Predictive Spectrum Access for Multimedia Users over Multi-Channel Wireless Networks

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Abstract **–In this paper, we study how users in a multi-channel wireless network can select frequency channels in a distributed and autonomous manner for transmitting their multimedia data such that their utilities (multimedia qualities) are maximized. In the multi-user network, the users' transmission actions (the channel selection) are coupled by their mutual interference. However, most of the current channel selection solutions respond myopically to the aggregate interference experienced in each frequency channel. Instead, it is important to develop accurate prediction models which enable multimedia users to predict the interference from the other users and, based on the models, foresightedly optimize their decisions to maximize multimedia qualities. Such foresighted decision making is crucial for multimedia users, since they care more about long-term multimedia qualities rather than instantaneous throughput. In this paper, we discuss two multi-user interaction scenarios – non-collaborative and collaborative communication. In the non-collaborative scenario, users adapt the prediction models to maximize their own utilities. In the collaborative setting, users cooperatively maximize the same system utility (e.g. the sum of users' utilities). A user needs to decide in which setting (collaborative or non-collaborative) it should operate, and which models it should use to predict the response of the other users, such that its own utility is maximized. We show that whether a user obtains a performance gain or experiences performance degradation depends on the prediction models adopted by the other users in different interaction settings. Therefore, to maximize its own multimedia quality, a user needs to adapt its prediction model depending on the models adopted by the other users. Hence, we propose an adaptive algorithm for the multimedia users to determine their prediction models that outperform the conventional channel selection schemes in the multi-channel wireless networks.**

Index Terms **–multi-user spectrum access, multimedia users, autonomous decision making, collaborative and non-collaborative interaction**

I. INTRODUCTION

Multi-user spectrum access is an important problem in multi-channel wireless networks [1][2], where users compete for the limited spectrum resources to transmit their applications. The majority of this research focuses on centralized settings [3][4], where the spectrum is allocated by a central moderator (e.g. an access point or a base station), which gathers information from all the users and makes spectrum allocation decisions for each of them. These centralized approaches are able to provide Pareto efficient allocations in the utility (e.g. multimedia quality) domain [4][5]. However, such centralized approaches can have two limitations that make them undesirable for practical implementations. First, the centralized approaches are usually very complicated and potentially inefficient, especially when users possess various utilities for the multimedia applications which have various traffic characteristics (e.g. required bit rates, delay deadlines, etc.). This disadvantage of centralized solutions further intensifies as the number of users and frequency channels increase. Secondly, due to the informationally decentralized nature of the wireless network, it is impractical to assume that all the users' information and the time-varying application requirements can be relayed to the central moderator in a timely manner. To cope with this, distributed suboptimal solutions that adapt the transmission strategies based on well-designed localized information exchanges among users should be adopted for the multimedia applications [28][29].

Hence, in this paper, we focus on decentralized solutions, where users autonomously make their own spectrum access decisions based on locally gathered information [7]-[12]. For instance, an interference minimization algorithm for users to access the frequency channels in the multi-channel networks was proposed [7]. These users individually measure the signal power in each channel and select the frequency channel that contains the minimum energy. In [8], the authors proposed heuristic channel selection strategies where users select the previously available channel for data transmission. Local bargaining solutions were studied in [9], where users self-organize into bargaining groups with their neighbors, and adaptively negotiate the spectrum division. The negotiation and coordination schemes for users to access the spectrum in a collaborative manner were studied in [10] and [11]. These prior works allow the users to coordinate with others and locally negotiate the spectrum access. However, in these decentralized solutions, users only respond to a measurement of the aggregate interference without predicting the channel selection strategies of the other users. Such myopic decisions may result in a significant performance degradation compared to the centralized solutions [12].

An important issue for these decentralized approaches is that the users' transmission actions are coupled, i.e. a user's channel selection impacts and is impacted by the channel selection of the other users in the network. Hence, it is important to develop an appropriate prediction model for wireless users to predict the

Manuscript received February 27, 2009; revised June 23, 2009; accepted August 19, 2009

doi:10.4304/jcm.4.9.640-653

channel selection of the other users [16][17]. In this paper, we study how the performances of *autonomous multimedia users* can be improved by adopting models that predict the channel selection strategies of the other users. To the best of our knowledge, the advantages of such predictive spectrum access for autonomous multimedia users have not been addressed yet. We assume a simple interference model, where users cannot use the same frequency channel at the same time. Specifically, a user selects the optimal frequency channel to transmit its traffic based on the prediction of the other users' transmission strategies (i.e. the expectation of the other users' channel selection). Based on these prediction models, users are able to select the frequency channels to maximize their resulting multimedia qualities.

The goal of the paper is to study how a multimedia user can maximize its own utilities by adapting prediction models in different interaction settings, which is illustrated in Figure 1. We show that the performance of a user depends on the prediction models adopted by the other users in different interaction settings. This is because these prediction models can lead to different channel selection strategies (i.e. decisions by its competing users), which influence the resulting multimedia qualities. Hence, the prediction model that a user should adopt also depends on the prediction models adopted by the other users.

Importantly, different prediction models can have different complexities and lead to different prediction accuracies and various application performances in different interaction settings. In this paper, we define two classes of users. One class is the myopic users, who select the frequency channels by myopically responding to the aggregate interference to maximize their current utilities, as in [8][12]. The other class is the foresighted users, who adopt various prediction models for channel selection, as in [15][16]. Based on the composition of these two classes of users, we investigate the interaction among users when there are different numbers of foresighted users in the wireless networks. We propose a metric based on the Kullback-Leibler Distance (KL distance) [22] to evaluate the prediction accuracy of the prediction models. We show that in the non-collaborative setting, if only one user is foresighted, a complex prediction model should be deployed by a user, since it provides more accurate prediction of other users' actions. Alternatively, if multiple users are foresighted and deploy complex prediction models for selecting their actions, all participating users can experience significant performance degradation, because they cannot accurately predict each others' actions. Hence, in this case, simple prediction models, which are easily inferred by other users, are desirable. On the other hand, in the collaborative setting, since the foresighted users are having a common system utility, the performance can reach the Pareto boundary in the utility domain for these foresighted users [17]. However, when there are also myopic users in the network, maximizing the sum of utilities is not the optimal choice for these

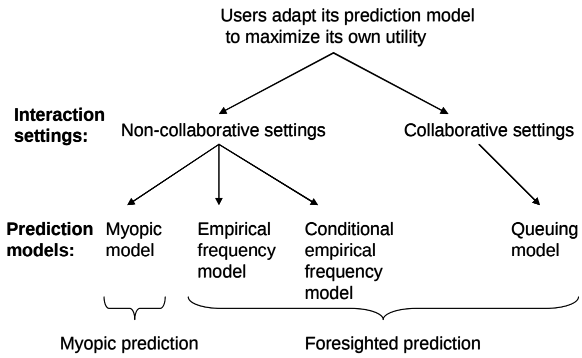

Fig. 1. Users' selections of the interaction settings and the prediction models.

foresighted multimedia users. Hence, we propose an adaptive algorithm to determine what prediction models an autonomous multimedia user should adopt according to different user interaction scenarios.

The contributions of this paper are listed as follows:

- **Predictive spectrum access framework for autonomous multimedia users.**
  We propose the predictive spectrum access framework for multimedia users to model the other users' channel selection strategies. By using these prediction models, users are able to select their frequency channels to transmit multimedia applications in a foresighted manner.
- **Comparisons of various prediction models in the collaborative or non-collaborative setting.**
  We analyze the performance of various prediction models in the two interaction settings. We compare these prediction models in terms of the size of memory used for the prediction results as well as the computational complexity. We show the pros and cons by analyzing each of the prediction models, which provide important insights that can guide the design of wireless spectrum access protocols for multimedia transmission.
- **Adaptive algorithm for selecting prediction models by foresighted users to maximize their multimedia qualities.**
  Based on the KL distance metric, we propose an adaptive algorithm for a foresighted multimedia user to determine which prediction model it should adopt to maximize its multimedia quality. Based on the selected model, foresighted users can determine which interaction scenarios they should deploy (collaborative or non-collaborative) and what model they should use for predicting other users' channel selection strategies.

