Data-Driven Service Provisioning over Shared Spectrums with Statistical QoS Guarantee

Xuanheng Li, Haichuan Ding, Miao Pan, Jie Wang, Haixia Zhang and Yuguang Fang

***Abstract*—With the rapid growth on data traffic, spectrum shortage becomes increasingly serious, leading to the paradigm shift in spectrum usage from an exclusive mode to a sharing mode. However, how to utilize shared spectrums effectively for service provisioning is not straightforward due to its uncertain availability, known as spectrum uncertainty. In this paper, we propose a new metric to evaluate the achievable rate of a link on a share band under a confidence level, called probabilistic link capacity, which offers us an effective way to guarantee the quality of service statistically when using the shared spectrum for service delivery. Different from most existing works where the distributional information is explicitly given based on certain structural assumption, we develop a data-driven distributionally robust approach by using the first and second order statistical information. To achieve the result, we formulate it into a tractable semidefinite programming problem based on the worst-case of conditional-value-at-risk. Finally, as a use case, we design a service-based spectrum-aware transmission scheme, so that different kinds of spectrums (licensed and shared) can be efficiently utilized to satisfy the diverse service requirements.**

***Index Terms*—Spectrum sharing, spectrum uncertainty, service provisioning, distributionally robust optimization, data-driven.**

I. Introduction

Recently, wireless data traffic has shown an explosive growth, calling for more spectrums. Unfortunately, spectrum is an extremely scare resource, especially for the golden bands spanning 100MHz to 6GHz with desired propagation characteristics. Although most sub-6GHz spectrums have been occupied, many measurement campaigns have shown that lots of licensed bands are significantly underutilized [1]. Facing such a dilemma, as a promising solution, spectrum sharing has received increasing attentions in recent years [2]. During the sharing, users can be divided into two groups. One is primary users (PUs) who own the license and have the highest accessing right. The other is secondary users (SUs) who opportunistically use the spectrum when PUs are inactive (interweave mode) [3] or the interference on PUs can be limited (underlay mode) [4]. Such a hierarchical sharing, especially for the interweave mode, can well comply with the current spectrum assignment situation, and has promoted many governmental initiatives [5].

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Cognitive radio (CR) has been regarded as an effective technology to enable such the spectrum sharing [6], [7]. However, service provisioning based on shared spectrums is very challenging, because the shared spectrums have to be vacated when PUs return to use them, which makes the availability of them uncertain, a.k.a., spectrum uncertainty. Such an unique feature brings some new problems when providing services accordingly, such as which bands should be employed when multiple idle bands are captured, how to guarantee the quality of service (QoS) under the uncertainty, etc., which needs to thoroughly study the impact of spectrum uncertainty from the view on the whole service and find an effective way to evaluate the achievable QoS based on the shared band.

Spectrum uncertainty issue has been considered in many research works from different perspectives on spectrum sharing. Most of them are based on certain specific probability or distribution models [8]–[11]. Nevertheless, in practice, such information is usually difficult to obtain precisely, and using an inaccurate probability or distribution model might lead to an over-optimistic solution. Besides the modeling based method, some data-driven spectrum prediction algorithms have been proposed recently for capturing the spectrum state, such as linear prediction methods, Markov model based methods, artificial neural network based methods, and so on [12]. However, most of them mainly focus on the prediction method itself and generally use it as the guideline for spectrum sensing before each time slot, not aiming at solving the spectrum uncertainty problem from the perspective on QoS. Furthermore, since the predicted result is usually inaccurate, the prediction with estimation errors might overestimate the achievable QoS of a shared band, making the spectrum management solution fail to satisfy the service requirement.

In this paper, to facilitate the shared spectrum based service provisioning under spectrum uncertainty, by modelling the average available bandwidth of a shared band within a service period as a random variable, we propose a new metric to evaluate the achievable rate of a link on a shared band under certain confidence level, called probabilistic link capacity (PLC). Such a metric can be used to guarantee the QoS statistically. Instead of assuming a specific distribution function, we adopt the first and second order statistical information and develop a distributionally robust (DR) data-driven approach [13]. To obtain the solution, we make a conservative approximation based on the concept of conditional-value-at-risk (CVaR) [14], and formulate it into a tractable semidefinite programming (SDP) problem. Finally, as a use case, by considering different types of services (delay-sensitive and delay-tolerant) and different kinds of spectrums (licensed and shared), we design a service-based spectrum-aware (S^2) transmission scheme to utilize both licensed and shared spectrums efficiently. Our main contributions are listed as follows.

