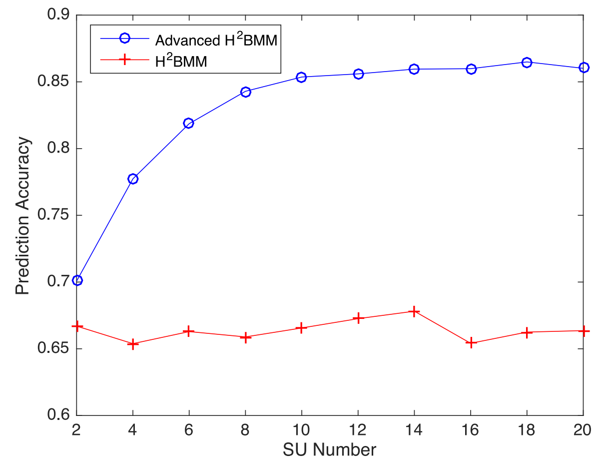

Fig. 5. Prediction accuracy of H^2BMM and advanced H^2BMM.

PBSM adopts the centralized spectrum sensing, where the CBS collects the sensing results from multiple SUs. In contrast, in the H^2BMM, each SU detects the PU individually and performs spectrum prediction relying on local sensing result. When a mobile SU moves into the protected area of a PU, both the advanced H^2BMM and H^2BMM can update their training matrix based on the new sensing result so that the prediction model can adapt to the new spectrum environment timely. However, as demonstrated in Fig. 5, their prediction accuracies have significant differences. The advanced H^2BMM in PBSM achieves higher prediction accuracy than the H^2BMM benefiting from the centralized spectrum sensing on the CBS. The increased number of SUs sending the sensing data to the CBS brings better training on the matrix of H^2BMM and improves the prediction accuracy, as illustrated in Fig. 5. By contrast, for H^2BMM, the increased number of SUs has no evidential impact on the prediction accuracy since each SU conducts the spectrum sensing and prediction independently. The prediction accuracy of H^2BMM, therefore, is much lower than that of the advanced H^2BMM in PBSM in a mobile CRN environment.

B. M-AHP and GRA-Based Channel Selection

This section assesses the performance of the proposed spectrum selection method, i.e., the hybrid of M-AHP and GRA algorithm, in terms of handoff times and bandwidth utilization.

The ping-pang effect is a phenomenon of frequent spectrum handoffs occurred in the intersection of two cells. The superfluous handoffs not only degrade the spectrum utilization but also affect the stability of communication links in a CRN. Therefore, in this simulation, we only take the SUs inside the intersection area of PUs to evaluate the impact of ping-pang effect on the channel selection. In Section V-A, we have introduced the M-AHP judgment matrix. The value of each component in the judgment matrix of M-AHP, JM_{MAHP}, is assigned as follows

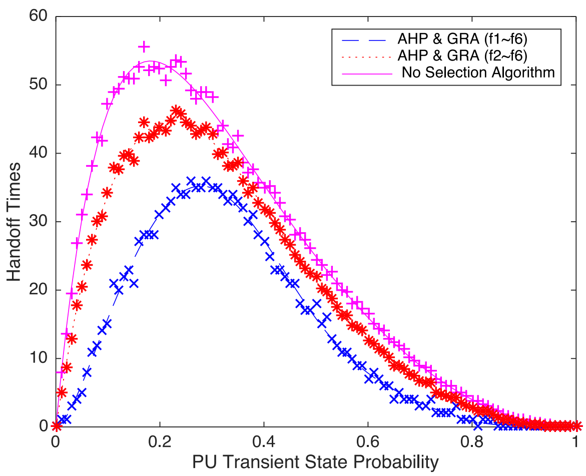

Fig. 6. Handoff time of different channel selection algorithms changes along with PU transient state probability. M-AHP and GRA ($f1 \sim f6$); M-AHP and GRA ($f2 \sim f6$); and random selection.

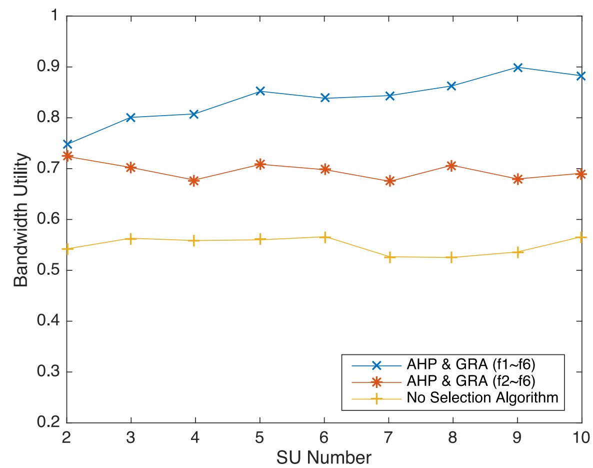

Fig. 7. Users satisfaction of different channel selection algorithms changes along with the number of SUs.

