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A Data-Driven Cost-Effective Session-Oriented Cognitive Radio Transmission Scheme Under Spectrum Uncertainty

Xuanheng Li, *Member, IEEE*, Haichuan Ding, Yuguang Fang, *Fellow, IEEE*

***Abstract*—Due to the emerging Internet of Things (IoT) services, the spectrum shortage problem becomes more and more serious. To tackle this challenge, many research works have been conducted to employ the cognitive radio technology to exploit under-utilized spectrums for IoT services. However, the operation of a cognitive radio transmission system is usually time-energy-consuming due to the requirement on the wideband sensing and spectrum switching, which might be hardly supportable by the light-weighted IoT devices. In this paper, we propose a data-driven cost-effective session-oriented cognitive radio transmission scheme, where the bands are directly selected based on the historical data and a "transmit-wait-transmit" mode is employed to reduce the cost. For the spectrum selection, we first attempt to determine the bands with minimal total bandwidth that could make the session accomplished with certain confidence level by modeling the available duration of a band within the session period as a random variable. Then, from the historical data, we develop a distributionally robust approach, where Kullback-Leibler divergence is used to capture the distributional ambiguity. Finally, based on the real data we collected using USRP-2922, we evaluate the effectiveness of our proposed scheme.**

***Index Terms*—Cognitive radio, spectrum uncertainty, distributional ambiguity, robust optimization, data-driven.**

I. Introduction

WITH the popularity of Internet of Things (IoT), numerous devices are expected to connect with existing telecommunications networks, which poses a great challenge to the already crowded spectrum resource. To support the exponentially increasing wireless data traffic, high frequency spectrums are exploited. Unfortunately, due to the undesired propagation characteristics, the applicable scenario for such high frequency spectrums is limited [1]. Considering the current status of spectrum under-utilization, how to improve the spectrum efficiency for the sub-6GHz golden bands has attracted intensive interests [2], [3].

Cognitive radio (CR) is a promising technology that can enable IoT devices, regarded as secondary users (SUs), to opportunistically access the unused spectrums belonging to the licensed users or primary users (PUs), and thus alleviate the spectrum scarcity problem [4], [5]. As a result, many research efforts have been dedicated to investigating the adoption of CR on IoT devices to enable the ubiquitous connectivity, such as the RERUM project in Europe [6].

In general, to enable opportunistic spectrum access, a CR device needs to implement a wideband spectrum sensing first and then make spectrum access decisions accordingly. Then, it needs to monitor the selected bands and vacate them whenever PUs reclaim them, where another wideband sensing phase will be started to find other available bands and the CR device will tune to them to continue the transmission [2], [7]. Such a procedure will be repeated until the session accomplished. Unfortunately, this kind of CR transmission is hardly practical for light-weighted IoT devices. First, implementing a wideband spectrum sensing is usually time-energy-consuming (sensing cost). Second, frequent RF-reconfiguration for spectrum switching will also bring considerable overhead (switching cost). Third, considering the uncertain spectrum supply, how to guarantee the quality of service (QoS) is challenging.

In parallel with that, we note that many IoT services are delay-tolerant, e.g., uploading 10Gbs surveillance video data within 10mins for cloud storage. Intuitively, if we could know the data volume that can be delivered by different bands within the period, we only need to sense these bands instead of employing wideband sensing, and stay on these bands during the session period instead of frequently switching among different ones, i.e., keep silence and wait for the release when PUs reclaim the bands. As a result, both sensing cost and switching cost could be reduced effectively. Following this idea, we develop a data-driven cost-effective session-oriented cognitive radio transmission (CSCT) scheme. By monitoring the spectrum from 2579.5MHz to 2580.5MHz, as well as from many existing spectrum measurement works [8], we find that the statistics of spectrum occupancy can be inferred from the historical data, which can be adopted to predict the usability of different bands. Considering a session that intends to transmit certain amount of data within a period, we model the available duration of a band within the period as a random variable and formulate the spectrum selection of the CSCT scheme into a chance constrained programming (CCP). Based on such a cost-effective session-oriented scheme, we attempt to fulfill the

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X. Li is with the School of Information and Communication Engineering, Dalian University of Technology, Dalian, China 116023, e-mail: xhli@dlut.edu.cn. H. Ding is with the Department of Electrical Engineering and Computer Science, the University of Michigan, Ann Arbor, MI 48109-2121, USA, e-mail: dhcbit@gmail.com. Y. Fang is with the Department of Electrical and Computer Engineering, University of Florida, Gainesville, FL 32611, USA, e-mail: fang@ece.ufl.edu. Y. Fang is also with the School of Information Science and Technology, Dalian Maritime University, Dalian 116026, China.

session statistically by sensing the least bandwidth without the requirement on spectrum switching.