This paper is organized as follows. In Section II, we present the adopted wireless multi-channel network setting and formulate the spectrum access problem for multimedia users. In Section III, we present our predictive spectrum access framework for users. We define various prediction models for users to model their competing users in different interaction settings. In Section IV, the performance of the prediction models for different number of foresighted users is analyzed. Based on the performance analysis, in Section V, we propose an

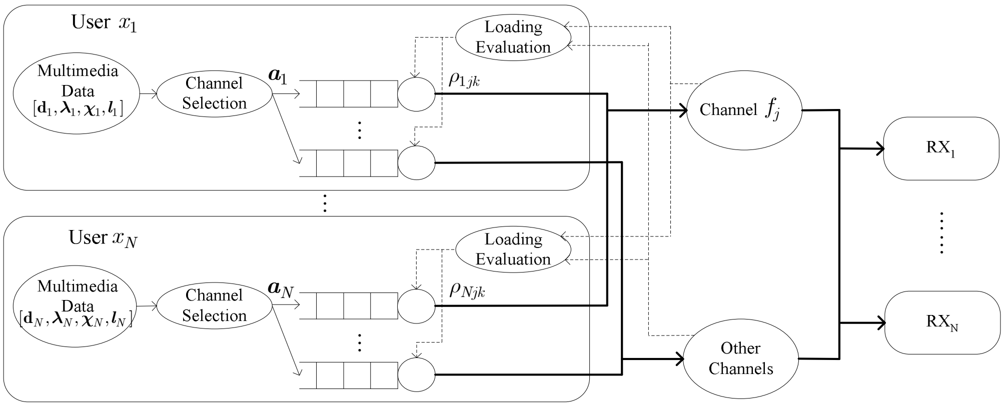

Fig. 2. Queuing model of multiple users sharing a wireless multi-channel network.

algorithm for multimedia users to adapt their prediction models and based on it, apply predictive distributed spectrum access to approach the performance of a centralized solution. Section VI gives the simulation results, and Section VII concludes the paper.

II. Problem Formulation

A. Considered network settings

We assume that there are N users $\{x_1,\ldots,x_N\}$ sharing the same wireless multi-channel networks. Each user is composed of a transmitter-receiver pair. The transmitters will select frequency channels to transmit their packets to the receivers. We assume that the multi-channel network has M traffic channels $\{f_1,\ldots,f_M\}$ as well as an additional control channel. The traffic channels are used for data transmission, while the control channel is used to enable users to exchange their information in order to coordinate with each other. Section III.*A* will discuss how users can coordinate with each other in more detail. If multiple users select the same frequency channel at the same time, we assume a distributed time sharing MAC protocol (e.g. ALOHA, Token Ring [24]) that coordinates the channel access of these users. Hence, these users can take turns to access the frequency channel. A user needs to wait for its turn to transmit the multimedia data. Once the user gets a transmission opportunity, it can transmit the multimedia data in its queue. More sophisticated MAC protocols can also be considered to deal with the spectrum heterogeneity (such as HD-MAC in [10]). Different MAC protocols will have different overheads including the time of waiting for the MAC acknowledgement, contention period, etc. that affect the experienced delays, which are crucial for multimedia transmission (such overheads are considered in Section III.*A*).

Importantly, these users are located at different locations and hence, a good frequency channel can be a poor frequency channel for another user, i.e. frequency channels are experienced differently by various users. Hence, users may prefer different frequency channels to transmit. We denote the experienced physical layer transmission rate and average packet error rate for user x_i in a frequency channel f_j as T_{ij} and p_{ij}, respectively. Moreover, these users also possess different application requirements, which will be discussed in Section II.*C*.

B. Actions and strategies

Figure 2 illustrates the considered multi-channel network and the queuing model for the users to evaluate their utilities and access the multi-channel network. User x_i first senses the frequency channels to check if there are other users accessing f_j before transmitting its packets. Subsequently, users estimate the "loading" already existing in each frequency channel (see Appendix). Based on the loading and the application requirements, user x_i can evaluate the packet loss rate and select an optimal strategy to transmit the packets to its receiver RX_i.

We denote the action of user x_i as a vector $\boldsymbol{a}_i = [a_{i1},\ldots,a_{ij},\ldots,a_{iM}] \in \mathcal{A}^M$ ($\mathcal{A} = \{0,1\}$), where $a_{ij} = 1$ indicates that x_i will transmit its packets using frequency channel f_j. Otherwise, $a_{ij} = 0$. Let $\boldsymbol{a}_{-i} = [a_{ij}] \in \mathcal{A}^{(N\text{-}1)\times M}$ denote the actions of the other users except x_i. Let $\mathbf{A}$ denote $[\boldsymbol{a}_1^T, \boldsymbol{a}_2^T,\ldots,\boldsymbol{a}_N^T] \in \mathcal{A}^{M\times N}$ as the overall action profile of all the users.

A strategy of a secondary user x_i is a vector of probabilities $\mathbf{s}_i = [s_{i1}, s_{i2},\ldots,s_{iM}] \in \mathcal{S}^M$, where $s_{ij} \in \mathcal{S}$ ($\mathcal{S} \in [0,1]$) represents the probability of the user x_i to take the action a_{ij} (i.e. to choose the frequency channel f_j). Hence, the summation over all the frequency channels is $\sum_{j=1}^{M} s_{ij} = 1$. Note that s_{ij} can also be viewed as the fraction of data from x_i transmitted on frequency channel f_j, and hence, multiple frequency channels are selected for a user with $s_{ij} > 0$. Also, let $\mathbf{s}_{-i} = [s_{ij}] \in \mathcal{S}^{(N\text{-}1)\times M}$ denote the strategies of the other users except x_i. Let $\mathbf{S} = [\mathbf{s}_1^T, \mathbf{s}_2^T,\ldots,\mathbf{s}_N^T] \in \mathcal{S}^{M\times N}$ denote the overall strategy profile across all the users.

C. Utilities of the multimedia users

We assume that the user x_i possesses K_i priority classes for its multimedia applications. Hence, there are $K = \sum_{i=1}^{N} K_i$ priority classes $C_1,...,C_K$ for all multimedia applications, where C_1 is assumed to have the highest priority and C_K the lowest priority. We assume that the traffic in the higher priority classes can preempt the transmission of the lower priority classes. Denote $\mathbf{C}_i$ as the set of priority classes that belong to the user x_i. The priority affects a user's ability to access the channel. The multimedia application of a user x_i can be characterized by the following parameters:

- $\boldsymbol{\chi}_i = [\chi_k, \text{ for } C_k \in \mathbf{C}_i]$: The quality impact factors of the application of x_i [14], where χ_k represents the quality impact for the packets in priority class C_k. The multimedia packets are prioritized based on this quality impact parameter, i.e. $\chi_1 \geq \chi_2 \geq ... \geq \chi_k \geq ... \geq \chi_K$.
- $\boldsymbol{\lambda}_i = [\lambda_k, \text{ for } C_k \in \mathbf{C}_i]$: The average packet arrival rates of the application of x_i, where λ_k represents the average packet arrival rate for priority class C_k.
- $\mathbf{d}_i = [d_k, \text{ for } C_k \in \mathbf{C}_i]$: The delay deadlines of the application of x_i, where d_k represents the packet delay deadline for the packets in priority class C_k. Packets will be regarded useless if they are received after this delay deadline.
- $\boldsymbol{l}_i = [l_k, \text{ for } C_k \in \mathbf{C}_i]$: The average packet lengths of the application of x_i, where l_k represents the average packet length for the packets in priority class C_k.

For multimedia applications, a packet in priority class C_k will be regarded useless if it misses its delay deadline d_k. This will result in significant quality degradation for such delay-sensitive applications. The utility of user x_i is defined as the probability that the packets can be successfully received by the receiver, i.e.

$$U_i(\mathbf{s}_i, \mathbf{s}_{-i}) = 1 - P_i(\mathbf{s}_i, \mathbf{s}_{-i}), \quad (1)$$

where $P_i(\mathbf{s}_i, \mathbf{s}_{-i})$ represents the packet loss rate of the most important priority class of user x_i. Based on the multimedia parameters $[\boldsymbol{\chi}_i, \boldsymbol{\lambda}_i, \mathbf{d}_i, \boldsymbol{l}_i]$, sophisticated multimedia quality models can be applied based on the packet loss rates (as in [14][29]). For simplicity, in this paper, we assume that each user intends to minimize the packet loss rate for the most important priority class of their applications, due to the content dependency characteristic of multimedia applications (as in [30]). The lower priority class traffic usually highly depends on the higher priority class traffic. Note that $U_i(\mathbf{s}_i, \mathbf{s}_{-i})$ is also a function of the other users' strategies $\mathbf{s}_{-i}$. The packet loss rate $P_i(\mathbf{s}_i, \mathbf{s}_{-i})$ can be calculated by:

$$P_i(\mathbf{s}_i, \mathbf{s}_{-i}) = \sum_{j=1}^{M} s_{ij} \mathrm{Prob}(D_{ij} > d_i), \quad (2)$$

where D_{ij} and d_i denotes the packet delay and the delay deadline of the highest priority class of the user x_i. Denote D_{jk} as a random variable of the packet delay (including the queuing delay and the transmission delay) for the packets in priority class C_k using a frequency channel f_j. The packet loss probability $\mathrm{Prob}(D_{ij} > d_i)$ is the same as $\mathrm{Prob}(D_{jk'} > d_{k'})$ if $C_{k'} \in \mathbf{C}_i$ and $\chi_{k'} = \max_{C_k \in \mathbf{C}_i} \chi_k$. The decentralized spectrum access problem can be formulated as:

$$\mathbf{s}_i^{opt} = \arg\max_{s_i \in \mathcal{S}_i} U_i(\mathbf{s}_i, \mathbf{s}_{-i}) = \arg\min_{s_i \in \mathcal{S}_i} P_i(\mathbf{s}_i, \mathbf{s}_{-i}), \ \forall x_i. \quad (3)$$

Throughout this paper, we discuss how x_i can model the strategies of the other users $\mathbf{s}_{-i}$ and select an optimal strategy $\mathbf{s}_i^{opt}$ to minimize this packet loss rate, and hence maximize its utility. In the Appendix, we will briefly present how to evaluate this packet loss rate $P_i(\mathbf{s}_i, \mathbf{s}_{-i})$, when the strategies $(\mathbf{s}_i, \mathbf{s}_{-i})$ are known using a queuing analysis similar to that presented in [14][18].

