Implementation of an Opportunistic Spectrum Access System with Disruption QoS Provisioning and PU Traffic Parameter Estimation

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***Abstract*—Opportunistic Spectrum Access (OSA) is one of the models proposed in the literature for Dynamic Spectrum Access (DSA). Providing *disruption QoS* in terms of interference caused to the Primary Users (PUs) is crucial in such systems. In this paper, we use a residual idle time based scheme called RIBS, to provide disruption QoS to the PUs. The transmission duration of a Secondary User (SU) is carefully computed such that the interference to the PU remains below a threshold. We propose two disruption Quality of Service (QoS) metrics and show the computation of maximum transmission duration for the two metrics. We have implemented RIBS with these two new disruption QoS metrics using GNU Radio over Universal Software Radio Peripheral (USRP) hardware. We also use maximum likelihood estimation (MLE) to dynamically estimate the parameter of PU traffic, which is then used to compute SU transmission duration. This eliminates the requirement, widely assumed in the literature, that SUs know the PU traffic characteristics a priori. Results from our experiments show that RIBS is able to provide the required QoS and that the MLE based parameter estimation method works reasonably well.**

I. Introduction

Opportunistic Spectrum Access (OSA) is one of the models proposed in the literature for dynamic spectrum access (DSA). In the OSA model, Secondary Users (SUs) search for idle periods or white spaces and opportunistically transmit in those white spaces. But the challenge is for the SUs to back out of the spectrum when the incumbent or Primary User (PU) reappears so that the PU does not encounter significant interference.

Unless the traffic pattern of the PUs is known a priori, restricting interference to zero is impossible. Thus, in most practical DSA systems, SUs will cause a certain amount of disruption to the PUs. Hence, a DSA system which can provide quality of service (QoS) guarantees in terms of disruption caused to the PUs is attractive to the PUs. We refer to this QoS as *Disruption QoS*. There are some OSA schemes proposed in the literature which provide disruption QoS. In [1], [2], authors propose OSA schemes which restrict the interference probability below a given threshold. One shortcoming of these schemes is that they assume that the PU traffic characteristics are known to the SU. This may not always be possible in practice. A better approach is to estimate the PU traffic parameters on the fly and then apply the methodology to provide disruption QoS. This also has the added advantage that the DSA system would be able to adapt to changing PU traffic pattern. In this paper, we use a residual idle time based scheme (RIBS) [2] to provide disruption QoS. But we propose two new disruption QoS metrics to be used with RIBS. The first metric restricts the probability of interference as observed by a PU, whereas the second metric constrains the duration of interference caused to a PU. These metrics are more appropriate than that proposed in [2], because they are defined from the PU's perspective. We show how the maximum duration of SU transmission is computed such that the required disruption QoS is provided to the PUs. We use maximum likelihood estimation to obtain PU traffic parameters. As an SU senses the spectrum, it stores the sensing results. Based on a certain number of past sensing results, it then applies a maximum likelihood function to dynamically estimate the traffic parameters.

Most of the schemes proposed in the literature have been validated using simulation. In fact, actual implementations of DSA systems are very rare. We have a prototype implementation of RIBS with the two proposed disruption QoS metrics along with dynamic estimation of PU traffic parameters on a USRP[1] based testbed. Our experimental results validate that the proposed methodology indeed provides the required disruption QoS. Our prototype implementation eliminates one of the major assumptions used in many OSA schemes in the literature: that the SUs know the PU traffic characteristics in advance. The prototype implementation dynamically estimates the PU traffic parameters, then computes the maximum duration of transmission by SUs to meet a given disruption QoS constraint.

II. Related Work

There have been different OSA schemes with disruption QoS proposed in the literature. Disruption QoS in terms of collision probability and in terms of duration of interruption have been proposed in [3]. An OSA system using Partially Observable Markov Decision Process (POMDP) is reported in [4] which maximizes SU throughput while keeping the probability of collision of an SU below a given threshold. The OSA model in [5] keeps the probability of interference below a threshold while maximizing spectrum utilization of

[1]The identification of any commercial product or trade name does not imply endorsement or recommendation by the National Institute of Standards and Technology, nor is it intended to imply that the materials or equipment identified are necessarily the best available for the purpose.

an SU. The scheme proposed in [6] computes ON and OFF duration of SU in a legacy cellular network such that average fraction of time that an SU interferes with PU is kept below a threshold. In this scheme, SUs do not sense the channel, but transmit during ON period and remain idle during OFF period.