In fact, such a stochastic modeling for spectrum uncertainty has been used in many existing works [9]–[11]. Most of them study the uncertainty issue based on certain specific distribution. However, the exact distribution is usually hardly known in practice, making the solution under such an assumption suboptimal or even infeasible in practice. Hence, instead of directly applying the distribution estimated by fitting the historical data, we regard it as a reference and construct an ambiguity set based on the Kullback-Leibler (KL) divergence, to account for the ambiguous spectrum uncertainty, and develop a distributionally robust (DR) solution accordingly [12]. Compared with our previous work [13], where a moment-based model is adopted to characterize the ambiguity set, such a KL divergence based method is more accurate and especially suitable for the case where sufficient data could be used to derive the referential distribution. Our main contributions are summarized as follows:

- To reduce both sensing and switching costs in traditional CR transmissions, we propose a CSCT scheme, where the used bands are determined in advance based on the statistical information of spectrum availability in the past and a "transmit-wait-transmit" mode is adopted with a probabilistic guarantee on the session.
- Unlike most existing works which assume the perfect knowledge on probability distribution, we take the distribution fitted from data as the reference and construct an ambiguity set to represent all possible distributions based on the KL divergence, and develop a DR solution so that the session can be guaranteed even though the exact true distribution is unknown.
- Real data on spectrum occupancy is collected by using USRP-2922 on the campus of Dalian University of Technology to verify the effectiveness of our proposed scheme.

II. Problem Formulation

Consider a CR transmission session, which intends to transmit z bits over a link by using spectrum holes within a duration of T time units. For the CSCT scheme, to reduce the sensing cost, instead of making decisions after a wideband sensing, we directly select some bands and adopt a "transmit-wait-transmit" mode to further cut the switching cost, while ensuring the session completion with a confidence level.

Denote all candidate bands as $\mathcal{M}$ and the bandwidth of band $m \in \mathcal{M}$ is W_m. The achievable rate of the link over band m is expressed as $c_m = W_m \log(1+\eta)$, where η is the signal-to-noise-ratio (SNR) at the receiver. Considering the uncertain activities of PUs, we model the available duration of band m within the period T as a random variable T_m, and formulate the spectrum selection of the CSCT scheme into the following CCP problem:

$$\begin{aligned} \mathrm{P1}: \quad & \min \sum_{m\in\mathcal{M}} W_m x_m \\ \text{s.t.} \quad & \Pr\left\{\sum_{m\in\mathcal{M}} T_m c_m x_m \geq z\right\} \geq \beta, \end{aligned} \tag{1}$$

where $x_m \in \{0,1\}$ is the decision variable, representing whether or not band m is selected, and $\beta \in (0,1)$ is the confidence level.

Remark: Note that the problem P1 might have no feasible solution, indicating that the candidate bands for sensing cannot support the session with the confidence level even if all of them are employed. If that is the case, part of session will be carried by the operators' own licensed bands.

As shown in many spectrum measurement works, by using sufficient historical data, the probability distribution of $\mathbf{t} = [T_1, T_2, \cdots, T_M]^{\mathrm{T}}$ can be estimated, which can be used to make the chance constraint in P1 a tractable deterministic one. However, such an estimation is usually inaccurate, and thus the solution based on it might be suboptimal or even infeasible in practice. To account for this inaccuracy, we model the distribution within an ambiguity set and develop a DR approach to satisfy the chance constraint.

