Robust End-to-End QoS Maintenance in Non-Contiguous OFDM Based Cognitive Radios†

Joseph Wynn Mwangoka∗‡, Khaled Ben Letaief∗, Zhigang Cao‡

∗Department of Electronic and Computer Engineering
Hong Kong University of Science and Technology, Clear Water Bay, Hong Kong
Email: {eejoseph, eekhaled}@ust.hk
‡Department of Electronic Engineering, Tsinghua University, 100084 Beijing- China
Email: czg-dee@mail.tsinghua.edu.cn

Abstract—A recent development in wireless communication is Cognitive Radio (CR) technology, an innovative radio design approach which allows the realization of intelligent allocation of the scarce radio resources such as spectrum. In this paper, we attempt to exploit past channel information and the flexibility of non-contiguous orthogonal frequency division multiplexing (NC-OFDM) based CRs to maintain end-to-end QoS performance under dynamic spectrum sharing environments. So far, most research works in resource allocation in CRs have mainly concentrated on the spectrum opportunity discovery aspect while the robust QoS performance problem has remained largely unexplored. In this work, we use the concept of portfolio optimization to achieve QoS maintenance in NC-OFDM CR systems. The problem of allocating power to maintain throughput is cast into a channel gain variance minimization and mean-variance maximization frameworks to achieve a given throughput performance under fixed BER and power limitation constraints. Numerical results are presented to demonstrate the QoS maintenance performance in various wireless channel settings.

I. INTRODUCTION

Future wireless communication systems are expected to have the intelligence to perform tradeoffs between user quality of service (QoS) requirements and scarce radio resources constraints. This intelligence will be based on the innovative cognitive radio design philosophy which allows for devices to make clever decisions on spectrum usage, power allocation, type of network service to access/subscribe, collaboration with other devices etc., while meeting QoS requirements [1]. Recently, environment sensing, specifically spectrum sensing, which is the first stage of the cognition process, has attracted a lot of research works. However, work on the exploitation of the information obtained to achieve the intelligent and ubiquitous communication goal is still at its infancy. Our work attempts to use collected information to maintain a desired QoS for non-contiguous orthogonal frequency division multiplexing (NC-OFDM) based cognitive radio (CR) systems.

The modularity of OFDM and the fact that it can be easily integrated with spectrum sensing modules make it very appealing for the design of efficient resource allocation mechanisms in CR wireless systems. More importantly, the use of orthogonal signaling and the inherent frequency diversity in a well-designed OFDM system are especially useful in attempting to dynamically satisfy the system’s QoS requirements (like SNR, throughput, BER or delay constraints) while tracking changes in resources availability. This is because the availability of resources, such as spectrum, might not be contiguous due to their use by higher priority users (licence holders, or primary users) or because of radio channel degradation. The multi-carrier system which dynamically operates in non-contiguous frequency bands and enabled by cognition technology is referred to as NC-OFDM [2]. The flexibility offered by NC-OFDM based CR can be employed to devise resource allocation strategies which ensures QoS requirements by jointly considering variations in channel state information and spectrum availability.

Previous works on conventional OFDM systems have based the resource allocation problem on an implicit assumption, that the allocated transmission spectrum is fixed and always available; and an explicit assumption that channel variations are quasi-static. In such scenarios, QoS satisfaction is achieved by exploiting the time varying nature of fading gains across subchannels through adaptive modulation and power loading schemes [3]. However, this approach might not be directly applicable to the NC-OFDM cognitive radio systems.

In cognitive radio networks, the spectrum is co-shared and the operating bandwidth is not continuously available in time, frequency and geographical domains. Also, in situations

† This work is supported in part by the Hong Kong Research Grant Council under Grant # N_HKUST622/06.
where the channel is changing too quickly to be tracked, reliable feedback of the channel state information (CSI) to the transmitter is compromised. In such cases, it is difficult to model a rate maximization or power minimization problem while considering channel changes and bandwidth (subchannels) availability [4]. Fig. 1 gives an illustration of such situation where the cognitive radio is operating as a secondary spectrum user under dynamic spectrum usage scenario [5] and hence subject to interference and usage patterns of the primary users or license holders. In this particular case, where the available bandwidth is changing and there is imperfect CSI at the transmitter (CSIT), trying to ensure QoS under power constraints is a daunting task. In this paper, we take a statistical approach and consider an NC-OFDM cognitive radio communication link under a varying available bandwidth and imperfect CSIT and try to maintain end-to-end SNRs of subchannels under total power constraints.