- We propose a new metric to evaluate the achievable rate of a link on a shared band under uncertainty, named PLC. Such a metric offers us an effective way to make the QoS guaranteed statistically when using a shared band for service provisioning.
- Unlike most existing works where certain specific distribution is assumed for the random variable, we adopt its first and second order statistical information, and develop a distributionally robust data-driven approach to make the obtained PLC achievable under all possible distributions subject to the same statistics.
- Based on the newly proposed metric, we design a S^2 transmission scheme to use different kinds of spectrums efficiently, which is formulated into a two-step optimization problem, including an admission control step and a spectrum re-allocation step.

II. Network Model

A. Cognitive Capacity Harvesting Network Architecture

In general, most light-weighted mobile devices have no capability to implement spectrum sensing, even hardly work on those non-contiguous shared bands. Thus, before introducing the proposed PLC, as the network scenario considered in this paper, we first present a cognitive capacity harvesting network (CCHN) architecture as shown in Fig. 1 [6]. The macro-cell base station (MBS) provides a basic coverage and is mainly in charge of the control signalling. The femto-cell base stations (FBSs) connect to the Internet, acting as data aggregation points for CR routers (CRRs). The CRRs are equipped with multiple radio interfaces and deployed at the edge of the network. On the one hand, they serve as gateways for end-users with the support for various accessing technologies. On the other hand, CRRs construct a bridge between end-users and FBSs, or directly between two end-users to enable an extended device-to-device communication, which have the capability to work on the shared bands.

Each user can select a nearby CRR to connect and submit the service request, which will be forwarded to the MBS for scheduling. We consider two service types, i.e., delay-sensitive (DS) and delay-tolerant (DT), denoted by $\mathcal{L}_{\mathrm{DS}}$ and $\mathcal{L}_{\mathrm{DT}}$, respectively. For any $l \in \mathcal{L}_{\mathrm{DS}}$, the request information includes the rate requirement $r_{\mathrm{DS}}(l)$, the source node $s_{\mathrm{DS}}(l)$ and the destination node $d_{\mathrm{DS}}(l)$. Such a DS request can

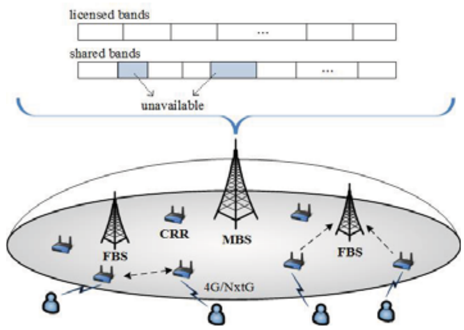


Fig. 1. Cognitive capacity harvesting network architecture for service delivery by using both licensed and shared spectrums.

only be satisfied by the stable licensed bands, denoted as $\mathcal{M}_{\mathrm{l}}$, to guarantee its QoS. For any $l \in \mathcal{L}_{\mathrm{DT}}$, that includes the amount of data $z_{\mathrm{DT}}(l)$, the source node $s_{\mathrm{DT}}(l)$ and the destination node $d_{\mathrm{DT}}(l)$. Assuming that the maximal delay insured by the operator is $T_{\max}$[1], then it corresponds to have a rate requirement as $r_{\mathrm{DT}}(l) = \frac{z_{\mathrm{DT}}(l)}{T_{\max}}$. Such a DT request can be achieved by either licensed bands or shared bands $\mathcal{M}_{\mathrm{s}}$. Assume that there are $\mathcal{N}$ nodes (including CRRs and FBSs) deployed in the network. For any node $i \in \mathcal{N}$, all licensed bands are available, whereas, only part of the shared bands is available, represented by $\mathcal{M}_{\mathrm{s}}^{i} \subseteq \mathcal{M}_{\mathrm{s}}$. Then, all available bands at this node is denoted as $\mathcal{M}^{i} = \mathcal{M}_{\mathrm{s}}^{i} \cup \mathcal{M}_{\mathrm{l}}$, and the common band set for two different nodes i and j is expressed by $\mathcal{M}^{ij} = \mathcal{M}^{i} \cap \mathcal{M}^{j}$.