D. Predictive spectrum access framework

Although the strategies of the other users $\mathbf{s}_{-i}$ are necessary to solve equation (3) and determine the optimal spectrum access strategy for the users, they cannot be easily obtained in informationally-decentralized wireless networks. Conventionally, the users will measure some aggregate effects of other users' strategies on the utility, such as the aggregate interference in [12]. These autonomous users then myopically respond to these measurements. Such solutions are not efficient and lead to poor multimedia users' utilities (as shown in Table III of Section VI). Hence, we propose a predictive spectrum access framework for a multimedia user x_i to directly predict the strategies of the other users $\mathbf{s}_{-i}$ based on observed information about the other users and, based on it, determine its optimal spectrum access strategy $\mathbf{s}_i$. Let $\mathbf{B}_{-i}^t(Z_i, \mathcal{I}_i^{t-1}) \in \mathcal{S}^{(N-1)\times M}$ denote x_i 's prediction results (belief) on $\mathbf{s}_{-i}$ at time slot t. Note that the prediction results $\mathbf{B}_{-i}^t$ are based on the gathered information $\mathcal{I}_i^{t-1}$ at the previous time slot $t-1$ and the adopted prediction model Z_i. Then, equation (3) can be modified as:

$$\mathbf{s}_i^t(\mathbf{B}_{-i}^t(Z_i, \mathcal{I}_i^{t-1})) = \arg\min_{s_i \in \mathcal{S}_i} P_i(\mathbf{s}_i, \mathbf{B}_{-i}^t(Z_i, \mathcal{I}_i^{t-1})), \quad (4)$$

where $\mathbf{s}_i^t$ is the optimal strategy of x_i based on the prediction results $\mathbf{B}_{-i}^t(Z_i, \mathcal{I}_i^{t-1})$. Starting from an initial prediction results $\mathbf{B}_{-i}^0$, the strategies of the other users $\mathbf{s}_{-i}$ are modeled using the prediction model Z_i based on constantly gathered information $\mathcal{I}_i$. The predictive spectrum access procedure for user x_i is presented in Algorithm 1.

The performance of the predictive spectrum access procedure relies on how accurate the prediction results $\mathbf{B}_{-i}^t(Z_i, \mathcal{I}_i^{t-1})$ are. Surprisingly, this depends not only

Algorithm 1 The predictive spectrum access for user x_i with a fixed prediction model Z_i :

Step 1. Initialization: Set $\mathbf{B}_{-i}^0 = 1/M \times \mathbf{I}$, where $\mathbf{I}$ is an $(N-1)\times M$ matrix in which all the elements are 1.

Step 2. Gather the information: $\mathcal{I}_i^t$.

Step 3. Utility evaluation: Evaluate the utility for the highest priority class C_k of user x_i.

Step 4. Optimize the channel selection strategies: Use $\mathbf{B}_{-i}^t$ in equation (4) to optimize $\mathbf{s}_i^t$ that minimizes P_i and select an action $\boldsymbol{a}_i^t$ from the $\mathbf{s}_i^t$ for packet transmission.

Step 5. Update the prediction results: Set time slot $t := t+1$ and update $\mathbf{B}_{-i}^t$ using the prediction model Z_i and the available information $\mathcal{I}_i^{t-1}$.

on user x_i's prediction model Z_i, but also on the prediction models adopted by the other users in the network. In Section III, we will discuss how to construct these prediction models Z_i in order to build the prediction results $\mathbf{B}_{-i}^t(Z_i, \mathcal{I}_i^{t-1})$ as well as the required information for these models. Then, in Section IV, we will analyze the performance of these prediction models when different prediction models are adopted by the other users in the network.

III. Prediction Models in Various Interaction Settings

In the proposed predictive spectrum access framework, we endow the users with the ability to broadcast or exchange information with each other as in [14]. We also assume that users are truthfully declaring their information. Based on the gathered information $\mathcal{I}_i$, users build models of their competing users' spectrum access strategies and implement the model-based spectrum access in equation (4). We first discuss the required information in Section III.*A*, which also includes how frequently users need to gather this information. Then, we present the definitions of various prediction models in the two different interaction scenarios.

A. Required information for the prediction models

In order to evaluate the packet loss rate P_i and build models for the other users, a user needs to gather information about the other users. We classify the required information in the following two classes: the traffic information and the action information.

- **Traffic information**

The traffic information includes the parameters that characterize the application deployed by each user. Based on the traffic information, a user is able to construct its traffic specification as in [14] (similar to the TSPEC in current IEEE 802.11e [19] for multimedia transmission) and announce its traffic specification when it first joins the networks. The traffic specification for x_i is denoted as $\boldsymbol{TS}_i = [\mathbf{b}_i, \boldsymbol{l}_i, \mathbf{X}_i, \mathbf{X}_i^2]$, where $\mathbf{b}_i$ represents the required bit rates of each priority class of user x_i and l_i represents the average packet length. Assume $\mathbf{X}_i = [E[X_{ijk}], j = 1,...,M, \forall C_k \in \mathbf{C}_i]$ and $\mathbf{X}_i^2 = [E[X_{ijk}^2], j = 1,...,M, \forall C_k \in \mathbf{C}_i]$. Let $E[X_{ijk}]$ and $E[X_{ijk}^2]$ represent the first two moments of the packet transmission time for user x_i to transmit a packet in priority class C_k using the frequency channel f_j. From the $\boldsymbol{TS}_i$, the packet arrival rate is $\lambda_k = \dfrac{b_k}{l_k}$ for each priority class $C_k \in \mathbf{C}_i$. Each user retransmits the packets when the packets are not correctly received (as the ARQ protocol in [19][25]). Specifically, a packet will be retransmitted until it is correctly received or exceeds the application delay deadline. Hence, the packet transmission time X_{ij} (packet service time in Appendix) can be modeled as a geometric random variable. The first two moments of X_{ij} can be calculated as:

$$E[X_{ij}] = \frac{\hat{l}_i}{T_{ij}(1-p_{ij})}, \text{ and} \tag{5}$$

$$E[X_{ij}^2] = \frac{\hat{l}_i^2(1+p_{ij})}{T_{ij}^2(1-p_{ij})^2}. \tag{6}$$

$\hat{l}_i = l_i + l^o$ represents the effective packet length of the user x_i, where l^o represents the overhead including the traffic information exchange overheads and the overheads introduced by the MAC protocols. We denote $\boldsymbol{TS}_{-i}$ as the traffic specification of all the other users except the user x_i.

From equation (5) and (6), l^o costs additional transmission bandwidth for exchanging the traffic information. Importantly, since the traffic specification $\boldsymbol{TS}_i$ is assumed to stay unchanged for the duration of an application session, other users do not need to gather such traffic information often. This is important because it reduces the information exchange overhead significantly as shown in [14].

- **Action information**

In the considered multi-channel wireless networks, users can change their channel selection during every time slot. In this paper, we assume that the action information is observed at the beginning of every time slot, as in [14]. We denote the actions a_{ij} at the specific time slot t as a_{ij}^t. Similarly, $\boldsymbol{a}_i$ at time slot t are denoted as $\boldsymbol{a}_i^t$. Besides the traffic information, the required information for the predictive spectrum access at time slot t is defined as $\mathcal{I}_i^t = \{\boldsymbol{a}_{-i}^{\tau}, \tau = 1,...,t\}$. In the non-collaborative setting, such information is observed by every user through the control channel over time. In the collaborative setting, additional information is required

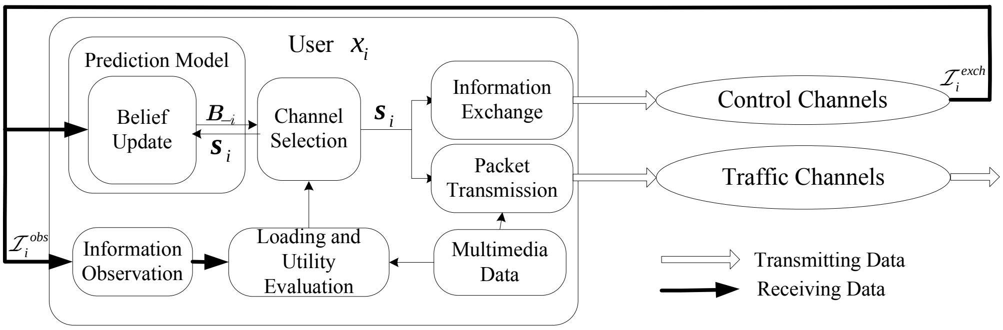

Fig. 3. Block diagram of the proposed predictive spectrum access framework.

and such information will be exchanged through the control channel as well, which will be discussed in Section III.*C*. In this paper, we refer generically to either observed information and exchanged information using this notation $\mathcal{I}_i^t$. Figure 3 provides a block diagram for the proposed predictive spectrum access framework.