Many proposed OSA schemes in the literature either assume that the distribution of idle and busy duration is known or they get those information through measurements. For example, in [5], the authors assume the PU idle and busy distribution is known. In [1], authors have used simulated measurement of idle times to empirically determine the idle time distribution of PU traffic. These methods may not be suitable for a practical system, where the PU traffic characteristics may not be known or the PU traffic may be dynamic, so that any empirical computation of PU traffic distribution may not be valid at all times. So, researchers have used various traffic parameter estimation methods to address this issue. Traffic parameter estimation using a maximum likelihood estimator with periodic sampling was introduced in [7]. A Bayesian estimator which is computationally expensive but more accurate was presented in [7]. A Hidden Markov Model (HMM)-based channel state prediction method was proposed in [8]. In [9], authors present channel estimation for periodic and random sensing schemes using maximum likelihood estimation when PU traffic is modeled as an ON-OFF alternating renewal process. Our channel estimation method is based on the method reported in [9].

III. Providing QoS using RIBS

In RIBS, an SU accesses the channel opportunistically when the PUs are silent. The access mechanism of RIBS is depicted in Figure 1. The PU traffic is modeled as an Alternating Renewal Process (ARP) with alternating *ON* (or busy) and *OFF* (or idle) periods. An SU senses the channel and transmits if the channel is free. In Figure 1, an SU senses the channel for duration ab and finds it to be idle. Then it transmits for duration bc. This duration of transmission of the SU is calculated such that the disruption QoS constraint is met. After a successful transmission, the SU backs off exponentially with respect to the previous sensing instant (a). Sometimes, after a successful transmission, an SU may has to perform multiple backoffs to go beyond the current time. For example, if the the backoff duration ad is less than ac, then the SU have to perform multiple backoffs until the cumulative backoff duration becomes larger than ac. If the channel is busy (e.g., at time instant d in Figure 1), then the SU backs off with a random duration which is exponentially distributed. In this paper, we propose two *disruption QoS metrics* and derive expressions for maximum transmission duration of an SU such that it provides the required disruption QoS.

The sensing instant of an SU is modeled as a random incidence into an ARP. From the theory of random incidence into an ARP [10, p. 331], the density function of the residual idle (RI) time is given by

$$f_{RI}(y) = \frac{1 - F_I(y)}{E[I]}, \tag{1}$$

where $f_X(.)$ and $F_X(.)$ represent the pdf and cdf of random variable X, respectively, and $E[I]$ denotes the expectation of idle time of the channel.

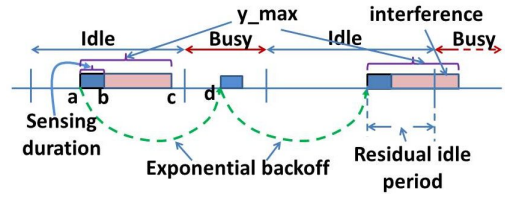

Fig. 1. Illustration of SU Channel Access in RIBS

A. Disruption QoS Metrics

In this section, we present two disruption QoS metrics and derive the maximum duration of transmission by an SU such that it honors the QoS. Let N_x be the number of SU transmissions in duration T. Let I and B be random variables representing idle and busy periods of PU traffic respectively. Let $C = I + B$ be the random variable representing an idle-busy cycle of PU traffic. Let random variable BO, which is exponentially distributed, denote the backoff duration between sensing instances of the SU. The maximum duration for which an SU can transmit without violating the QoS constraint is denoted as y_{max}.

1) Probability of Interference observed by PU (PIP): The Probability of Interference observed by a PU (PIP) is the probability that transmission of any SU interferes with that PU. We define it as the ratio of number of SU transmissions which overlapped with PU busy periods to the number of busy periods of the PU over a long duration T. Thus,

$$PIP = \frac{N_{intf}}{N_B}, \tag{2}$$

where N_{intf} is the number of interference caused by SU transmissions and N_B is the number of busy periods of the PU over a long time period T. This QoS metric may be useful for PU applications which are sensitive to the number of interference events (as opposed to the duration of interference). For example, a packet based system which does not use channel coding would incur packet loss even when there is interference of short duration. So, a metric based on the number of interference, e.g., PIP, is appropriate for PU performance.

Since the backoff incidence is a Poisson process, the average number of backoff incidences in duration T is $T/E[BO]$. From the Poisson Arrival Sees Time Average (PASTA) property [11, pp. 77-78], the fraction of these backoff incidences which fall into idle periods is $E[I]/E[C]$. So the number of SU transmissions in time period T is given by

$$N_x = \frac{E[I]}{E[C]} \cdot \frac{T}{E[BO]}. \tag{3}$$

The SU interferes with a PU busy period when $RI < y$, where y is the duration of SU transmission. Hence,

$$N_{intf} = N_x \cdot P\{RI < y\}. \tag{4}$$

We know from renewal theory (see [12], p. 424) that the number of PU cycles, N_C, in time period T is equal to the number of busy periods, N_B and is given by