B. Related Models for Data Transmission

Transmission Neighbor and Interfering Neighbor: We consider a transmission successful only if the received power can exceed certain power threshold $P_{\mathrm{th}}^{\mathrm{T}}$. We adopt a widely used model [15] to represent the power propagation gain from node i to node j described as $g_{ij} = \tau \cdot d_{ij}^{-\alpha}$, in which τ is an antenna related parameter, α is the path loss factor, and d_{ij} is the distance between these two nodes. Supposing the transmission power at node i on band $m \in \mathcal{M}^{i}$ is p_i^m, then the transmission range can be expressed as $R_{i,m}^{\mathrm{T}} = \left(\tau \cdot p_i^m / P_{\mathrm{th}}^{\mathrm{T}}\right)^{1/\alpha}$. For any node j that $m \in \mathcal{M}^{j}$, if $d_{ij} \leq R_{i,m}^{\mathrm{T}}$, then we define it as the transmission neighbor of node i on band m, and the corresponding neighbor set is described as

$$\mathcal{T}_{i,m} = \left\{ j \in \mathcal{N} | d_{ij} \leq R_{i,m}^{\mathrm{T}}, j \neq i, m \in \mathcal{M}^{ij} \right\}. \tag{1}$$

Similarly, we consider the received interference power at each node from an unexpected transmitter ignored only if it is below certain power threshold $P_{\mathrm{th}}^{\mathrm{I}}$. Thus, there exists an interference range for any node i on band m as well denoted as $R_{i,m}^{\mathrm{I}} = \left(\tau \cdot p_i^m / P_{\mathrm{th}}^{\mathrm{I}}\right)^{1/\alpha}$. All nodes receiving data on band m located within this range will be interfered by it, and similar to (1), the interfering neighbor set of node i on band m can be defined as

$$\mathcal{I}_{i,m} = \left\{ j \in \mathcal{N} | d_{ij} \leq R_{i,m}^{\mathrm{I}}, j \neq i, m \in \mathcal{M}^{ij} \right\}. \tag{2}$$

[1] If a DT service request is not completed within the period, it will turn to be a DS service and carried over licensed spectrums

Link Capacity: The capacity of the link from node i to node j on band m, $j \in \mathcal{T}_{i,m}$, can be expressed as $c_{m,ij} = W_m \cdot \log_2\left(1+\frac{\hat{p}_i \cdot g_{ij}}{\gamma}\right)$, where γ is the ambient Gaussian noise density at node j, W_m is the bandwidth of band m, and $\hat{p}_i$ is the transmission power density at node i[2].

C. Probabilistic Link Capacity

Since the shared band m might not be always available during the service period, the average available bandwidth within the period $T_{\max}$ is actually less than W_m. We model it as a random variable $\tilde{W}_m$, and define a probabilistic link capacity (PLC) accordingly as

$$\tilde{c}_{m,ij} = \max\left\{c : \Pr\left\{\tilde{W}_m \cdot \log_2\left(1+\frac{\hat{p}_i \cdot g_{ij}}{\gamma}\right) \geq c\right\} \geq \alpha\right\} \quad (3)$$

where $0 < \alpha < 1$ represents the confidence level. Taking $\alpha = 0.9$ as an example, the link can achieve the capacity $\tilde{c}_{m,ij}$ as in (3) on band m with probability 90%.

Remark: Based on the metric PLC, operators can provide a statistical guarantee on QoS for DT services with certain confidence level. Furthermore, frequency switching is avoided when the selected available bands become unavailable during the transmission, where waiting until they are available again turns to be a better decision, because it is with a high probability that the task can be accomplished over these bands.

III. A Distributionally Robust Data-Driven Approach for Probabilistic Link Capacity

In practice, the precise distributional information of the random variable $\tilde{W}_m$ is usually hardly to obtain. Therefore, in this section, to make the PLC robust against the uncertainty in the distribution of $\tilde{W}_m$, we will develop a data-driven approach by using the first and second order statistical information to achieve a distributionally robust (DR) result[3].