B. Prediction models in the non-collaborative setting

In the non-collaborative setting, users gather the observed information $\mathcal{I}_i^t = \mathcal{I}_i^{t,obs} = \{\boldsymbol{a}_{-i}^\tau, \tau = 1,...,t\}$ and adopt the prediction models Z_i to maximize their own utilities U_i^{nc}. The optimization formulation is:

$$\mathbf{s}_i^t(Z_i, \mathcal{I}_i^{t-1}) = \arg\max_{s_i \in \mathcal{S}_i} U_i^{nc}(\mathbf{s}_i, Z_i, \mathcal{I}_i^{t-1}). \quad (7)$$

In this paper, we define the following three prediction models.

<u>Definition 1:</u> *Myopic Model (* $Z_i = MP$ *)*

In this model, user x_i does not predict the other users' actions. It myopically selects the best action based on the other users' actions it observed, i.e.

$$\mathbf{B}_{-i}^t(MP, \mathcal{I}_i^{t-1}) = \boldsymbol{a}_{-i}^{t-1}. \quad (8)$$

The resulting channel selection strategy in equation (4) is also called the myopic best response strategy, which is widely applied in current multi-user spectrum access solutions, such as in [8][12].

<u>Definition 2:</u> *Empirical Frequency Model (* $Z_i = EF$ *)*

By counting the empirical frequency of the other users' actions $\boldsymbol{a}_{-i}$ based on the gathered action information, x_i can derive the prediction results $\mathbf{B}_{-i}^t(EF, \mathcal{I}_i^{t-1})$ on $\mathbf{s}_{-i}$ at time slot t as:

$$\begin{aligned}\mathbf{B}_{-i}^t(EF, \mathcal{I}_i^{t-1}) &= \frac{1}{t-1}(\boldsymbol{a}_{-i}^1 + \boldsymbol{a}_{-i}^2 + ... + \boldsymbol{a}_{-i}^{t-1}) \\ &= \frac{1}{t-1}\cdot \boldsymbol{a}_{-i}^{t-1} + \frac{t-2}{t-1}\cdot \mathbf{B}_{-i}^{t-1}(EF, \mathcal{I}_i^{t-2})\end{aligned}. \quad (9)$$

Such prediction models are also termed fictitious play [23] in the multi-agent learning literature, which is applied in [14][15].

<u>Definition 3:</u> *Conditional Empirical Frequency Model (* $Z_i = CE$ *)*

From equation (3), we know that the packet loss rate $P_i(\mathbf{s}_i, \mathbf{s}_{-i})$ is also a function of other users' strategies. On the other hand, user x_i's action can also influence the packet loss rate of x_{-i} as well as their channel selection strategies $\mathbf{s}_{-i}$. Hence, to perform equation (4) using the conditional empirical frequency model, users count the empirical frequencies of other users' strategies conditioned on its own actions, i.e. instead of merely counting $\boldsymbol{a}_{-i}$ in the empirical frequency model, the users count $\boldsymbol{a}_{-i}(f_j)$ for each possible frequency channel f_j that it can select. The prediction results $[B_{-i}^t(CE, \mathcal{I}_i^{t-1}, f_j), \forall f_j] \in \mathcal{S}^{M\times(N-1)\times M}$ now become a vector of the prediction results $B_{-i}^t(CE, \mathcal{I}_i^{t-1}, f_j)$ for each frequency channel f_j. Each $B_{-i}^t(CE, \mathcal{I}_i^{t-1}, f_j)$ can be updated as follows:

$$B_{-i}^t(CE, \mathcal{I}_i^{t-1}, f_j) = \begin{cases}\frac{1}{t-1}\cdot \boldsymbol{a}_{-i}^{t-1} + \frac{t-2}{t-1}\cdot B_{-i}^{t-1}(CE, \mathcal{I}_i^{t-2}, f_j) \\ \quad , \text{ if } \boldsymbol{a}_i^{t-1} \text{ select } f_j \\ B_{-i}^{t-1}(CE, \mathcal{I}_i^{t-2}, f_j), \text{ otherwise}\end{cases}. \quad (10)$$

The conditional empirical frequency model considers both the empirical frequency calculation as well as the coupling effects among users and thus, creates a more sophisticated model than the empirical frequency model. The resulting prediction results of the other users' strategies become:

$$\begin{aligned}\mathbf{B}_{-i}^t(CE, \mathcal{I}_i^{t-1}) &= \mathbf{s}_i \bullet [B_{-i}^t(CE, \mathcal{I}_i^{t-1}, f_j), \forall f_j] \\ &= \sum_{j=1}^{M} s_{ij} \times B_{-i}^t(CE, \mathcal{I}_i^{t-1}, f_j)\end{aligned}. \quad (11)$$

where $\mathbf{s}_i \bullet [B_{-i}^t(CE, \mathcal{I}_i^{t-1}, f_j), \forall f_j]$ represents the inner product of the strategy vector $\mathbf{s}_i$ and the vector $[B_{-i}^t(CE, \mathcal{I}_i^{t-1}, f_j), \forall f_j]$ over different frequency channels. Hence, the resulting utility maximization becomes:

$$\begin{aligned}&\mathbf{s}_i^t(\mathbf{B}_{-i}^t(CE, \mathcal{I}_i^{t-1})) \\ &= \arg\max_{s_i \in \mathcal{S}_i} U_i^{nc}(\mathbf{s}_i, \mathbf{s}_i \bullet [B_{-i}^t(CE, \mathcal{I}_i^{t-1}, f_j), \forall f_j]),\end{aligned} \quad (12)$$

This prediction model is similar to the prediction model used in [16].

C. Prediction models in the collaborative setting

In the collaborative setting, users maximize a system utility $U^{tot} = F(U_1^{co},...,U_N^{co})$, which is a function of the users' utilities and U_i^{co} represents the utility of user x_i using the collaborative prediction model. The optimization formulation is:

$$\mathbf{s}_i^t(Z_i, \mathcal{I}_i^{t-1}) = \arg\max_{s_i \in \mathcal{S}_i} U^{tot}(\mathbf{s}_i, \mathbf{B}_{-i}^t(Z_i, \mathcal{I}_i^{t-1})) . \quad (13)$$

Importantly, although a user x_i maximizes the system utility, the user will only adopt this collaborative prediction model, if it can benefit in terms of utility (i.e. $U_i^{co} \geq U_i^{nc}$). The system utility is determined by the system designer or assigned by the communication protocols. A possible system utility can be the sum of the users' utilities, the max-min of the users' utilities or comply with the proportional fairness among users' utilities (as in [10]). In this paper, we assume that the system utility is the sum of the users' utilities. In order to do so, in addition to the mentioned traffic information $\boldsymbol{TS}_{-i}$ and the action information $\mathcal{I}_i^{t,obs} = \{\boldsymbol{a}_{-i}^{\tau}, \tau = 1,...,t\}$, users need also to exchange their applications' delay deadlines, i.e. $\mathcal{I}_i^{t,exch} = \{\mathbf{d}_i\}$ for evaluating other users' utilities. Based on the delay deadline information exchange, the expected delays $E[D_{ij}]$ at time t for user x_i to use frequency channel f_j as well as its utility U_i^{co} can be evaluated. Hence, all the queuing parameters are available through the information exchange to evaluate the utility function of each user (see Appendix). Hence, the required information now becomes $\mathcal{I}_i^t = \{\mathcal{I}_i^{t,obs}, \mathcal{I}_i^{t,exch}\}$.