III. Distributionally Robust Solution Under Kullback-Leibler Divergence Based Ambiguity

We denote the distribution obtained from data-driven fitting as $f_0(\mathbf{t})$, i.e., the empirical distribution, and take it as the reference[1]. KL divergence is adopted to describe the distribution ambiguity by considering that the true distribution $f(\mathbf{t})$ is within certain distance from $f_0(\mathbf{t})$. For simplicity, we denote $f_0(\mathbf{t})$ and $f(\mathbf{t})$ as f_0 and f, respectively, and the ambiguity set can be expressed as

$$\mathcal{U} = \{f \geq 0 : D_{\mathrm{KL}}(f, f_0) \leq d, \mathbb{E}_f(1) = 1\}, \tag{2}$$

where $D_{\mathrm{KL}}(f, f_0) = \mathbb{E}_f(\ln f - \ln f_0)$. We define $x\ln(x/0) = +\infty$ for any $x > 0$ and $0\ln(0/0) = 0$. Then, for any $\mathbf{t}$, $f_0(\mathbf{t}) = 0$ implies $f(\mathbf{t}) = 0$. d is a positive value, representing the risk-aversion on the empirical approximation. Accordingly, we can formulate the DR counterpart of the chance constraint in P1 as

$$\min_{f\in\mathcal{U}} \mathbb{E}_f\left(\mathbf{1}\left(\mathbf{t}^{\mathrm{T}}\mathbf{s} \geq z\right)\right) \geq \beta, \tag{3}$$

where $\mathbf{s} = [c_1x_1, \cdots, c_Mx_M]^{\mathrm{T}}$ and $\mathbf{1}(\cdot)$ is the indicator function. Replacing (1) by (3) in P1, we can achieve a DR-CSCT scheme and get a DR solution, where the chance constraint can be satisfied under all possible distributions around the empirical distribution within the KL divergence based ambiguity set expressed as (2).

Next, we will demonstrate that such a DR constraint (3) is equivalent to (1) under the empirical distribution f_0 but with a more conservative confidence level.

To be specific, let $F = f/f_0$. According to the change-of-measure technique [15], we have

$$D_{\mathrm{KL}}(f, f_0) = \mathbb{E}_f\left(\ln\frac{f}{f_0}\right) = \int_{\mathcal{T}} \frac{f}{f_0}\ln\frac{f}{f_0} f_0 d\mathbf{t} = \mathbb{E}_{f_0}(F\ln F). \tag{4}$$

Similarly, using $\mathbf{1}(\mathbf{t}, \mathbf{s})$ to denote $\mathbf{1}\left(\mathbf{t}^{\mathrm{T}}\mathbf{s} \geq z\right)$, we can derive that $\mathbb{E}_f(\mathbf{1}(\mathbf{t},\mathbf{s})) = \mathbb{E}_{f_0}(\mathbf{1}(\mathbf{t},\mathbf{s})F)$. Thus, for the DR con-

[1] As studied in [8], different distribution models can be used to describe the idle periods of different bands in different cases. Many metrics can be used to evaluate the goodness of the fitting, such as the KL divergence [14].

straint (3), the left side of it can be reformulated as

$$\text{P2}: \pi = \min_{F\in\mathcal{F}} \mathbb{E}_{f_0}\left(\mathbf{1}\left(\mathbf{t},\mathbf{s}\right)F\right), \text{s.t. } \mathbb{E}_{f_0}\left(F\ln F\right) \le d, \tag{5}$$

where $\mathcal{F} = \{F \ge 0 : \mathbb{E}_{f_0}(F) = 1\}$. Then, by denoting $P = \Pr_{f_0}\left(\mathbf{t}^{\mathrm{T}}\mathbf{s} < z\right)$, we present two theorems as follows.

Theorem 1: The optimal objective value of P2, π, can be obtained by solving the following optimization problem as

$$\text{P3}: \quad \pi = \max_{\gamma\ge 0} -\gamma\ln\mathbb{E}_{f_0}\left(e^{-\mathbf{1}(\mathbf{t},\mathbf{s})/\gamma}\right) - \gamma d. \tag{6}$$

Proof: For P2, we can construct the Lagrangian function as

$$\Gamma\left(\gamma, F\right) = \mathbb{E}_{f_0}\left(\mathbf{1}\left(\mathbf{t},\mathbf{s}\right)F + \gamma F\ln F\right) - \gamma d, \tag{7}$$

where $\gamma \ge 0$ is the Lagrangian multiplier. Then, the Lagrangian dual problem of P2 can be expressed as

$$\text{P4}: \quad \max_{\gamma\ge 0}\min_{F\in\mathcal{F}} \Gamma\left(\gamma, F\right). \tag{8}$$

Due to the convexity of P2, the strong duality should hold for P4. Next, we discuss the inner minimization problem in P4 denoted as $\tilde{\pi}$ by considering the following two cases.