A. Worst-Case for Distributionally Robustness

We rewrite the stochastic constraint in (3) as

$$\Pr\left(\varphi\left(c, \delta_m\right) \leq 0\right) \geq \alpha, \quad (4)$$

where $\varphi\left(c, \delta_m\right) = c - \delta_m = c - \tilde{W}_m \cdot \log_2\left(1+\frac{\hat{p}_i \cdot g_{ij}}{\gamma}\right)$.

As aforementioned, the accurate distribution of the random variable δ_m associated with $\tilde{W}_m$, denoted as $f\left(\delta_m\right)$, is hardly to obtain in practice. Therefore, we consider the worst-case of it, regarded as the DR counterpart of (4), described as

$$\min_{f_\delta \in \mathcal{U}_f} \left\{\Pr\left(\varphi\left(c, \delta_m\right) \leq 0\right)\right\} \geq \alpha. \quad (5)$$

$\mathcal{U}_f$ represents all possible distributions that are consistent with the statistics of δ_m. Then, using (5) to replace the stochastic constraint in (3), we can get a DR solution to PLC, i.e., DR-PLC, formulated as

$$P1: \ \hat{c}_{m,ij} = \max\left\{c : \min_{f_\delta \in \mathcal{U}_f}\left\{\Pr\left(\varphi\left(c, \delta_m\right) \leq 0\right)\right\} \geq \alpha\right\}. \quad (6)$$

We employ the expectation and the variance of δ_m as the statistics to define the distributional ambiguity, denoted as μ and σ^2, respectively. Then, the ambiguity set $\mathcal{U}_f$ can be expressed as

$$\mathcal{U}_f = \left\{f\left(\delta_m\right) \geq 0 \middle| \mathbb{E}\left(\delta_m\right) = \mu, \mathbb{E}\left(\left(\delta_m - \mu\right)^2\right) = \sigma^2, \mathbb{E}\left(1\right) = 1\right\}. \quad (7)$$

B. Approximation Based on Conditional-Value-at-Risk

To solve P1, we will adopt the concept of conditional-value-at-risk (CVaR), a well-known metric for portfolio optimization problems, and focus on its worst-case. Based on the definition of CVaR in [14], we can derive that $\Pr\left(\varphi\left(c, \delta_m\right) \leq \text{CVaR}_\alpha\left(\varphi_m\right)\right) \geq \alpha$, where φ_m is the simplification for $\varphi\left(c, \delta_m\right)$. Thus, $\text{CVaR}_\alpha\left(\varphi_m\right) \leq 0$ is sufficient to imply the original stochastic constraint in (3). Considering the worst-case, we have

$$\max_{f_\delta \in \mathcal{U}_f}\left\{\text{CVaR}_\alpha\left(\varphi_m\right)\right\} \leq 0 \Rightarrow \min_{f_\delta \in \mathcal{U}_f}\left\{\Pr\left(\varphi\left(c, \delta_m\right) \leq 0\right)\right\} \geq \alpha. \quad (8)$$

Hence, the DR-PLC solved by P1 can be approximated by solving the following problem

$$P2: \ \hat{c}_{m,ij} = \max\left\{c : \max_{f_\delta \in \mathcal{U}_f}\left\{\text{CVaR}_\alpha\left(\varphi_m\right)\right\} \leq 0\right\}. \quad (9)$$

Based on Theorem 1 in [14], $\text{CVaR}_\alpha\left(\varphi_m\right)$ can be achieved from the following formula as

$$\text{CVaR}_\alpha\left(\varphi_m\right) = \min_\beta\left\{\beta + \frac{1}{1-\alpha}\mathbb{E}\left(\left[\varphi\left(c, \delta_m\right) - \beta\right]^+\right)\right\}, \quad (10)$$

in which $[x]^+ = \max\left\{x, 0\right\}$. Then, we can rewrite P2 as

$$\hat{c}_{m,ij} = \max\left\{c : \left(1-\alpha\right)\beta + \max_{f_\delta \in \mathcal{U}_f}\mathbb{E}\left(\left[c - \delta_m - \beta\right]^+\right) \leq 0\right\}, \quad (11)$$

which is denoted as P3, representing the worst-case CVaR based approximation for DR-PLC formulated as P1.