The organization of this paper is as follows. In Section II, we describe our problem scenario and introduce the NC-OFDM based data transmission system. In Section III, we formulate the QoS maintenance problem. Problem solutions under various user preferences and a robust power allocation algorithm are given in Section IV. Numerical results that demonstrate the performance of the approaches in different channels are given in Section V. Finally, Section VI concludes the paper.

II. SYSTEM FRAMEWORK

A. Spectrum sharing scenario

We assume an interference controlled spectrum sharing scenario [5]. In this general case, primary users or license holders allow secondary spectrum usage, whereas a secondary spectrum user is under certain interference limitations imposed by the license holder as well as primary user traffic patterns. We assume that the secondary spectrum user operates in a limited bandwidth (which could span different licence holders) divided into $N$ subchannels, which make set $\mathbb{N}$ of usable subchannels. At any communication session, there is a variable $N_{\text{ON}} \in \mathbb{N}$ amount of subchannels available for data transmission. This scenario has two implications with respect to conventional assumptions:

1) Operational bandwidth is flexible or not fixed: Notice that in conventional OFDM systems, it is explicitly assumed that there is fixed bandwidth available. This simplifies the rate or power optimization problems. However, in our case the available bandwidth is a variable.

2) Unpredictable channel variations: In the conventional case, channel changes are typically assumed to be quasi-static. However, in a spectrum sharing scenario, it might not be the case. In fact, the characterization of cognitive radio based channels is still an open problem.

In this uncertain setting, the task of ensuring QoS performance will require a robust framework. Our approach is to use past subchannel’s channel gain information and through appropriate power allocation, our aim is to minimize the variance of a transmission rate benchmark $r_{\text{des}}$. That is, we determine which are the subchannels to make up the $N_{\text{ON}}$, and how much power should be allocated in each to maintain $r_{\text{des}}$ under limited power constraints.

B. Data transmission

Consider an NC-OFDM transceiver as shown in Fig. 2. At the transmitter, Fig. 2(a), a high speed input data stream $x(n)$ of rate $\bar{r}$ bit/sec is split into lower rate sub-streams. In this case,

\begin{align}
\bar{r} = T r
\end{align}

where $1 = [1, \ldots, 1]_N^T$, and $r = [r_1, \ldots, r_{N_{\text{ON}}}^T$ while $N_{\text{ON}}$ is the number of sub-channels turned on. The value $r_i$ bits per subcarrier is assigned by a loading algorithm which maps the expected subcarrier’s signal-to-noise ratio $\gamma_i$ values to the corresponding constellation and coding mode that satisfies a target bit error rate (BER). That is,

\begin{align}
{r}_i = f(\gamma_i, \text{BER})
\end{align}

where the function $f(\cdot)$ is upper bounded by the Shannon capacity formula. Given the BER value, the specific $f(\cdot)$ function adopted to express the achievable data rate at the $i$th subchannel is

\begin{align}
f(\gamma_i, \text{BER}) = \log_2(1 + \beta \gamma_i),
\end{align}

where $\beta = -1.5/\ln(5\text{BER})$ is called the SNR gap, which indicates the gap of SNR that is needed to reach a certain capacity between practical implementations and information theoretical results [6].
The modulator translates the bit-stream by using \( M \)-ary phase shift keying (MPSK) or \( M \)-ary quadrature amplitude modulation (MQAM) into symbol \( X_i \), chosen from one of the \( M \) appropriate constellation where \( M_i \) consists of \( 2^M \) points. In the NC-OFDM CR system considered here, the channel sounding and spectrum analysis module jointly process the information on spectral availability and channel statistics across the transmission bandwidth. The statistical data output (e.g. channel gain mean and covariance matrix) is used for the QoS maintenance process by allocating power in such a way that the expected SNR per subcarrier is satisfied. The reception maintenance process by allocating power in such a way that channel gain mean and covariance matrix) is used for the QoS

The transmitted NC-OFDM signal is performed in reverse order as illustrated in Fig. 2(b).