$$N_B = \frac{T}{E[C]}. \tag{5}$$

Using (3), (4) and (5) in (2), we have

$$PIP = \frac{E[I] \cdot P\{RI < y\}}{E[BO]}. \tag{6}$$

Note that N_x computed in (3), does not take into account the fact that some of the backoff incidences may fall in the duration y and hence those may not result in SU transmissions. Let us denote the number of backoff incidences which are in the idle period but fall within duration y as W_{inc}. The incidences in this interval can be modeled as successes in a Bernoulli process. Noting that W_{inc} is the expected number of consecutive successes in a Bernoulli process, W_{inc} can be shown to be equal to $p/(1-p)$, where p is the probability of success. Then, the probability of failure, which is the probability of incidenting outside of the duration under consideration can be shown to be $1/(1+W_{inc})$. So, the actual number of SU transmissions is $(N_x) \cdot (1/(1+W_{inc}))$ (see [13] for details of this derivation).

We present the method to compute W_{inc} below. We should only count the backoff incidences which fall within the y duration of SU transmission, but which are not in the busy period of PU. So the expected duration in which we look for such backoff incidences is $E[min(RI, y)]$, which is given by

$$\begin{aligned} E[min(RI,y)] &= \int_0^\infty P\{min(RI,y) > t\}dt \\ &= \int_0^y P\{min(RI,y) > t\}dt + \\ &\quad \int_y^\infty P\{min(RI,y) > t\}dt \\ &= \int_0^y P\{RI > t\}dt \\ &= \int_0^y (1 - P\{RI < t\})dt \\ &= y - \int_0^y P\{RI < t\}dt \end{aligned} \tag{7}$$

and W_{inc} is give by $E[min(RI, y)]/E[BO]$.

Making this correction, the expression for PIP in (6) is modified as follows.

$$PIP = \frac{1}{1 + \frac{y - \int_0^y P\{RI<t\}dt}{E[BO]}} \cdot \frac{E[I].P\{RI < y\}}{E[BO]} \tag{8}$$

When I is exponentially distributed, RI is also exponentially distributed with the same parameter. Noting that $P\{RI < t\}$ is the distribution function of RI and that W_{inc} is give by $E[min(RI, y)]/E[BO]$, using (7), it can be shown that $(1/(1+W_{inc}))$ is given by

$$\frac{1}{1+W_{inc}} = \frac{E[BO]}{E[BO] + (1 - e^{-y_{max}/E[I]}) \cdot E[I]}. \tag{9}$$

Hence, when I is exponentially distributed, the corresponding PIP can be shown to be

$$PIP_{exp} = \frac{(1 - e^{-y/E[I]})}{\frac{E[BO]}{E[I]} + (1 - e^{-y/E[I]})}. \tag{10}$$

To provide disruption QoS, PIP should remain below a threshold which we denote as η_{pip}. It is easy to see that PIP_{exp} is an increasing function of y. So, the maximum transmission duration, y_{max}, can be computed by solving

$$\frac{(1 - e^{-y_{max}/E[I]})}{\frac{E[BO]}{E[I]} + (1 - e^{-y_{max}/E[I]})} = \eta_{pip}, \tag{11}$$

which leads to

$$y_{max} = -E[I].\ln\Big(1 - \frac{E[BO]/E[I]}{\frac{1}{\eta_{pip}} - 1}\Big). \tag{12}$$

2) Fraction of overlap with PU (FoP): The Fraction of overlap with PU (FoP) is defined as the duration, expressed as a fraction of total PU busy duration, for which an SU transmission overlaps with that of a PU. Thus, it is suitable for PU applications which are sensitive to the duration of interference, such as voice.

Let X_i represent the duration of overlap of the ith SU transmission with a PU busy period. Let B_j be the duration of the jth busy period of the PU. Then FoP is given by

$$FoP = \frac{\sum_i X_i}{\sum_j B_j}. \tag{13}$$

X_i's are independent and identically distributed with mean $E[X]$. By the law of large numbers we have

$$\sum_i X_i = E[X] \cdot N_x \tag{14}$$

and

$$\sum_j B_j = E[B] \cdot N_B. \tag{15}$$

Thus, FoP is given by

$$FoP = \frac{E[X].N_x}{E[B].N_B}. \tag{16}$$

Using the values of N_x from (3) and N_B from (5), we have

$$FoP = \frac{E[X]}{E[B]} \cdot \frac{E[I]}{E[BO]}. \tag{17}$$

Now, $X = max((y - RI), 0)$.
So, $E[X]$ is given by

$$\begin{aligned} E[X] &= \int_0^\infty P\{max((y-RI),0) > t\}dt \\ &= \int_0^y P\{max((y-RI),0) > t\}dt + \\ &\quad \int_y^\infty P\{max((y-RI),0) > t\}dt \\ &= \int_0^y P\{(y-RI) > t\}dt \\ &= \int_0^y P\{(RI < (y-t)\}dt. \end{aligned} \tag{18}$$

and FoP is given by

$$FoP = \frac{(\int_0^y P\{(RI < (y-t)\}dt)}{E[B]} . \frac{E[I]}{E[BO]}. \quad (19)$$