1) $\gamma = 0$: For this case, $\tilde{\pi} = \min_{F\in\mathcal{F}} \mathbb{E}_{f_0}\left(\mathbf{1}\left(\mathbf{t},\mathbf{s}\right)F\right)$. If $P = 0$, obviously, $\tilde{\pi} = 1$. If $P \ne 0$, we have $\tilde{\pi} = \min_{f\in\tilde{\mathcal{U}}} \int_{\mathcal{T}} \mathbf{1}\left(\mathbf{t},\mathbf{s}\right) f d\mathbf{t}$, where $\tilde{\mathcal{U}} = \{f \ge 0 : \mathbb{E}_f(1) = 1\}$. It corresponds to a probability density allocation. $P > 0$ means that there exists points that $\mathbf{1}\left(\mathbf{t},\mathbf{s}\right) = 0$. Then by allocating densities only on these zero points, we can obtain $\tilde{\pi} = 0$ under this situation.

2) $\gamma \ne 0$: Considering the definition of $\mathcal{F}$, we can rewrite the inner minimization problem as

$$\begin{aligned} \text{P5}: \quad \tilde{\pi} = \min_{F\ge 0} &\ \mathbb{E}_{f_0}\left(\mathbf{1}\left(\mathbf{t},\mathbf{s}\right)F + \gamma F\ln F\right) - \gamma d \\ \text{s.t.} &\ \ \mathbb{E}_{f_0}\left(F\right) = 1. \end{aligned} \tag{9}$$

We construct the Lagrangian function associated with P5 as

$$\tilde{\Gamma}\left(F, \alpha\right) = \mathbb{E}_{f_0}\left(\mathbf{1}\left(\mathbf{t},\mathbf{s}\right)F + \gamma F\ln F + \alpha F\right) - \gamma d - \alpha, \tag{10}$$

where α is the Lagrangian multiplier. It can be easily proved that P5 is a convex optimization problem[2]. Thus, we observe that if there exists a pair (F^*, α^*) satisfying $F^* \ge 0$,

$$\nabla_F\tilde{\Gamma}\left(F^*, \alpha^*\right) = \mathbb{E}_{f_0}\left(\mathbf{1}\left(\mathbf{t},\mathbf{s}\right) + \gamma\left(\ln F^* + 1\right) + \alpha^*\right) = 0, \tag{11}$$

$$\nabla_\alpha\tilde{\Gamma}\left(F^*, \alpha^*\right) = \mathbb{E}_{f_0}\left(F^*\right) - 1 = 0, \tag{12}$$

then F^* is the optimal solution of P5 [12]. Since $\gamma \ne 0$, by jointly solving (11) and (12), we can obtain

$$F^* = \frac{e^{-\mathbf{1}(\mathbf{t},\mathbf{s})/\gamma}}{\mathbb{E}_{f_0}\left(e^{-\mathbf{1}(\mathbf{t},\mathbf{s})/\gamma}\right)}. \tag{13}$$

Then, by substituting F^* into $\tilde{\pi}$, we can achieve the optimal objective value of P5 as $\tilde{\pi} = -\gamma\ln\mathbb{E}_{f_0}\left(e^{-\mathbf{1}(\mathbf{t},\mathbf{s})/\gamma}\right) - \gamma d$, which can be further represented as

$$\tilde{\pi} = -\gamma\ln\left(\left(1 - P\right)e^{-1/\gamma} + P\right) - \gamma d. \tag{14}$$

Similarly, consider two situations. If $P = 0$, we can obtain $\tilde{\pi} = 1 - \gamma d$ and $\lim_{\gamma\to 0}\tilde{\pi} = 1$. If $P \ne 0$, since $\gamma > 0$, we can derive that $-\gamma d < \tilde{\pi} < -\gamma\ln(P) - \gamma d$ and $\lim_{\gamma\to 0}\tilde{\pi} = 0$.