Definition 4: Queuing Model ($Z_i = QM$)

In this model, user x_i not only evaluates its own utility used in equation (4), it also evaluates the utilities $U_{-i}(\mathbf{s}_i, \mathbf{s}_{-i})$ (packet loss rate $P_{-i}(\mathbf{s}_i, \mathbf{s}_{-i})$) of the other users based on $\mathcal{I}_i$. Then, instead of maximizing its own utility as in equation (4), a user x_i collaboratively maximizes the summation of the utilities, i.e.

$$\mathbf{s}_i^t(\mathbf{B}_{-i}^t(QM, \mathcal{I}_i^{t-1})) = \arg\max_{s_i \in \mathcal{S}_i} \sum_{i=1}^{N} U_i^{co}(\mathbf{s}_i, \mathbf{B}_{-i}^t(QM, \mathcal{I}_i^{t-1})) , \quad (14)$$

where the prediction results $\mathbf{B}_{-i}^t(QM, \mathcal{I}_i^{t-1})$ is updated by counting the empirical frequency of $\boldsymbol{a}_{-i}$:

$$\mathbf{B}_{-i}^t(QM, \mathcal{I}_i^{t-1}) = \frac{1}{t-1} \cdot \boldsymbol{a}_{-i}^{t-1} + \frac{t-2}{t-1} \cdot \mathbf{B}_{-i}^{t-1}(QM, \mathcal{I}_i^{t-2}) . \quad (15)$$

Note that all the above prediction models can be plugged into the Algorithm 1 to provide the corresponding prediction results $\mathbf{B}_{-i}^t(Z_i, \mathcal{I}_i^{t-1})$. Finally, we compare the differences of the four prediction models in Table I.

D. Convergence of the predictive spectrum access framework

If the other users adopt stationary channel selection strategies, i.e. $\mathbf{s}_{-i}$ is fixed, the prediction results $\mathbf{B}_{-i}^t(Z_i, \mathcal{I}_i^{t-1})$ will converge to $\mathbf{s}_{-i}$ over time. However, in a real network, all the other users dynamically optimize their channel selection strategies based on their own prediction models. In [5][6], it has been shown that when the myopic prediction model is performed by all the users, the considered problem can be regarded as a channel selection game that will converge to Nash equilibrium. By allowing the user x_i to make foresighted decisions, the game converges to the Stackelberg equilibrium [16] when the belief of the user x_i is correct. However, in a practical system, the user x_i can only build its belief based on the proposed prediction models, and the belief may not be perfect. Such interactions among users, which are based on the users' beliefs, are referred to as Bayesian games [23] and the associated equilibrium concept is the Bayesian or Bayesian Stackelberg equilibrium.

IV. Performance of the Prediction Models for Different Number of Foresighted Users

As discussed previously, in a multi-channel network, users can have different capabilities to model the other users, meaning that they may adopt different prediction models to predict the other users' transmission strategies. Some of the users have the ability to adopt high complexity prediction models, while some of the users are only capable of taking myopic best response strategies. However, as mentioned before, in the decentralized settings, the different prediction models adopted by a user can influence the decisions of its competing users. Hence, the prediction model a user should adopt also depends on the prediction models adopted by the other users in the various interaction settings. To address this issue, we define two classes of users. One class is the myopic users, who adopt the myopic model (selecting the frequency channels by myopically responding to the interference from the other users, as in [8][12]). The other class is the foresighted users, who adopt one of the other mentioned prediction models for channel selection. In this section, we investigate the performance of using the presented prediction models when different numbers of foresighted users exist in the multi-channel wireless networks.

A. Considered network compositions

A simple illustration of the interaction among users is shown in Figure 4. In this figure, we emphasize the interaction between a user x_i and the rest of the users x_{-i} with different prediction models. A foresighted user

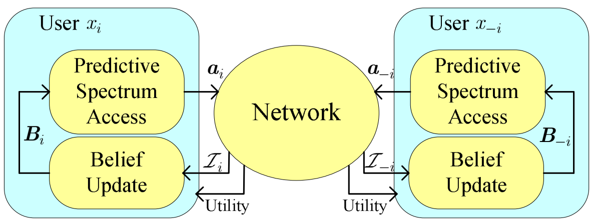

Fig. 4 . A simple illustration of the interaction among users.

can adopt three prediction models $Z_i = \{EF, CE, QM\}$ that perform prediction on other users' transmission strategies. A myopic user, on the other hand, can only adopt the myopic model $Z_i = MP$ that best responds to the current measurement of the other users' actions. Next, we discuss two extreme cases to analyze the performance when multimedia users adopt different prediction models.

- **Homogeneous network**

In common decentralized communication scenarios, users are usually assumed to adopt the same prediction model. To verify the performance in this scenario, we define the homogeneous network to construct an environment in which every user applies the same prediction model, i.e. both user x_i and users x_{-i} adopt the same prediction model $Z_i = \{MP, EF, CE, QM\}$. The concept of the homogeneous network was similarly adopted in [26].

Remark 1: When all the users take the same prediction model, the prediction accuracy will not increase as the complexity of the adopted prediction model increases (as shown in Section VI). In a non-collaborative setting, while users adopt the same prediction model $Z_i = \{MP, EF, CE\}$, the interaction leads to the Nash equilibrium [5][6].

Remark 2: In the collaborative setting when each user adopts the same collaborative prediction model $Z_i = QM$, all the users will maximize the same objective function in equation (14) and comply with the resulting spectrum access decisions. This collaborative interaction drives the optimization solution to the Pareto boundary in the utility domain, which can lead to a better overall performance than the Nash equilibrium [31].

- **SFU (Single-Foresighted-User) network**

In the SFU network, only one user is a foresighted user adopting a prediction model, while the remainder of the users are myopic users, i.e. they only take myopic best response strategies (see equation (8)). Such networks are also discussed in [16]. This scenario enables the performance evaluation of various prediction models a user can gain while the other users are myopic. Since all the other users are non-collaborative myopic users, if the foresighted user x_i adopts the collaborative prediction model, i.e. $Z_i = QM$, the performance of the user x_i will be even worse than merely taking a myopic best response strategy ($Z_i = MP$). This is because the utility function of user x_i is not directly maximized, while the other users x_{-i} always deploy their best response strategies. Hence, user x_i will only adopt the non-collaborative prediction model $Z_i = \{MP, EF, CE\}$. The rest of the users x_{-i} make myopic decisions using equation (4) with the myopic model $Z_i = MP$.

Remark 3: Since the other users x_{-i} adopt the same myopic model, the more complex model the user x_i adopts to model the other users, the more accurate the prediction results $\mathbf{B}_{-i}^t$ will be. Hence, if the user x_i adopts the non-collaborative prediction models, i.e. $Z_i = \{MP, EF, CE\}$, the more accurate prediction results $\mathbf{B}_{-i}^t$ will lead to a better performance (as shown in Section *V*.B). As shown in Section VI, the foresighted user using the conditional empirical frequency model has the most accurate prediction results $\mathbf{B}_{-i}^t$, since it counts the empirical frequencies of other users' strategies conditioned on its own actions.

Remark 4: The two presented networks are the two extreme cases in the sense of the number of foresighted users in the network. Denote the number of foresighted users in the network as L. The SFU network has $L = 1$, while the homogeneous network has $L = N$. A more general case when $1 < L < N$ will be discussed in Section VI.

B. Prediction accuracy analysis of prediction models

The utility metric in this paper, which is the packet loss rate $P_i(\mathrm{s}_i, \mathrm{s}_{-i})$ in equation (3), is a highly complex function. Therefore, it is impractical to evaluate the prediction models using the packet loss rate directly. In order to provide a practical performance comparison for the prediction models, we discuss the prediction accuracy as an alternative metric for evaluating the prediction models. To quantify the prediction accuracy, we adopt the KL distance [22] to represent the prediction accuracy. The KL distance is defined as:

$$Dist_i^t(\boldsymbol{a}_{-i}^t \parallel \mathbf{B}_{-i}^{t-1}) = \sum_m q_m \log \frac{q_m}{r_m}, \qquad (16)$$

where q_m and r_m represent the m^{th} entry in the $\boldsymbol{a}_{-i}^t$ and $\mathbf{B}_{-i}^{t-1}$ vectors, respectively. We then accumulate the KL distance $Dist_i^t(\boldsymbol{a}_{-i}^t \parallel \mathbf{B}_{-i}^{t-1})$ for K time slots, i.e.

$$\Delta_i^t = \sum_{k=0}^{K} e^{-\alpha k} \times Dist_i^{t-k}(\boldsymbol{a}_{-i}^{t-k} \parallel \mathbf{B}_{-i}^{t-k-1}), \qquad (17)$$

where $\alpha > 0$ represents the exponential decay rate for accumulating the KL distances of the previous time slots.

Claim 1: If the KL distance $\Delta_i^t > 0$, user x_i will experience performance degradation ΔU_i^t from the optimal performance $U_i^{opt} = \max_{s_i \in \mathcal{S}_i} U_i(\mathrm{s}_i, \mathrm{s}_{-i})$, i.e. $\Delta U_i^t > 0$, where

$$\Delta U_i^t \equiv U_i^{opt} - U_i(\mathbf{s}_i^t(\mathbf{B}_{-i}^t), \mathrm{s}_{-i}). \qquad (18)$$

Recall that $\mathbf{s}_i^t(\mathbf{B}_{-i}^t)$ is the adopted channel selection strategy of x_i in equation (4). $U_i(\mathbf{s}_i^t(\mathbf{B}_{-i}^t), \mathrm{s}_{-i})$ is the actual expected utility that user x_i will experience.