The 4th subchannel signal-to-noise ratio is given as

\[ \gamma_i = \frac{P_i |H_i|^2}{2\sigma_i} \]  

where \( P_i \) is the power allocated, \( |H_i|^2 \) is the channel gain and \( \sigma_i \) is unit noise power on subchannel \( i \). We denote \( G_i = \frac{|H_i|^2}{2\sigma_i} \), then we have

\[ \gamma_i = P_i G_i. \]  

III. PROBLEM FORMULATION

Our problem formulation is inspired by the portfolio theory where the characterization of random future returns is formalized as a risk-minimization problem under a constraint of expected return. Portfolio risk is often measured in terms of variance of return, an approach which was introduced by Markowitz [7]. By applying this concept in QoS maintenance in NC-OFDM systems, it can be seen analogically as: Once the variance and the mean of throughput (a QoS parameter) are known, a power allocation vector to minimize the (throughput) variance and keep its mean constant can be found. Formally, the problem can be stated as follows:

\[
\begin{align*}
\text{minimize} \quad & \quad \text{Var}[\tilde{r}] \\
\text{subject to} \quad & \quad \mathcal{E}\{\tilde{r}\} = r_{\text{des}} \\
& \quad \sum_{i=1}^{N} P_i = P_{\text{max}} \\
& \quad P_i \geq 0.
\end{align*}
\]

That is, our objective is to find a power allocation vector \( \mathbf{P} = P_1, \ldots, P_N \) such that the variance of the transmission rate \( \text{Var}[^{\tilde{r}}] \) is minimized and its mean is maintained at a desired rate \( r_{\text{des}} \) subject to a design or policy power constraint \( P_{\text{max}} \). This formulation has the following advantages:

1) Problem formulation: The formulation addresses possible features of robust QoS maintenance in CR environments.

2) Problem solution: The problem can be casted into a convex optimization framework, leading to global solutions or efficient numerical solutions. This is very important for data intensive cognitive systems.

IV. PROBLEM SOLUTIONS AND ALLOCATION ALGORITHM

A. Problem simplification

We first simplify the optimization objective so that we may be able to use past channel information. Since \( r_i = f(\gamma_i, \text{BER}) \), then, with a given BER, \( \tilde{r} = f(\gamma) = \sum_i \log(1 + \gamma_i) \) where \( \gamma = \{\gamma_1, \ldots, \gamma_N\} \). Thus, the objective function can be written as

\[ \text{Var}[\tilde{r}] = \text{Var}[f(\gamma)]. \]  

Obtaining an analytical expression for (7) is important because it will provide a direct way to process past channel information. Nonetheless, it is not a trivial task. We, therefore, resort to the delta-approximation [8]; namely, given a random variable \( x \), then the variance of \( f(x) \) is given as \( \text{Var}[f(x)] \approx f'(\mathcal{E}\{x\})^2 \text{Var}[x] \). Since \( \gamma \) is a vector, it follows that

\[ \text{Var}[f(\gamma)] \approx \text{Var}_D[f(\gamma)] = \gamma' \text{Var}(\gamma)(\gamma')^T \]

where \( \text{Var}_D[f(\gamma)] \) denote the rate \( \tilde{r} \) variance obtained from the delta-approximation, and \( \gamma' \) is the first-order derivative of \( \gamma \) evaluated at \( \gamma = \bar{\gamma} \), i.e., \( \gamma' = \left\{ \frac{\partial f}{\partial \gamma_1}, \ldots, \frac{\partial f}{\partial \gamma_N} \right\} \). We assume that the channel gain information vector \( \mathbf{G} = \{G_1, \ldots, G_N\} \), which is a random variable with known mean \( \mathbf{G} \) and covariance \( \mathbf{\Sigma} \) that is assumed to be positive definite. In Subsection IV-E, we show how \( \mathbf{G} \) and \( \mathbf{\Sigma} \) are obtained from raw data. Through performing simple manipulations to Eqns. (5) and (8), we can arrive at the following expression

\[ \text{Var}_D[f(\gamma)] = \mathbf{P} \mathbf{\Sigma} \mathbf{P}^T. \]

This simplified expression allows direct processing of the raw channel gain information. In the next subsections, we use this simplification to solve the original problem by considering two approaches, namely variance minimization and mean-variance maximization.

B. Variance minimization

In this subsection, the user does not care about maximizing its throughput but simply maintaining a certain desired threshold \( r_{\text{des}} \) by minimizing (9). Denoting \( \text{Var}_D[f(\gamma)] \) as \( \mathcal{U}\{\mathbf{P}\} \), then, the optimization problem becomes

\[
\begin{align*}
\text{minimize} \quad & \quad \tilde{\mathcal{U}}\{\mathbf{P}\} \\
\text{subject to} \quad & \quad 1^T \mathbf{P} = P_{\text{max}} \quad \mathbf{P} \succeq 0.
\end{align*}
\]

This is a quadratic program [9]. By solving (10), we get

\[ \mathbf{P}_{\text{min var}} = \mathbf{\Sigma}^{-1} \left\{ \frac{1}{1^T \mathbf{\Sigma}^{-1}} \right\} \]

where \( \mathbf{P}_{\text{min var}} \) is the desired power allocation vector.