C. Semidefinite Programming Based Reformulation

To solve P3, we first give the following proposition, and then, reformulate P3 into a SDP problem accordingly.

Proposition 1: For the following optimization problem as

$$\begin{aligned} &\min_{f_\delta \geq 0} \mathbb{E}\left(-\left[c - \delta_m - \beta\right]^+\right) \\ &\text{s.t. } \ \mathbb{E}\left(\delta_m\right) = \mu, \mathbb{E}\left(\left(\delta_m - \mu\right)^2\right) = \sigma^2, \mathbb{E}\left(1\right) = 1 \end{aligned} \quad (12)$$

it is equivalent to solving the SDP problem below

$$\begin{aligned} &\max_{\lambda, \eta, k} -\lambda\mu - k - \left(\sigma^2 + \mu^2\right)\eta \\ &\text{s.t. } \ \begin{bmatrix} \eta & \frac{\lambda}{2} \\ \frac{\lambda}{2} & k \end{bmatrix} \succeq 0, \begin{bmatrix} \eta & \frac{\lambda+1}{2} \\ \frac{\lambda+1}{2} & k - c + \beta \end{bmatrix} \succeq 0, \end{aligned} \quad (13)$$

in which λ, η, and k are Lagrangian multipliers associated with the three statistic constraints in (12). Detailed proof can be found in the journal version [16].

[2]Interference is not considered here because it can be eliminated by the transmission scheduling as introduced in Section IV.

[3]The first and second order statistical information can be derived from the historical observations, such as the usage data within the same period in several previous days.

Based on Proposition 1, we can find that the constraint in P3 is equivalent to a feasibility check as follows:

$$\begin{aligned} &\exists\,(\beta,\lambda,\eta,k) \\ \text{s.t.}\ &(1-\alpha)\,\beta+\lambda\mu+k+\left(\sigma^2+\mu^2\right)\eta\le 0, \\ &\begin{bmatrix} \eta & \frac{\lambda}{2} \\ \frac{\lambda}{2} & k \end{bmatrix}\succeq 0, \begin{bmatrix} \eta & \frac{\lambda+1}{2} \\ \frac{\lambda+1}{2} & k-c+\beta \end{bmatrix}\succeq 0. \end{aligned} \tag{14}$$

Consequently, P3 can be reformulated into a tractable SDP problem as

$$\hat{c}_{m,ij}=\max_{\beta,\lambda,\eta,k}\ c\ , \tag{15}$$

subject to the constraints as in (14), and DR-PLC can be obtained accordingly.

IV. Service-Based Spectrum-Aware Data Transmission Scheme

Taking the CCHN as the network scenario, next, we will develop a service-based spectrum-aware (S^2) data transmission scheme to satisfy different service requirements by efficiently using different spectrums, where two types of services (DS and DT) and two kinds of spectrums (licensed and shared) are considered. We formulate it into a two-step optimization problem. Step-1 is an admission control to maximize the number of admitted services with the consideration on their different importance levels and rate requirements. Step-2 focuses on the spectrum efficiency to minimize the occupied bandwidth of the licensed bands. During the scheduling, we only consider the links transmitting the aggregated data, i.e., CRR $\leftrightarrow$ FBS and CRR $\leftrightarrow$ CRR.

A. Step-1: Admission Control

We exploit a binary variable $k\,(l)$ to describe whether or not the service request $l\in\{\mathcal{L}_{\mathrm{DT}}\cup\mathcal{L}_{\mathrm{DS}}\}$ can be admitted as

$$k\,(l)=\begin{cases}1, & \text{if service request } l \text{ is admitted,}\\ 0, & \text{otherwise.}\end{cases} \tag{16}$$

Denote $w\,(l)$ as the weight attributed to the service request l corresponding to its importance level. Then, the objective of the step-1 can be expressed as

$$\max \sum_{l\in\{\mathcal{L}_{\mathrm{DT}}\cup\mathcal{L}_{\mathrm{DS}}\}} w\,(l)\,k\,(l). \tag{17}$$

Next, we will show the constraints for the spectrum allocation. We employ a binary variable x_{ij}^m to denote whether or not band $m\in\mathcal{M}^{ij}$ is allocated on the link from i to j as

$$x_{ij}^m=\begin{cases}1, & \text{if band } m \text{ is allocated on the link } i\to j,\\ 0, & \text{otherwise.}\end{cases} \tag{18}$$