Proof: Since s_{-i} cannot be observed by the user x_i, it can only predict s_{-i} using the prediction results $\mathbf{B}_{-i}^t$. Note that the other users x_{-i} will select their actions $\boldsymbol{a}_{-i}^t$ according to their strategies s_{-i}. Hence, if the prediction results $\mathbf{B}_{-i}^t$ deviate from the strategies s_{-i},

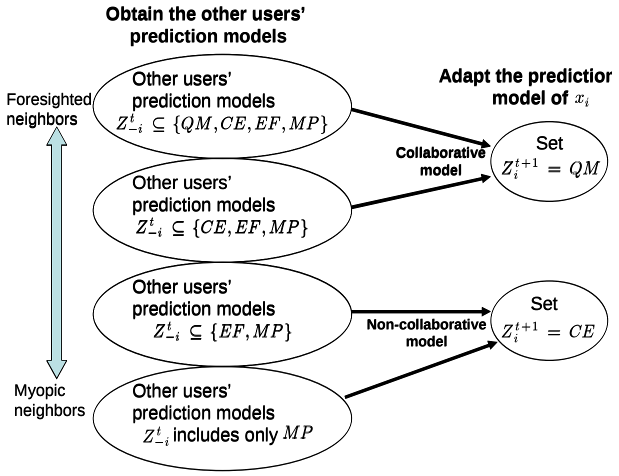

Fig. 5. Rules to adapt the prediction model in the proposed APM algorithm.

the KL distance $Dist_i^t(\boldsymbol{a}_{-i}^t \,||\, \mathbf{B}_{-i}^{t-1})$ will become positive and so will Δ_i^t. Once the prediction results $\mathbf{B}_{-i}^t$ deviate from the strategies $\mathbf{s}_{-i}$, $\mathbf{s}_i^t(\mathbf{B}_{-i}^t)$ will be different from $\mathbf{s}_i^{opt}$ (recall that $\mathbf{s}_i^{opt} = \arg\max_{s_i \in \mathcal{S}_i} U_i(\mathbf{s}_i, \mathbf{s}_{-i})$). Hence, the performance degradation ΔU_i^t will be positive.

<u>*Claim 2:*</u> The larger KL distance Δ_i^t results in a larger expected performance degradation $\Delta U_i = \sum_{t=1}^{T} \Delta U_i^t / T$.

<u>*Proof:*</u> The KL distance Δ_i^t is measured over time. The larger Δ_i^t means that the prediction results $\mathbf{B}_{-i}^t$ keep deviating from the strategies $\mathbf{s}_{-i}$. Due to Claim 1, the expected performance degradation ΔU_i will also be larger over time. Thus, the metric Δ_i^t measures the prediction accuracy of the prediction models and reflects the expected performance degradation ΔU_i.

V. Adaptive-Prediction-Model Algorithm for Foresighted Users

In this section, we present an algorithm for the foresighted users in the network to adapt their prediction models, such that these users are able to self-organize themselves to maximize their utilities. We call this adaptive algorithm the Adaptive-Prediction-Model (APM) spectrum access. Figure 5 illustrates the proposed rules for updating the new prediction model in APM algorithm. The algorithm starts with selecting the myopic model in Section III.*B* and then determining the new prediction model based on the prediction models Z_{-i}^t adopted by the other users in the networks. Hence, the required information $\mathcal{I}_i^{t,exch}$ in Section III needs to include Z_{-i}^t as well. The rules set the prediction model of user x_i to a non-collaborative prediction model $Z_i^{t+1} = CE$, when the other users are myopic, while set to a collaborative prediction model $Z_i^{t+1} = QM$, when

Algorithm 2: The APM spectrum access for user x_i that dynamically adapt prediction model Z_i^t

Step 1. Initialization: Set $Z_i^0 = MP$ and $\mathbf{B}_{-i}^0 = 1/M \times \mathbf{I}$, where $\mathbf{I}$ is an $(N-1) \times M$ matrix in which all the elements are 1.

Step 2. Gathers Traffic information: User x_i gathers traffic information $\boldsymbol{TS}_{-i}$ from other users.

Step 3. Gathers action information as well as the prediction model parameter: User x_i gathers its action information $\boldsymbol{a}_{-i}^t$ and the adopted prediction models Z_{-i}^t from other users.

Step 4. Update the prediction model: If $\Delta_i^t \le \theta_{th}$, keep the prediction model $Z_i^{t+1} = Z_i^t$. Otherwise, select a new model Z_i^{t+1} using the following rules:

If $Z_{-i}^t \subseteq \{CE, QM\}$ and QM is feasible for user x_i, then $Z_i^{t+1} = QM$.

Else if $Z_{-i}^t \subseteq \{MP, EF\}$ and CE is feasible for user x_i, then $Z_i^{t+1} = CE$.

Else if EF is feasible for user x_i, then $Z_i^{t+1} = EF$.

Else $Z_i^{t+1} = MP$.

Step 5. Predict the other users' strategies: Based on the required information $\mathcal{I}_i^t = \{\boldsymbol{TS}_{-i}, \boldsymbol{a}_{-i}^t\}$ and the selected prediction model Z_i^{t+1}, user x_i builds its prediction results $\mathbf{B}_{-i}^{t+1}(Z_i^{t+1}, \mathcal{I}_i^t)$ about the other users x_{-i} (using equation(8), (9), (10), (15), when $Z_i^{t+1} = MP, EF, CE, QM$, respectively).

Step 6. Utility evaluation: Evaluate the utility for the highest priority class C_k of user x_i.

Step 7. Optimize the channel selection strategy: User x_i then updates its strategy $\mathbf{s}_i^{t+1}(\mathbf{B}_{-i}^{t+1}(Z_i^{t+1}, \mathcal{I}_i^t))$ based on equation (4) for $Z_i^{t+1} = MP, EF, CE$. Otherwise, based on equation (14) for $Z_i^{t+1} = QM$.

Step 8. Select a frequency channel according to the strategy: User x_i selects its action $\boldsymbol{a}_i^{t+1}$ according to the strategy $\mathbf{s}_i^{t+1}(\mathbf{B}_{-i}^{t+1}(Z_i^{t+1}, \mathcal{I}_i^t))$.

Step 9. Set $t := t+1$. Go back to **Step 3**.

the other users are also foresighted. As later in Section VI, we will show that the performance of user x_i can be enhanced when adopting the prediction model $Z_i^{t+1} = CE$ and the other users in the network adopt the prediction model $Z_{-i}^t = \{MP, EF\}$. Importantly, if user x_i adopt the prediction model $Z_i^{t+1} = CE$, this will make the other users that also apply the APM algorithm to choose a collaborative prediction model $Z_i^{t+1} = QM$. This shows that in a homogeneous network, when all the foresighted users are able to adopt

$Z_i^{t+1} = QM$, the APM algorithm allows them to collaborate with each other in order to operate on the Pareto boundary.

By measuring the KL distance metric Δ_i^t presented in the previous section, we propose a predictive spectrum access algorithm that dynamically adapts the prediction model in Algorithm 2. Note that in the proposed algorithm, user x_i will select a new prediction model Z_i to predict the other users' transmission strategies once the measured Δ_i^t larger than a certain threshold θ_{th} (due to Claim 2). As the result, if all the prediction models are selectable, the algorithm has the following three properties:

1) If the other users x_{-i} cannot change their actions (or no other users exists in the network), the user x_i will continue using the MP model, since Δ_i^t will always be 0 (due to $\mathbf{B}_{-i}^t = \boldsymbol{a}_{-i}^t = \boldsymbol{a}_{-i}^{t-1}$). This allows user x_i to perform the best response strategy to maximize its own utility.

2) If the other users x_{-i} are myopic (i.e. they only adopt myopic best response strategies as in [8]), user x_i will try to adopt prediction models with high complexities as much as possible and hence, x_i is able to predict the other users' actions more accurately.

3) If the other users x_{-i} also have the capability to adopt high complexity prediction models, the user x_i will try to collaborate with these foresighted users by adopting the collaborative QM prediction model. When all the users in the network adopt the proposed algorithm, all the users will eventually change their prediction models from non-collaborative MP model to the collaborative QM model.