according to our subjective preference:

$$\mathrm{JM_{MAHP}} = \begin{array}{c@{}c} \begin{array}{cccccc} f1 & f2 & f3 & f4 & f5 & f6 \end{array} & \\ \begin{bmatrix} 1 & 3 & 5 & 7 & 5 & 5 \\ 1/3 & 1 & 2 & 2 & 2 & 2 \\ 1/5 & 1/2 & 1 & 2 & 1 & 1 \\ 1/7 & 1/2 & 1/2 & 1 & 1/2 & 1/2 \\ 1/5 & 1/2 & 1 & 2 & 1 & 1 \\ 1/5 & 1/2 & 1 & 2 & 1 & 1 \end{bmatrix} & \begin{array}{c} f1 \\ f2 \\ f3 \\ f4 \\ f5 \\ f6 \end{array} \end{array}. \quad (26)$$

Each element of this matrix represents the relative importance between factors. For example, the second element in the first row of the judgment matrix, i.e., integer 3, indicates that factor $f1$ is slightly more important than factor $f2$. Then, the eigenvector according to the maximum eigenvalue of judgment matrix is $(-0.8861, -0.3195, -0.1829, -0.1109, -0.1829, -0.1829)'$. This eigenvector is normalized to derive the weight vector of M-AHP

$$w' = (0.4750, 0.1713, 0.0981, 0.0595, 0.0981, 0.0981)'. \quad (27)$$

The values in the weight vector represent the weights of factors, that is, the weight of $f1$ to $f6$ is 47.50%, 17.13%, 9.81%, 5.95%, and 9.81%, respectively. We sort the factors in the descending order of the weight values and get $f1$, $f2$, $f3$, $f5$, $f6$, $f4$.

We compare the M-AHP and GRA-based channel selection algorithm with and without factor $f1$. The handoff delay with varying transient state probability of PU is depicted in Fig. 6. As demonstrated in Fig. 6, the hybrid weighted algorithm proposed in this paper can significantly reduce the handoff delay since the channel availability indicates a longer residence time at each channel. The three lines in this figure have the similar trend. At first, handoff times increase along with the increase of PU transient state probability because the spectrum environment becomes more and more variable. However, the handoff times start to decline when PU transient state probability continues to increase. This is because when the environment becomes less stable for SUs to find a stable channel, a handoff should not be conducted.

Second, we evaluate the users' satisfaction which is determined by the influence factors $f1 \sim f6$. We use $u_i (0 \le u_i \le 1)$ to indicate the utility value of factor fi, where "0" and "1" indicate that the worst and the best value of the factor, respectively. The overall utility value $u(0 \le u \le 1)$ is the average of $u_i (1 \le i \le 6)$. The comparison of users' satisfaction is shown in Fig. 7.

Users' satisfaction reflects the communication quality including the link stability. A high utility value indicates a high satisfaction. For a traditional selection algorithm, QoSs ($f2 \sim f6$) are the main effect factors, but the side effect is frequent handoffs [35]. After adding the channel availability $f1$ in this paper, we can reduce the handoff delay and hence improve user's satisfaction. As shown in Fig. 7, with the consideration of factor $f1$, remarkable improvement of users' satisfaction is achieved, especially with a large number of SUs, e.g., 10.

C. Performance Comparison on Mobility Prediction

In this section, we evaluate the performance of the mobility prediction algorithm in PBSM. The mobility prediction schemes used for comparison are listed as follows

1) UMP (User mobility prediction only scheme): In this scheme, there is no spectrum prediction process and the CBS only predicts user mobility. If an SU is predicted to approach a PU, it will avoid to access channels belonging to this PU and search for other available channels in advance.
2) SP (Spectrum prediction only scheme): In this scheme, no user mobility prediction process is involved and the CBS is responsible for predicting spectrum status. The SU decides whether or not to switch to other available channel based only upon the channel status predicted in advance.
3) UMP & SP: Joint user mobility and spectrum prediction scheme, which is the proposed scheme used in PBSM. The

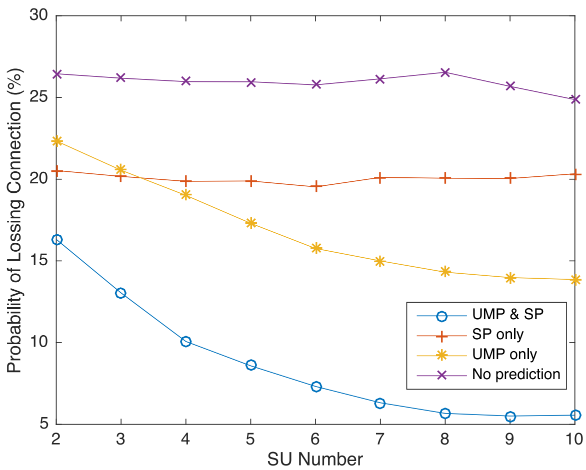

Fig. 8. Probability of no connection for different spectrum management schemes changes along with the SU number.