First, we need to avoid the mutual interference among different links. For any node $i\in\mathcal{N}$, it cannot transmit to or receive from other nodes on the same band, which can be described as

$$\sum_{j\in\mathcal{T}_{i,m}} x_{ij}^m\le 1, \sum_{\{h|i\in\mathcal{T}_{h,m}\}} x_{hi}^m\le 1, \forall i\in\mathcal{N}. \tag{19}$$

Furthermore, any node cannot transmit and receive on the same band simultaneously due to the self-interference, which can be expressed as

$$x_{ij}^m+\sum_{q\in\mathcal{T}_{j,m}} x_{jq}^m\le 1, \forall i\in\mathcal{N}, \forall j\in\mathcal{T}_{i,m}. \tag{20}$$

Moreover, if $x_{ij}^m=1$, all interfering neighbors of node i cannot receive data on band m, and we can obtain the constraint as

$$x_{ij}^m+\sum_{\{k|g\in\mathcal{T}_{k,m},k\neq i\}} x_{kg}^m\le 1, \forall i\in\mathcal{N}, \forall g\in\mathcal{I}_{i,m}. \tag{21}$$

Second, for the admitted services, we need to guarantee: 1) the admitted DS services should be carried by the licensed bands; 2) the achievable rate of the link transmitting admitted services' data should reach the rate requirement. Then, we can get the following two constraints as

$$\sum_{\{l\in\mathcal{L}_{\mathrm{DS}}|s_{\mathrm{DS}}(l)=i,d_{\mathrm{DS}}(l)=j\}} r_{\mathrm{DS}}\,(l)\,k\,(l)\le\sum_{m\in\mathcal{M}_l} x_{ij}^m c_{m,ij}, \tag{22}$$

and

$$\begin{aligned} &\sum_{\{l\in\mathcal{L}_{\mathrm{DS}}|s_{\mathrm{DS}}(l)=i,d_{\mathrm{DS}}(l)=j\}} r_{\mathrm{DS}}\,(l)\,k\,(l)+\sum_{\{l\in\mathcal{L}_{\mathrm{DT}}|s_{\mathrm{DT}}(l)=i,d_{\mathrm{DT}}(l)=j\}} r_{\mathrm{DT}}\,(l)\,k\,(l) \\ &\qquad\le\sum_{m\in\mathcal{M}_l} x_{ij}^m c_{m,ij}+\sum_{m\in\mathcal{M}_s^i} x_{ij}^m\hat{c}_{m,ij}. \end{aligned} \tag{23}$$

By solving the integer linear programming (ILP) problem with the objective as (17), subject to the constraints from (19) to (23), we can achieve the optimal admission control result $k^*\,(l)$ for any service request $l\in\{\mathcal{L}_{\mathrm{DT}}\cup\mathcal{L}_{\mathrm{DS}}\}$.

B. Step-2: Spectrum Re-allocation

The objective of step-2 is minimizing the total occupied bandwidth of the licensed bands. On the one hand, some links with low rate requirements may be assigned with a wide bandwidth. On the other hand, some DT services may be carried by the licensed bands, leaving the relatively sufficient shared bands under-utilized. By using the same notations as those in step-1, we can formulate the objective as

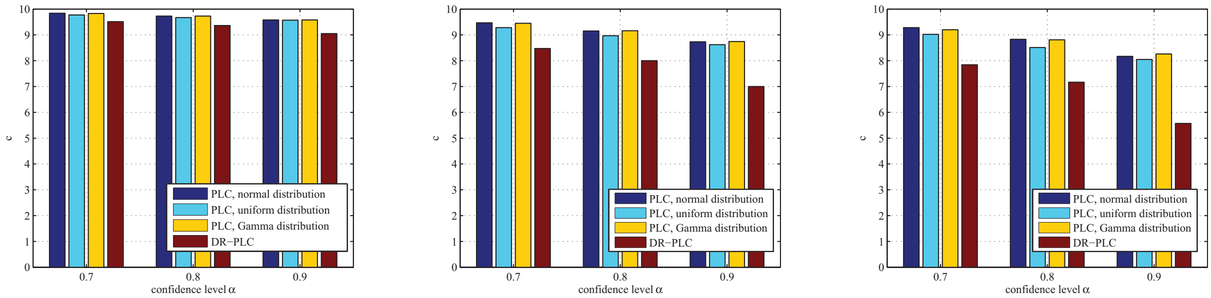
$$\min\sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{T}_{i,m}}\sum_{m\in\mathcal{M}_l} x_{ij}^m W_m. \tag{24}$$