Obviously, the first case can be incorporated into the second case, and thus the conclusion can be achieved. ■

Theorem 2: The KL divergence based DR counterpart of the chance constraint in P1, presented as (3), is equivalent to

$$\Pr_{f_0}\left(\sum_{m\in\mathcal{M}} T_m c_m x_m \ge z\right) \ge \tilde{\beta}, \tag{15}$$

where

$$\tilde{\beta} = \min_{0<\delta<1} \frac{e^{-d}\delta^\beta - 1}{\delta - 1}. \tag{16}$$

Proof: From Theorem 1, we can rewrite (3) into a feasibility check problem under the empirical distribution f_0 as

$$\exists\ \gamma > 0, \text{ s.t. } -\gamma\ln\mathbb{E}_{f_0}\left(e^{-\mathbf{1}(\mathbf{t},\mathbf{s})/\gamma}\right) - \gamma d \ge \beta, \tag{17}$$

where the case $\gamma = 0$ is removed because $0 < \beta < 1$. Let $\bar{P} = \Pr_{f_0}\left(\mathbf{t}^{\mathrm{T}}\mathbf{s} \ge z\right)$. Then, (17) can be rewritten as

$$\exists\ \gamma > 0, \text{ s.t. } \bar{P} \ge \frac{e^{(\beta+\gamma d)/-\gamma} - 1}{e^{-1/\gamma} - 1}. \tag{18}$$

Using δ to denote $e^{-1/\gamma}$, we can achieve the conclusion. ■

To calculate $\tilde{\beta}$, let $g(\delta) = \frac{e^{-d}\delta^\beta - 1}{\delta - 1}$. Since $\delta \in (0, 1)$ and $d > 0$, it can be derived that $\frac{d^2g(\delta)}{d\delta^2} > 0$, $\lim_{\delta\to 0^+}\frac{dg(\delta)}{d\delta} = -\infty$, and $\lim_{\delta\to 1^-}\frac{dg(\delta)}{d\delta} = +\infty$. Then, the optimal solution of (16) can be achieved by forcing $\frac{dg(\delta^*)}{d\delta^*} = 0$, where the bisection line search algorithm can be adopted. Furthermore, let $h(\delta) = g(\delta) - \beta$. It can be found that $h(\delta) > 0$ for any $\delta \in (0, 1)$, which indicates $\tilde{\beta} > \beta$, representing a more conservative confidence level, and $\tilde{\beta} \to \beta$ when $d \to 0$.

IV. Problem Reformulation Based on Value-at-Risk

Although the DR constraint has been reformulated as a traditional one under a specific distribution f_0 expressed as (15), it is still intractable. Next, based on the concept of value-at-risk (VaR) [16], we will further reformulate (15) into a set of linear constraints. First, we recall the definition of VaR as follows [16].

Definition 1: Use $q(\mathbf{x}, \mathbf{y})$ to denote the loss function of a portfolio, where $\mathbf{x}$ is the decision vector and $\mathbf{y}$ is a random vector representing the uncertainties in the market. Use $f(\mathbf{y})$ to denote the probability density function. Then, with respect to a probability level λ, VaR_λ can be expressed as $\text{VaR}_\lambda\left(q\left(\mathbf{x},\mathbf{y}\right)\right) = \min\left\{\varsigma : \int_{q(\mathbf{x},\mathbf{y})\le\varsigma} f\left(\mathbf{y}\right)d\mathbf{y} \ge \lambda\right\}$, i.e., the lowest value such that the loss is no more than it with at least λ probability. Accordingly, we can reformulate (15) as

$$z \le \text{VaR}_{1-\tilde{\beta}}\left(\sum_{m\in\mathcal{M}} T_m c_m x_m\right). \tag{19}$$

Assume that the candidate bands have equal bandwidth denoted as W, and the empirical distribution of the available du-

[2]The decision variables of P5 can be regarded as all points of $F(\mathbf{t})$ for each possible $\mathbf{t}$. If we consider the discrete case, then it corresponds to the probability mass for each possible value.

ration of each band is an independent and identical distributed one. Let $B_\tau = \sum_{m=1}^{\tau} T_m c_m,\ 1 \le \tau \le M$. Using an indicator $\omega_\tau \in \{0,1\}$ to represent whether or not $\sum_{m\in\mathcal{M}} x_m = \tau$, we can rewrite (19) as

$$z \le \sum_{\tau=1}^{M} \omega_\tau \mathrm{VaR}_{1-\tilde{\beta}}\left(B_\tau\right), \tag{20}$$

where ω_τ's should satisfy the following two linear constrains

$$\sum_{\tau=1}^{M} \tau\omega_\tau = \sum_{m\in\mathcal{M}} x_m, \quad \sum_{\tau=1}^{M} \omega_\tau \le 1. \tag{21}$$