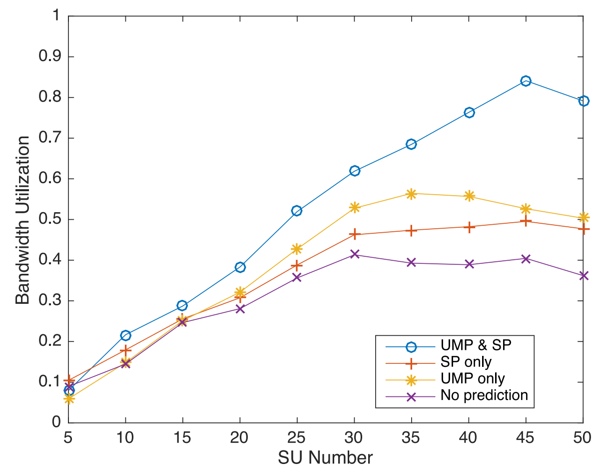

Fig. 9. Bandwidth utilization of different spectrum management scheme changes along with the number of SUs.

CBS predicts both user mobility and spectrum availability, from which the CBS recommends available channels to SUs.

4) No prediction: In this scheme, SUs have no knowledge of future user mobility or spectrum status. The SU exit the current channel immediately and search for other available channels when it senses the appearance of PU in the current channel.

The probability of losing connection (PLC) is defined to indicate the ratio of no connection time to whole simulation time. PLC is an important indicator to evaluate communication quality and channel utilization. Low PLC means a stable communication link and a low degree of communication degradation. On the contrary, high PLC means a poor QoS and low channel utilization. Results of PLC for four different schemes are depicted in Fig. 8.

In general, UMP has a lower PLC than SP because UMP conducts handoff before entering PUs' interference region. Spectrum prediction requires powerful computing and storage capabilities, but in the SP only scheme, the SU has to depend on itself to obtain the knowledge about future spectrum status, which means that the SP only scheme is not applicable to a user-mobile environment. However, when the number of SUs is less than three, SP has lower PLC than UMP because the CBS cannot gather sufficient training data from SUs to model and predict the user mobility. The joint UMP & SP scheme takes the advantage of both UMP and SP and the CBS obtains a sufficient information to conduct spectrum and user mobility prediction. Therefore, it is reasonable for the joint UMP & SP scheme to reach the lowest PLC. For both the joint UMP & SP and UMP only schemes, a larger number of SUs bring a lower PLC because more SUs are helpful for the CBS to receive enough training data to obtain high prediction accuracy.

Another important indicator of CRNs is the bandwidth utilization, which is evaluated as well. Five channels are assumed in the spectrum pool and each channel has 100 Mb/s bandwidth. The channel utilization at PU side is around 10%; the frequency band occupied by each SU is 10 MkHz. Therefore, the network allows up to 45 SUs to communicate simultaneously. The comparison of channel utilization amongst different approaches is shown in Fig. 9.

In simulation, we assume the average bandwidth utilization of PUs is around 10%. Ideally, the SUs achieve the highest channel utilization if SUs perform perfect spectrum sensing and utilize the channel whenever it is idle. Therefore, the maximum theoretical bandwidth utilization of SUs is around 90%. As we can see from Fig. 9, our proposed spectrum management scheme can achieve about 82% bandwidth utilization. For other three schemes, SP only, UMP only, and no prediction, the maximum utilization is around 50%. We increase the network size to 50 to investigate the trend of bandwidth utilization with varying number of SUs. When the number of SUs is less than 20, four schemes exhibit a similar performance because spectrum resource is enough to accommodate all SUs and spectrum competition is relatively mild. When the number of SUs continues to increase, spectrum competition becomes intense and SUs spend more time on spectrum searching. However, with the PBSM scheme, each SU can find its best channel with least conflicts with other SUs.

D. Evaluation on Prediction Cost

Prediction cost indicates the cost to CRN system resulted from the errors in spectrum and mobility prediction. In Section VI, we have analyzed the influence of prediction failure to the cost value theoretically. In this section, the prediction cost under different prediction accuracy conditions are evaluated and results are shown in Fig. 10. From Fig. 10, we observe a positive correlation between the prediction cost and prediction inaccuracy. The increase of spectrum prediction error or mobility prediction error both bring a rise of the cost. In order to better observe the trend of the prediction cost, we fix the spectrum accuracy and plot the influence of mobility prediction, as shown in Fig. 10(a). Similarly, we also fix the mobility accuracy and investigate the influence of spectrum prediction, as shown in Fig. 10(b).