VI. SIMULATION RESULTS

We simulate a network with 25 users and 15 available frequency channels. We assume that all users stream the same video sequence ("Coastguard", frame rate of 30 fps, CIF format, delay deadline 500ms) compressed using a scalable video codec [27]. The average packet length l_i is 1000 bytes for all the users and the required bit rate b_i is ranging from 1 Mbps to 2Mbps. For each user x_i and frequency channel f_j , we assume that the physical transmission rate T_{ij} ranges from 2.5 to 5 Mbps. We define the network efficiencies in the simulations as the physical transmission rate T_{ij} (the higher transmission rate T_{ij} gives a multi-channel network with higher network efficiency) and we model the packet error rate p_{ij} using a dense probability mass function (PMF) centered at 0.1 shown in Figure 6. The simulation parameters are listed in Table II.

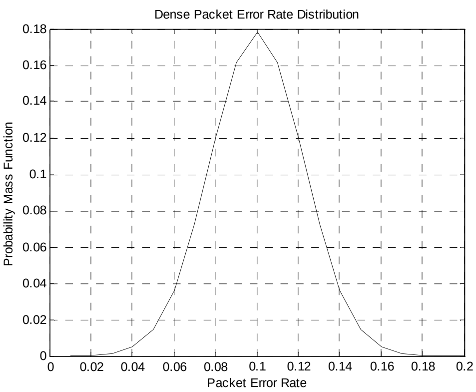

Fig. 6. Packet error rate distribution

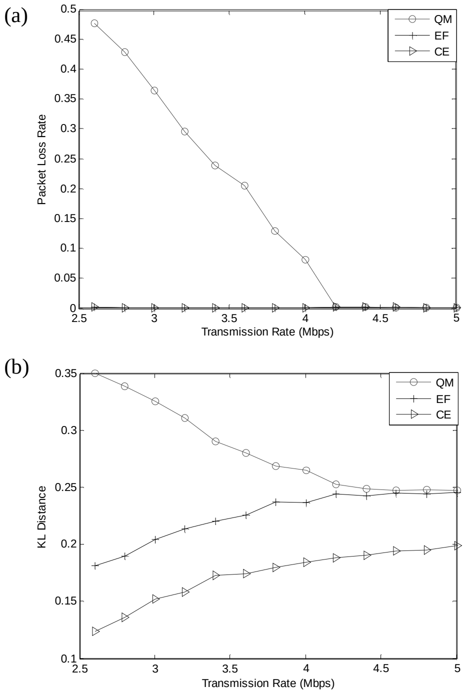

Fig.7 (a) Packet loss rate of x_i for different network efficiencies (the other users using MP model in a SFU network).
(b) KL distance of x_i for different network efficiencies (the other users using MP model in a SFU network).

We first simulate various prediction models in the two extreme networks – the SFU network (the number of foresighted users $L = 1$) and the homogeneous network ($L = N$). Then we extend our simulation to a more general case, with $1 < L < N$. Finally, we provide comparisons of the proposed predictive spectrum access algorithm with the state-of-the-art spectrum access algorithms.

A. SFU network

In the SFU network, one foresighted user and several myopic users jointly operate. We compare the performance (packet loss rate) of the foresighted user x_i when all the other users are using the myopic model with various network efficiencies. Figure 7 shows the packet loss rate of the user x_i using different prediction models $Z_i = \{EF, CE, QM\}$ under various network efficiencies while the rest of the users apply the myopic model $Z_{-i} = MP$. The results are averaged over 100 different realizations of packet error rates. Figure 7(a) shows the performance (packet loss rates) and Figure 7(b) shows the prediction accuracy (KL distance Δ_i^t) under

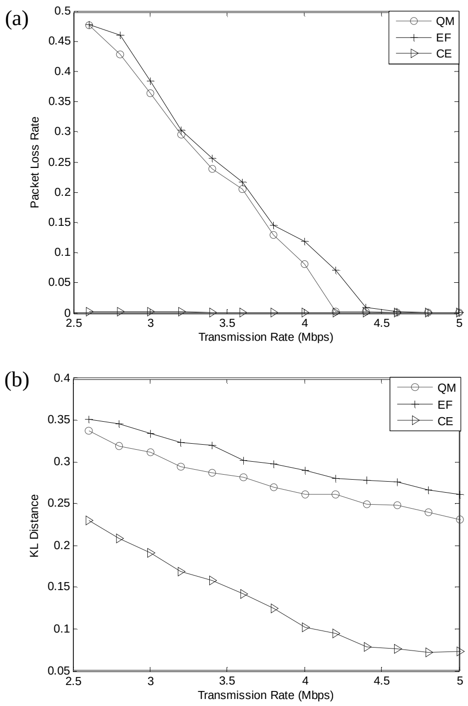

Fig. 8 (a) Packet loss rate of x_i for different network efficiencies (the other users using EF model in a SFU network).
(b) KL distance of x_i for different network efficiencies (the other users using EF model in a SFU network).

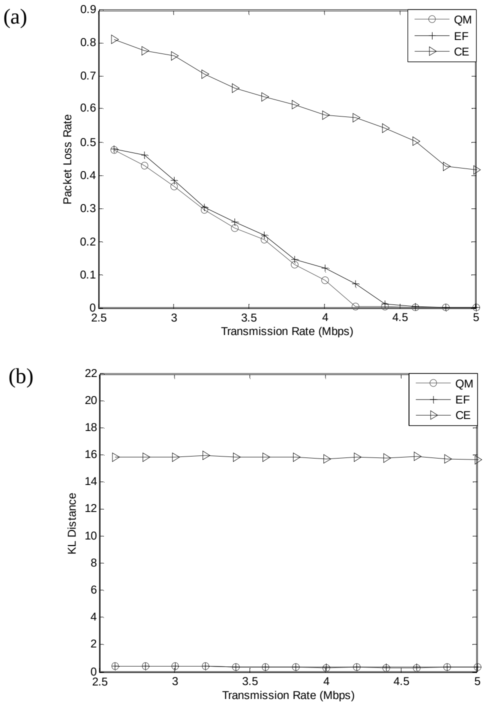

Fig. 9 (a) Packet loss rate of x_i for different network efficiencies (in a homogeneous network).
(b) KL distance of x_i for different network efficiencies in (in a homogeneous network).

various network efficiencies. It is shown that the non-collaborative prediction models $Z_i = \{EF, CE\}$ perform significantly better than the collaborative prediction model $Z_i = QM$ against the myopic models. This simulation results verify that a user should always maximize their own utility (adopt non-collaborative prediction models) when the other users are all myopic users. Both the empirical frequency model and the conditional empirical frequency model are able to achieve zero packet loss rates for the simulated network efficiencies ($T_{ij} = 2.5 \sim 5$ Mbps).

Next, we change the prediction models of the other users to the empirical frequency model, i.e. $Z_{-i} = EF$, and simulate the performance and the prediction accuracy of x_i to evaluate again these prediction models. Figure 8 shows that the conditional empirical frequency model still gives the smallest KL distance Δ_i^t, and leads to the minimum packet loss rate for x_i. However, the empirical frequency model gives a larger packet loss rate, since the user x_i uses the same prediction model as the other users and the prediction model can no longer provide an accurate prediction on the other users' strategies.

B. Homogeneous network

For homogeneous networks, we simulate the same simulation environment as in the SFU network, except that now all the users adopt the same prediction model $Z_i = \{EF, CE, QM\}$. Figure 9(a) shows the packet loss rate of the user x_i using different prediction models under various network efficiencies. Figure 9(b) gives the measured KL distance Δ_i^t of x_i. Compared to the performances in the SFU network in the previous figures, the packet loss rates increase, since now all the other users are foresighted and are able to compete for the spectrum resources. Importantly, Figure 9(a) shows that the conditional empirical frequency model $Z_i = CE$ now performs even worse than the empirical frequency model. Even though the conditional empirical frequency model intends to increase the prediction accuracy by increasing the prediction complexity, Figure 9(b) shows that the resulting KL distance Δ_i^t of the conditional empirical frequency model increases drastically. Note that the collaborative prediction model $Z_i = QM$ provides the best performance in the homogeneous network, which confirms the validity of Remark 2 in Section IV.

C. Different number of foresighted users in the network

We next simulate a different number of foresighted users that adopt the same prediction models $Z_i = \{EF, CE, QM\}$ in the networks, while the rest of the users are all myopic users $Z_i = MP$. The number of users is set to 5 ($N = 5$), and we simulate the number of foresighted users L from 2 to 5. The number of frequency channels is 3 ($M = 3$) and the network efficiency is fixed as 4Mbps. Figure 10 shows the average packet loss rate over the foresighted users using different prediction models. The results show that, when there are multiple foresighted users in the network $L \geq 2$, using a collaborative prediction model

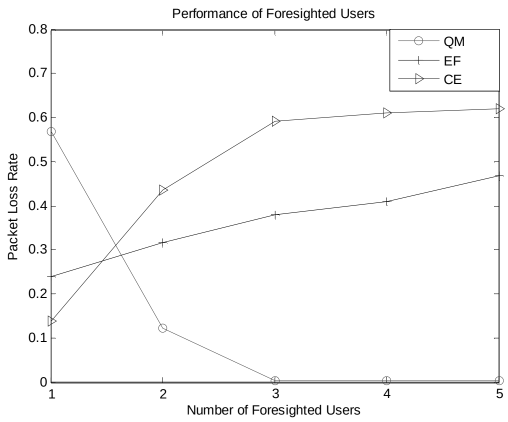

Fig. 10. Average packet loss rate of the foresighted users for different number of foresighted users in the network.