Therefore, the VaR based reformulation for the spectrum selection of DR-CSCT scheme can be expressed as

$$\text{P6}: \quad \min \sum_{\tau=1}^{M} W\tau\omega_\tau$$
$$z \le \sum_{\tau=1}^{M} \omega_\tau \mathrm{VaR}_{1-\tilde{\beta}}\left(B_\tau\right), \sum_{\tau=1}^{M} \omega_\tau \le 1,$$

where $\tilde{\beta}$ is computed by (16). Since the statistics of the candidate bands are assumed to be the same, the spectrum selection strategy for DR-CSCT scheme turns to be a decision making problem of the needed number of bands, and $\omega_\tau = 1$ indicates that τ bands are needed to fulfill the session.

According to the definition of VaR, it can be found that $\mathrm{VaR}_{1-\tilde{\beta}}\left(B_\tau\right)$ in (22) can be approximated based on the sampling approach. Specifically, for each B_τ, $\tau = 1, \cdots, M$, according to the empirical distribution of T_m, we can generate L samples, denoted as $\left\{B_\tau^1, \cdots, B_\tau^L\right\}$. Then, $\mathrm{VaR}_{1-\tilde{\beta}}\left(B_\tau\right)$ can be approximated by the $(1-\tilde{\beta})$-quantile of the sample set, i.e.,

$$\mathrm{VaR}_{1-\tilde{\beta}}\left(B_\tau\right) \approx \min{}^{\lfloor (1-\tilde{\beta})L \rfloor + 1} \left\{B_\tau^1, \cdots, B_\tau^L\right\}, \tag{22}$$

where $\min^k\{\cdot\}$ represents the k-th smallest one among the set, and $\lfloor k \rfloor$ is the largest integer not exceeding k. Then, the spectrum selection of DR-CSCT scheme formulated as P6 turns to be a standard integer linear programming problem.

V. Numerical Results

A. Spectrum Measurement

By using a software defined radio USRP-2922, we implement spectrum measurements on the campus of Dalian University of Technology, located at (N: $38°53'14''$; E: $121°32'3''$), for two days. Based on the collected data, we try to demonstrate that the idle duration of a band within certain period can be well modeled by a random variable, and find the empirical distribution by fitting the real data. To be specific, we monitor a band with 1MHz bandwidth allocated to China Mobile centering at 2580MHz under the sampling frequency as 100Hz, and get 360000 samples of the signal power per hour, which are further processed by the classical energy detection method [17] to capture the idle/busy states, i.e., each data is transformed to 0 or 1 representing the band is idle or busy. We consider the session period as $T = 2$s. Then, to determine the idle duration during every 2 seconds, we fuse every 200 data collected within 2 seconds into one by counting the total number of 0, leading to 1800 data per hour. By counting the frequency of each value in the data set, we can get the probability density function (pdf) of the idle duration within 2 seconds during each hour.

Fig. 1 presents the results for two different periods in each day, i.e., 10AM∼11AM and 3PM∼4PM. From Fig. 1, we can see that the idle duration of the band within 2 seconds can be modeled by the normal distribution. In different periods in each day, the fitted distribution has different parameters, where the mean and the standard deviation are (58.8, 10.6), (62.1, 12.8), (62.3, 12.1), and (48.4, 8.1), respectively. According to the observation, we will adopt normal distribution as the empirical distribution to model the available duration, where the true distribution is regarded away from the empirical distribution within certain KL divergence.

B. Performance Evaluation

In this subsection, we verify the effectiveness of the proposed DR-CSCT scheme by comparing its performance with that of three other schemes: 1) ED-CSCT: solve the problem P1 directly based on the Empirical Distribution extracted from the historical data without the consideration on distributional ambiguity. 2) S-CSCT: leverage the Statistics, e.g., expectation, of the available duration of each band to evaluate the data volume it can transmit, making the stochastic constraint in problem P1 a deterministic one. 3) TD-CSCT: solve the problem P1 based on the assumption that the True Distribution is known. Among them, ED-CSCT and S-CSCT are two general approaches to deal with the stochastic modeling, and TD-CSCT can be treated as the benchmark, which is actually unachievable in practice.

We consider three candidate bands with the same bandwidth as 1MHz. Assume the session period is 2s and the idle duration of each band within 2s is an i.i.d. random variable. The empirical distribution is set to normal distribution based on the observations in Fig. 1, where the mean and the standard deviation are set to 60 and 12, respectively, with the unit as 10ms. To calculate the VaR as in (24), we generate 10,000 samples for each band and set the true value around the generated samples. We consider a worse case that the true available duration is less than the empirical one, which will lead to an overestimation on each band when the empirical distribution is employed.