In each subfigure of Fig. 10, four lines demonstrate four different levels of spectrum or user mobility prediction accuracy.

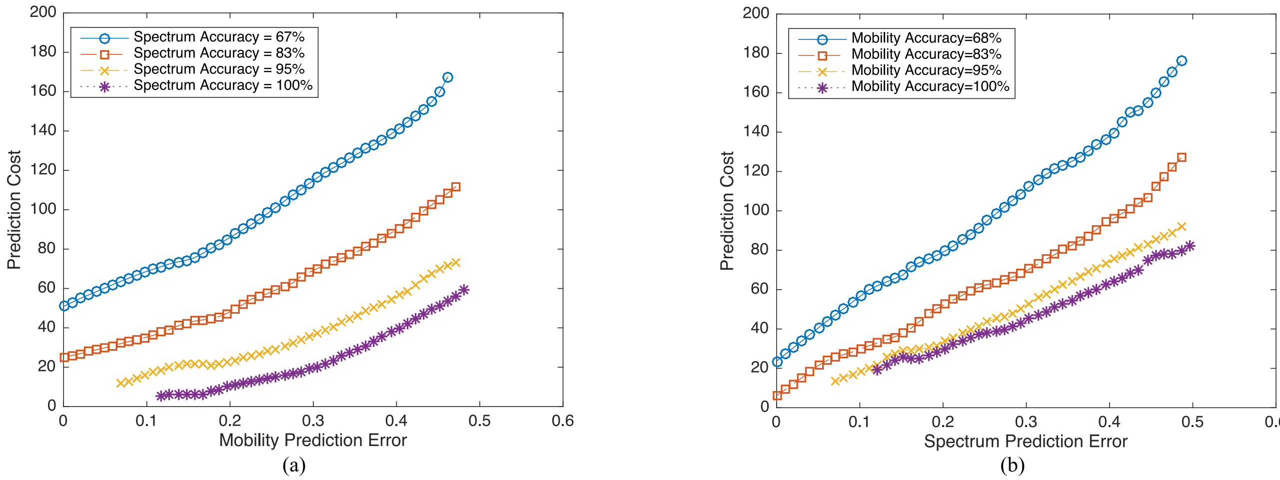

Fig. 10. Prediction cost of different spectrum management scheme changes along with prediction accuracy. (a) Prediction cost versus mobility prediction accuracy with fixed spectrum prediction accuracy. (b) Prediction cost versus spectrum prediction accuracy with fixed mobility prediction accuracy.

Note that prediction accuracy is almost impossible to approach 100% and the line with 100% accuracy is drawn under a special condition. The other three lines are generated from different prediction methods. Comparing these four lines, we draw a conclusion that a low prediction cost is obtained when the prediction accuracy is high. In Section VII-C, we have proved that a high spectrum prediction accuracy is achieved given a low transient state probability. Similarly, a high user mobility prediction accuracy is achieved with less unexpected motions of SUs. Therefore, under normal cases where transient state probability is low and unexpected motions of SUs are less, our prediction method will bring a high-performance improvement with a relatively low cost.

From the above analysis, we can also infer that the accuracy of spectrum prediction has a heavier impact on the cost than that of mobility prediction. The reason behind is that the failure of spectrum prediction is more prone to cause a lost connection compared with a wrong mobility prediction. For example, if the SU is moving away from any PU now, even if the SU fails to predict its mobility, spectrum prediction is still valid. When the number of SU increases sufficiently, spectrum prediction accuracy and mobility prediction accuracy are expected to impact equally on the cost.

VIII. Conclusion

In this paper, we have proposed a novel PBSM scheme, which integrated H^2BMM-based spectrum prediction, high-order Markov model-based user mobility prediction, and the hybrid of M-AHP and GRA-based weighted channel selection. This integration brings an accuracy prediction on channel status with a relatively low computational complexity. Based on prediction results, the CBS is capable of suggesting high-quality channels to SUs in a timely manner. Simulation results have verified significant performance improvements of PBSM on spectrum utilization by reducing handoff times and mitigating the probability of losing connection. As future work, we plan to evaluate the proposed PBSM scheme in a real spectrum environment rather than a simulation environment. Besides, we will focus on energy saving and secure communication to further improve the performance of the spectrum management scheme.

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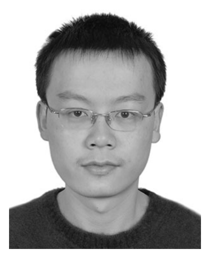

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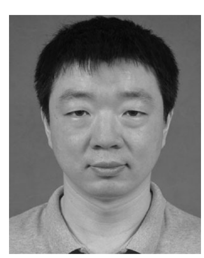

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