$Z_i = QM$ is better than using a non-collaborative model $Z_i = \{EF, CE\}$ for the foresighted users. Moreover, the cross-over in Figure 9 also implies that, when most of the users are myopic, it is better for the foresighted users to apply a complex conditional empirical frequency model in order to increase the prediction accuracy. However, when more and more users are foresighted, it is more beneficial for these users to collaborate with each other and perform a collaborative prediction model $Z_i = QM$. The results also verify the rules for determining an adaptive prediction model in the propose algorithm in Section V.

D. Comparisons with the existing approaches

In this subsection, we compare the packet loss rates of the proposed APM algorithm in Section V with two other existing approaches – the Myopic Decentralized (MD) approach [8] and the Predictive Learning (PL) approach [15]. The MD approach allows the users to remember the frequency channels on which they most recently had successful transmission and then each user performs the myopic best response strategy. The PL approach allows the users to learn the other users' transmission strategies based on the action history of every other users and performs a no-regret learning algorithm. To obtain a fair comparison, we only adopt the learning part of [15] without local bargaining. We look at the case with different number of users with the same Coastguard video sequence sharing 8 frequency channels ($M = 8$). The rest of the parameters are the same as previous simulations. The simulation results of the average packet loss rates (PLR) and Y-PSNR over N multimedia users are shown in Table III (X represents PSNR below 26 dB, which is unacceptable for a viewer). The results show that the proposed APM algorithm significantly outperforms the other two approaches. This is because when all the users are using the same approach, our proposed algorithm is able to adapt the prediction model and allow the users to collaborate with each other. Hence, the overall performance of the multimedia users becomes closer to the centralized optimal solution, which operates at the Pareto boundary in the utility domain.

E. Discussion

The APM algorithm starts with the MP prediction model ($Z_i = MP$) in the non-collaborative setting, which leads to a Nash equilibrium. In two-channel-two-user case, Nash equilibrium is the Pareto optimum. However, in our multi-user case, this Nash equilibrium is worse than the Pareto optimum. When multiple users are foresighted, Figure 10 shows that it is more beneficial for these users to collaborate with each other and deploy a collaborative prediction model ($Z_i = QM$). Hence, the APM algorithm allows them to exchange model parameters and to adapt their prediction models such that they can operate in a collaborative manner. Note that although these foresighted users are not maximizing their own utilities in this collaborative scenario, the resulting performance at the Pareto frontier using the collaborative prediction model outperforms Nash equilibrium for all users. Hence, the foresighted users will not deviate from the collaborative setting [31], since they will experience a utility degradation if they deviate from this collaborative setting, as shown in Figure 10. However, if there exists non-collaborative users (adopting $Z_i = \{MP, EF, CE\}$) in the network, the APM allows the foresighted users to adopt non-collaborative models $Z_i = \{EF, CE\}$ depending on the number of foresighted users in the network (see the results in Section VI.*C*).

VII. Conclusions

In this paper, we address the problem of distributed spectrum access by autonomous and multimedia users in wireless networks. We study the multi-user spectrum access problem, where each user selects an appropriate prediction model to build a belief on the channel selection strategies of the other users, and based on this belief, each user chooses a frequency channel to maximize the users' utilities. Based on the queuing analysis, we formulate the multimedia users' packet loss rates, which are jointly determined by the channel selection strategies of all users. To minimize such packet loss rates, a user needs to adapt its prediction model and keep building accurate prediction results for the other users' transmission strategies. We presented four prediction models with different complexities and prediction accuracy under various user interaction scenarios.

In summary, when most of the users are myopic, it is better for the foresighted user to apply a complex prediction model to increase its prediction accuracy and hence, its resulting performance. However, when an increasing number of users are foresighted and they are deploying various prediction models, it becomes more beneficial for these users to collaborate with each other and deploy a collaborative prediction model. We propose an adaptive algorithm for predictive spectrum access over a wireless multi-channel network to dynamically adapt the user's prediction model based on local information exchange among the users. The simulation results show that the proposed algorithm outperforms the state-of-the-art spectrum access algorithms when transmitting delay-sensitive applications over wireless multi-channel networks.

APPENDIX

We now briefly present how to evaluate this packet loss rate $P_i(\mathbf{s}_i, \mathbf{s}_{-i})$, when the strategies $(\mathbf{s}_i, \mathbf{s}_{-i})$ are known using queuing analysis. First, based on the exchanged traffic specification $\boldsymbol{TS}_{-i}$, a user x_i is able to calculate the normalized loading for all the users, i.e. $\rho_{ijk} = s_{ij} \cdot (\lambda_k \cdot E[X_{ijk}])$ and $\rho_{ijk}^2 = s_{ij} \cdot (\lambda_k \cdot E[X_{ijk}^2])$. Note that the normalized loading parameter ρ_{ijk} represents the actual fraction of time for user x_i to transmit its packet in priority class C_k in a frequency channel f_j.

Then, we adopt an M/G/1 queuing model (packet arrival of each application is assumed to be Poisson arrival as in [14][20]) and derive the average queue waiting time $E[W_{jk}]$ for packets in priority class C_k using frequency channel f_j according to the mean value analysis [18]:

$$E[W_{jk}] = \frac{\sum_{k'=1}^{k} \rho_{ijk'}^2}{2(1 - \sum_{k'=1}^{k-1} \rho_{ijk'})(1 - \sum_{k'=1}^{k} \rho_{ijk'})}. \quad (19)$$

The corresponding average delay $E[D_{jk}]$ for the packets in priority class C_k using frequency channel f_j is then:

$$E[D_{jk}] = E[W_{jk}] + E[X_{ijk}], \text{ for } C_k \in \mathbf{C}_i. \quad (20)$$

Finally, given the delay deadline d_k, the approximate packet loss rate of priority class C_k using frequency channel f_j can be approximated as [21][14]:

$$\text{Prob}(D_{jk} > d_k) = (\sum_{k'=1}^{k} \rho_{jk'}) \exp(-\frac{(\sum_{k'=1}^{k} \rho_{jk'}) \cdot d_k}{E[D_{jk}]}) \quad . \quad (21)$$

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TABLE I COMPARISONS OF THE DIFFERENT PREDICTION MODELS CONSIDERED

Prediction Model (Z)	Myopic Model ($Z = MP$)	Empirical Frequency Model ($Z = EF$)	Conditional Empirical Frequency Model ($Z = CE$)	Queuing Model ($Z = QM$)
Setting	Non-collaborative			Collaborative
Required information	$\boldsymbol{TS}_{-i}, \mathcal{I}_i^{t,obs}$	$\boldsymbol{TS}_{-i}, \mathcal{I}_i^{t,obs}$	$\boldsymbol{TS}_{-i}, \mathcal{I}_i^{t,obs}$	$\boldsymbol{TS}_{-i}, \mathcal{I}_i^{t,exch}, \mathcal{I}_i^{t,obs}$
Size of memory for the prediction results	$N-1$	$(N-1)M$	$(N-1)M^2$	$(N-1)M$
Utility evaluation for the other users	Not Required	Not Required	Not Required	Required
Complexity	Low	Medium	High	Highest
Prediction on $\mathbf{s}_{-i}^t$	No Prediction	Independent prediction with current action $\boldsymbol{a}_i^t$	Correlated prediction with current action $\boldsymbol{a}_i^t$	Correlated prediction with current action $\boldsymbol{a}_i^t$

TABLE II SIMULATION PARAMETERS

Network users N	Available channels M	Packet length l_i (bytes)	Delay deadline d_i (sec)	Physical transmission rate T_{ij} (Mbps)	Initial prediction results of other users B_{-i}^0	
					Conditional	Unconditional
25	15	1000	0.5	2.5~5	1/15 $\forall s_{ij}(m)$	1/15 $\forall s_{ij}$

TABLE III PROPOSED ADAPTIVE PREDICTIVE ALGORITHM WITH THE OTHER APPROACHES

Number of users	MD [8]		PL [15]		Proposed APM Algorithm		Centralized Optimal Solution	
	PLR	Y-PSNR (dB)	PLR	Y-PSNR (dB)	PLR	Y-PSNR (dB)	PLR	Y-PSNR (dB)
$N = 5$	0.28	31.08	0	35.61	0	35.61	0	35.61
$N = 10$	0.83	X	0.24	31.61	0.18	32.47	0.17	32.62
$N = 15$	0.96	X	0.55	28.27	0.42	29.48	0.40	29.69