Similar to step-1, the constraints for step-2 also involve two aspects. One is to avoid the co-channel interference, which can be described by (19), (20) and (21) as well. The other is to guarantee the QoS for the admitted services scheduled in step-1, which can be formulated by substituting $k\,(l)$ with $k^*\,(l)$ in (22) and (23).

V. Numerical Results

A. Evaluation for the Distributionally Robust Approach

In this subsection, by directly assuming that δ_m follows certain distribution, we evaluate the performance of the proposed distributionally robust approach through comparing the



(a) $\sigma^2 = 0.1$ (b) $\sigma^2 = 1$ (c) $\sigma^2 = 2$

Fig. 2. PLC and DR-PLC under different probability distributions.

PLC[4] as (3) and the DR-PLC as (15). Three common distributions are employed, including normal distribution, uniform distribution and Gamma distribution. We present DR-PLC and PLC under the three distributions with different confidence levels in Fig. 2. To be specific, we set the same statistics for each distribution in each experiment, where $\mu = 10$ and σ^2 is 0.1, 1, and 2 in (a), (b), and (c), respectively. Three confidence levels are considered, i.e., $\alpha = 0.7$, $\alpha = 0.8$, and $\alpha = 0.9$. From Fig. 2, we can find that DR-PLC is lower than PLC under any distribution because it is in fact a lower bound of PLC, robust to any possible distributions with the same statistics. When the variance is small, the difference between DR-PLC and PLC is little. As the variance increases, the gap becomes more obvious, because it is more difficult to achieve the distributional robustness when the random variable fluctuates more dramatically. Furthermore, considering the different confidence levels, we can observe that the higher confidence level employed, the lower PLC and DR-PLC can be achieved, because it has to make the result achievable with a higher probability. Moreover, the gap between DR-PLC and PLC increases as the adopted confidence level increases.

B. A Case Study For S^2 Transmission Scheme

We consider a grid network with nine nodes as shown in Fig. 3. The transmission power of each node on each band is assumed to be equal to 2W with a transmission and interference range as 210m and 260m, respectively. The transmission related parameters are set as follows: $\tau = 4$, $\alpha = 4$. The noise density power at each receiver is set as $\gamma = 10^{-16}$ W/Hz. Suppose that there are three DS requests and five DT requests as shown in Fig. 3. The weights of the three DS ones are set the same as 6, and those of the five DT ones are set as 5, 4, 3, 1, 2, respectively. Assume that there are two licensed bands, $\mathcal{M}_l = \{1, 2\}$, and three shared bands, $\mathcal{M}_s = \{3, 4, 5\}$, available in the network, and all nodes can use any of them. The bandwidth of the two licensed ones are $W_1 = 3$MHz, and $W_2 = 4$MHz, and that of the three shared ones are $W_3 = 3$MHz, $W_4 = 4$MHz, and $W_5 = 5$MHz, respectively. Due to the spectrum uncertainty, the actual available bandwidth of each shared band is a random

[4] As conducted in [1], [11], Monte Carlo experiment as an effective method is adopted to calculate the PLC under different distributions.

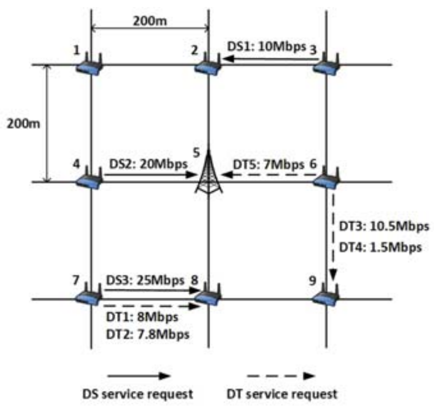
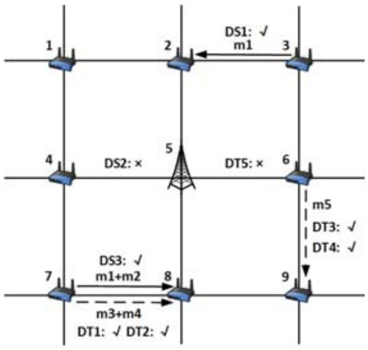