C. Mean-Variance maximization

We assume that in reality different CR users will have different data processing capability and preferences. In this subsection, the goal of the user is to simultaneously maximize the expected throughput and minimize the variance. So, the utility or mean-variance objective function is given as

\[ \mathcal{U}\{\mathbf{P}, \eta\} = \mathcal{E}\{\tilde{r}\} - \frac{1}{2} \eta \text{Var}[\tilde{r}]. \]  

Note that the utility \( \mathcal{U}\{\mathbf{P}, \eta\} \) is a function of the expected throughput, its variance and a regulating parameter \( \eta \), which

This full text paper was peer reviewed at the direction of IEEE Communications Society subject matter experts for publication in the ICC 2008 proceedings.
expresses the degree of tolerance to QoS performance by the user. Eqn. (9) already gives the approximation of $\text{Var}[\gamma]$. Through observation, we heuristically use similar parameters to define an expectation function corresponding to $E[\gamma]$ as $E_D[f(\gamma)] = P^T G$. It can be observed that for values greater than 1, $P^T G$ is a lower bound of $E[\gamma]$ whereas values less than 1 are invalid. Therefore, without loss of generality, we use $E_D[f(\gamma)]$ and $\text{Var}_D[f(\gamma)]$ to define an objective utility function equivalent to (12) as $\tilde{U}\{P, \eta\} = E_D[f(\gamma)] - \frac{1}{2} \eta \text{Var}_D[f(\gamma)]$. This objective allows the direct use of the CSI to reflect the system performance. Thus, the problem becomes

\[
\text{maximize } \tilde{U}\{P, \eta\} \\
\text{subject to } P^T P = P_{\max} \quad P \succeq 0.
\]

This is also a quadratic program and a convex optimization problem. By solving the problem and after some manipulations, we get the desired power allocation vector

\[
P_{\text{mean var}} = \frac{1}{\eta} \Sigma^{-1} \left[ G + 1 \left( \eta P_{\max} - a \right) \right] b
\]

where $a = 1^T \Sigma^{-1} \tilde{G}$ and $b = 1^T \Sigma^{-1} 1$.

The tolerance regulating parameter, $\eta$, gives the user the ability to manipulate the expected output depending on the application’s tolerance to channel perturbations or noise and interference, or fluctuation in any QoS parameter. This implies that, the user preferences can be mapped into physical parameters in the resource allocation algorithms at the PHY and MAC layers. Moreover, throughput can be flexibly maximized or maintained with changes in the channel gain variance. The range of values of $\eta$ can be set based on system specific considerations. In some way we can say that the ability of the device to intelligently consider user needs while optimizing resources is achieved through the parameter $\eta$.

D. Allocation algorithm

The two variance minimization and mean-variance or utility maximization approaches given above can be summarized in the following algorithm.

**Algorithm 1 Robust QoS Maintenance Algorithm**

- **Parameters**: User input e.g. $\eta$; application QoS e.g. $r_\text{des}$, BER; policy power limitation $P_{\max}$
- 1. Initialization: Collect past channel gain information;
- 2. Process past channel information to get channel gain mean $\bar{G}$ and channel gain covariance matrix $\Sigma$
- 3. Solve: **Optimize** an equivalent objective function $\tilde{U}(\cdot)$ **subject to** QoS constraints and user inputs
- 4. Use the $P$ results to select subchannels $N_{\text{ON}} \in \mathcal{N}$
- 5. Allocate power per subchannel as: $P_{i \in N_{\text{ON}}}$
- 6. Allocate bits per subchannel as: $r_i = f(\gamma_i, \text{BER})$
- 7. End

E. Processing raw data

Special care has to be taken when processing raw data. To characterize the collected past channel information, let the elements $g_{i,j}$ of the matrix $G$ denote the channel gain of subchannel $j$ at time $i$. If there are $M$ time periods for $N$ subchannels then matrix $G$ is an $M$ by $N$ matrix. The sample channel gain mean for subchannel $j$ is given by

\[
\hat{G}_j = \frac{1}{M} \sum_{i=1}^{M} g_{i,j}.
\]