Note that the decision on the needed number of bands closely depends on the data volume of the session. To make an effective evaluation, instead of running different schemes by setting certain specific data volume to transmit, we fix the band selection and calculate the boundary data volume (BDV) under each scheme, i.e., the maximum amount of data that can be delivered by each scheme. In our experiment, the confidence level β is set to 0.7 and the received SNR is set to 30dB.

In Table I, we present the BDV under the case with one band ($\omega_1 = 1$) and two bands ($\omega_2 = 1$), respectively, and calculate the session completion probability when the data volume is equal to BDV, denoted as p_c. Based on the BDV, the needed number of bands under certain data volume can be easily determined. For example, if $z \in [4.88, 9.97]$, then based

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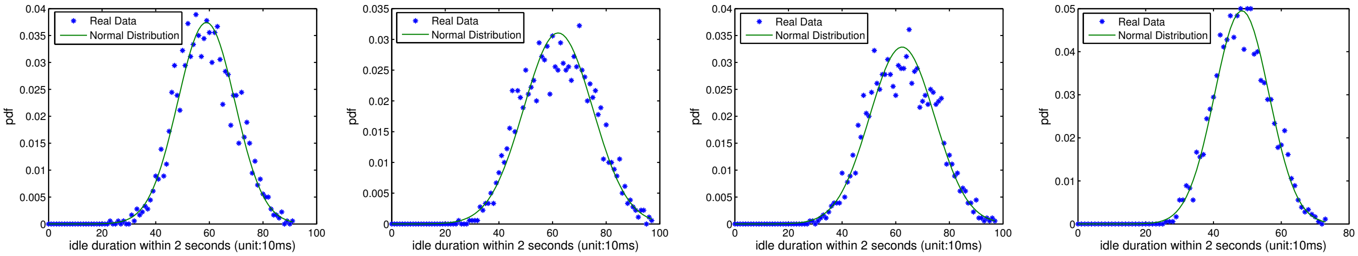

(a) Day 1: 10:00AM∼11:00AM (b) Day 1: 3:00PM∼4:00PM (c) Day 2: 10:00AM∼11:00AM (d) Day 2: 3:00PM∼4:00PM

Fig. 1. The fitted probability density function of the idle duration within 2 seconds.

on the proposed DR-CSCT scheme, only two bands are needed without the requirement on spectrum switching and the session can be fulfilled in an acceptable probability. Comparing with the traditional scheme where frequent wideband sensing and spectrum switching is required, obviously, the cost of DR-CSCT scheme is much less.

TABLE I
PERFORMANCE EVALUATION ON DIFFERENT SCHEMES

	$\omega_1 = 1$ (one band) KL: 0.126, $\tilde{\beta}: 0.886$		$\omega_2 = 1$ (two bands) KL: 0.248, $\tilde{\beta}: 0.933$	
	BDV(Mbs)	p_c	BDV(Mbs)	p_c
S-CSCT	6.03	34.4%	12.07	29.2%
ED-CSCT	5.48	57.1%	11.4	49.2%
TD-CSCT	5.08	69.6%	10.56	70.5%
DR-CSCT	4.88	78.2%	9.97	82.8%

From Table I, comparing with the TD-CSCT scheme, we can see that under both S-CSCT and ED-CSCT schemes, the session cannot be accomplished with an acceptable probability due to the overestimation on the available duration of each band. Whereas, DR-CSCT scheme can guarantee the QoS effectively, where the completion probability is close to that under the true distribution, indicating that the distribution ambiguity problem has been well addressed.

VI. Conclusions

In this paper, we have developed a cost-effective session-oriented cognitive radio transmission (CSCT) scheme to facilitate the dynamic opportunstic spectrum access, where wideband sensing and spectrum switching required in traditional cognitive transmissions could be avoided. By considering the ambiguity on the probability distribution extracted from the historical data, we have designed a distributionally robust (DR) approach by constructing a KL divergence based ambiguity set. According to the real spectrum usage data, we have verified the rationality of the modeling and demonstrated that our proposed DR-CSCT scheme could guarantee the session completion with certain confidence level even if the exact distribution is unknown.

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