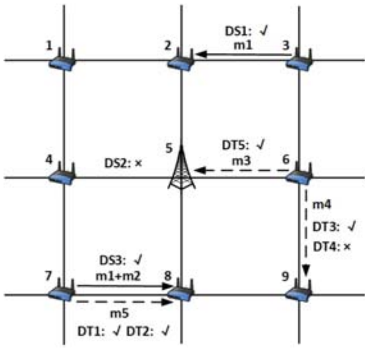
Fig. 3. A grid network with 9 nodes, 3 DS requests and 5 DT requests.

variable as $\tilde{W}_m \leq W_m$, $m=3, 4, 5$. Suppose that they follow the uniform distribution with the expectation as 1.5, 2.5, 3.5, respectively, and with the same variance as 0.2. The confidence level for PLC is set as 0.7.

We take the modelling based method for comparison, where an inaccurate distribution is adopted, e.g., by an incorrect modelling assumption or a noisy estimation with limited historical data, and the obtained PLC under the false distribution is denoted as PLC-F. We assume that the adopted inaccurate distribution is normal distribution with the same statistics as the real one. By adopting PLC-F and DR-PLC to evaluate the performance of each shared band, the scheduling result of the S^2 scheme is shown in Fig. 4. We can see that for the three DS requests which can only be carried by the licensed bands, DS1 and DS3 are admitted, working on $\{m_1\}$ and $\{m_1, m_2\}$, respectively. DS2 is rejected because the scheduling objective is maximizing the total weight of the admitted services and if it is admitted, both DS1 and DS3 with the same weight as DS2 would be rejected. For the five DT requests, when DR-PLC is adopted, DT1, DT2, DT3 and DT4 will be admitted as depicted in Fig. 4(a). Note that since the capacity provided by the licensed bands m_1 and m_2 exceeds the demand of DS3, some data of DT1 is actually carried by the licensed bands. If the operator mistakenly takes the PLC-F for the evaluation, DT5, which has a higher weight than DT4, will become the admitted one as shown in Fig. 4(b) because of



(a) Evaluation based on DR-PLC



(b) Evaluation based on PLC-F

Fig. 4. Scheduling result of the S^2 scheme.

TABLE I
GUARANTEE PROBABILITY OF THE QOS FOR EACH ADMITTED SERVICE

	DT1	DT2	DT3	DT4	DT5
DR-PLC	1	99.7%	1	91.6%	
PLC-F	1	59.0%	59.4%		63.0%

the overestimation of the achievable rate for each shared band. In Table. I, we present the guarantee probability of the QoS for each admitted DT service based on DR-PLC and PLC-F respectively by taking 1000 experiments. In each experiment, the available bandwidth of each shared band is generated randomly, following the uniform distribution with the aforementioned settings on statistics. We can see that if we directly use a specific distribution, which is probably an inaccurate one, to model the spectrum uncertainty, QoS can be hardly guaranteed. Whereas, when the metric DR-PLC is adopted, the QoS can be guaranteed with the probability higher than 90%, even though the confidence level is only set as 0.7 because we make the rate requirement less the DR-PLC during the scheduling, and such a DR-PLC is more conservative than PLC for the performance evaluation on each shared band.

VI. Conclusions

In this paper, we have studied the shared spectrum enabled service provisioning issue. Facing the spectrum uncertainty problem, by modeling the average available bandwidth within a service period as a random variable, we have proposed a new metric named PLC to evaluate the achievable rate of a link on a shared band, which offers us a way to guarantee the QoS statistically. Considering that the precise distributional information is usually hardly to obtain in practice, we have designed a distributionally robust data-driven approach by using the first and second order statistics, which is solved by a SDP-based reformulation according to the worst-case of CVaR. Finally, with the proposed metric, we have developed a S^2 transmission scheme to efficiently utilize the licensed and shared spectrums to fulfill diverse service requirements.

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