Then, the deviation $\hat{G}$ can be obtained as

\[
\hat{G} = G - \hat{G}^T,
\]

whereas the sample covariance matrix $\Sigma$ is computed as

\[
\Sigma = \frac{1}{M} \hat{G}^T \hat{G} \quad \text{or} \quad \Sigma = \frac{1}{M-1} \hat{G}^T \hat{G}.
\]

However, care should be taken since this way of computing the covariance matrix could lead to significant loss of information [10]. If the condition number is high, then $\Sigma$ is nearly positive semi-definite and this could lead to results which are unreliable. One of the ways to avoid information loss is to compute the $QR$ factorization of $\Sigma$, which is defined as

\[
QR = \hat{G}
\]

where the $M$ by $N$ matrix $Q$ contains orthogonal columns (i.e., $Q^TQ = I$) and $R$ is an $N$ by $N$ upper triangular matrix. Then, the Cholesky factor $R/\sqrt{M}$ can be used in the optimization algorithm to guarantee the reliability of the results.

V. SIMULATION RESULTS AND DISCUSSION

In this section, we present sample numerical results to demonstrate the potential of the proposed approaches. We evaluate the performance of the proposed second order statistics based QoS maintenance approach for CR systems in different channel conditions. The purpose is to first justify our approach by comparing it with the case where at any instant of transmission, the ‘instantaneous’ channel and spectral information is known to the transmitter. Next, we demonstrate how the proposed approaches achieve constant utility performance in uncertain CR environments.

A. Simulation setup

The setup for the numerical results is as follows. The maximum number of subchannels that can be used by the NC-OFDM air interface is set to be $N = 128$. Different modulation schemes are used adaptively for each subchannel depending on the loading criteria. MQAM values used for modulation are $\{0, 1, 2, 4, 6, 8\}$. We illustrate our results by using a Rician channel model with $K = 10$ and for the Doppler frequency of 0 or 25Hz. The target BER is set to be $10^{-5}$. 

This full text paper was peer reviewed at the direction of IEEE Communications Society subject matter experts for publication in the ICC 2008 proceedings.
B. Justification of our approach

Fig. 3 compares the spectral performance of the ‘instantaneous’ channel knowledge and the proposed approaches in two types of channels. As expected, a higher performance level is obtained when there is ‘instantaneous’ channel knowledge than when only a historical knowledge is used. However, under relatively low SNR, where the effect of multipath is significant, the proposed QoS maintenance approaches have better performance. These predictable results clearly heuristically justify our approach.

C. QoS maintenance performance

Fig. 4 shows how the utility values (bits/s) are maintained at constant levels by the different methods and under different channel conditions. Fig. 4a represents a situation where the CR environment is not very chaotic. We see that the variance minimization approach gives mild performance. However, when the mean-variance maximization approach is considered, and at the same time the tolerance level is set relatively high (\(\eta = 2\)), the utility is maintained at a relatively high level. On the other hand, when the tolerance level is set relatively low (\(\eta = 10\)), we get relatively low utility levels.

Fig. 4b represents a very chaotic CR environment. Here the utility levels are lower. We see that the variance minimization approach gives the best performance while the mean-variance maximization approach yields very low utility levels. This implies that, in chaotic cognitive communication environments, it is infeasible to use the mean-variance approach. Under these conditions, it is better to maintain the QoS by the variance minimization approach.

VI. CONCLUSION

Cognitive radios operating in dynamic spectrum sharing environments are faced with uncertainty of available spectrum bands. In this paper, we have taken preliminary steps in pragmatic formulation of a QoS maintenance problem for NC-OFDM CR systems based on the portfolio optimization theory. The problem has been cast into a channel gain variance minimization problem where power is allocated under BER and power limit constraints to maintain the desired QoS level. With some simplification, two possible user approaches have been considered namely variance minimization and mean-variance maximization. In the first approach, the user only focuses on minimizing the ‘risk’, i.e., channel gain variance. In the second approach, average throughput maximization and variance minimization are simultaneously considered. Furthermore, the tolerance regulating parameter included in the mean-variance formulation provides flexibility in setting the user’s QoS preference levels, hence, facilitating human-machine interfacing. Numerical results have been presented to illustrate the potential of the approaches. Nevertheless, the diverse benefits of second order statistical approach for developing practical robust QoS models in CR systems retains much to be investigated.

REFERENCES