When I (and hence RI) is exponentially distributed, $E[X]$ is given by

$$\begin{aligned} E[X] &= \int_0^y (1 - e^{-(y-t)/E[I]})dt \\ &= \int_0^y dt - e^{-y/E[I]} \int_0^y e^{t/E[I]}dt \\ &= y - (1 - e^{-y/E[I]}).E[I]. \end{aligned} \quad (20)$$

Hence, when I and B are exponentially distributed, FoP is given by

$$FoP_{exp} = \frac{y - (1 - e^{-y/E[I]}).E[I]}{E[B]} . \frac{E[I]}{E[BO]}. \quad (21)$$

As explained in the derivation of the expression for PIP, the above expression does not account for backoff incidences which occur within the transmission period y of the SU. Hence, the correct expression of FoP is obtained by multiplying the above expression by $(1/(1 + W_{inc}))$. Thus, when I and B are exponentially distributed, FoP is given by (using (9))

$$\begin{aligned} FoP_{exp} &= \frac{E[BO]}{E[BO] + (1 - e^{-y/E[I]}).E[I]} . \\ &\quad \frac{y - (1 - e^{-y/E[I]}).E[I]}{E[B]} . \frac{E[I]}{E[BO]} \\ &= \frac{y - (1 - e^{-y/E[I]}).E[I]}{E[BO] + (1 - e^{-y/E[I]}).E[I]} . \frac{E[I]}{E[B]}. \end{aligned} \quad (22)$$

It can be shown that FoP_{exp} is an increasing function of y, although the process is a little more complex than the case of PIP. Hence, if the FOP constraint is given by η_{fop}, then maximum duration of transmission of SU, y_{max}, can be obtained by solving

$$\frac{y_{max} - (1 - e^{-y_{max}/E[I]}).E[I]}{E[BO] + (1 - e^{-y_{max}/E[I]}).E[I]} . \frac{E[I]}{E[B]} = \eta_{fop}. \quad (23)$$

The above equation does not have a closed form solution for y_{max}. Since FoP_{exp} is an increasing function of y, we find y_{max} using a binary search.

IV. PU Traffic Parameter Estimation

As presented earlier, RIBS models PU traffic as an ON-OFF ARP. So, to use RIBS, the parameters of the ON-OFF process should be known. One possibility is to observe PU traffic for a long period and then try to fit a distribution for the ON-OFF process. This approach was followed in [2]. But the drawback of this approach is that it assumes that the PU traffic seen by an SU is similar to the past observed traffic. A better approach is to estimate the parameters of the ON-OFF process on the fly to model PU traffic. We use *Maximum Likelihood Estimation (MLE)* on an ARP to estimate the parameters of PU traffic. We use the method presented in [9], which uses state transition probabilities of semi-Markov kernel of an ARP in computing MLE to estimate parameters. Although the method works for any distribution of ON and OFF processes, we have used the exponential distribution for ON and OFF processes in this study. The exponential distribution has been shown to be a good approximation of channel occupancy [14]. We briefly present the method for ARP with exponentially distributed ON and OFF periods which has been used in [9]. Note that, if the actual process is not exponential, the estimator effectively finds the best exponential fit for that process. Since the ON and OFF periods are exponentially distributed, they are defined by a single parameter θ_1 and θ_0, respectively. The corresponding expected duration of the ON and OFF periods are $1/\theta_1$ and $1/\theta_0$. The channel utilization is given by

$$u = \frac{1/\theta_1}{1/\theta_1 + 1/\theta_0}. \quad (24)$$

Let $[z_1, z_2, .., z_m]$ be m samples obtained at time instants $[t_1, t_2, .., t_m]$ respectively. $z_i = 1$ if the channel was ON (busy) and $z_i = 0$ if the channel was OFF (idle) at time t_i. It is shown in [9] that the likelihood function is given by

$$\begin{aligned} L(\theta_0, \theta_1) = u^{z_1}(1-u)^{1-z_1} \prod_{i=2}^{m} (u^{z_i}(1-u)^{1-z_i} \\ + (-1)^{z_i+z_{i-1}} u^{1-z_{i-1}} (1-u)^{z_{i-1}} e^{-(\theta_0+\theta_1)\Delta t_i}), \end{aligned} \quad (25)$$

where $\Delta t_i = t_i - t_{i-1}$. The ML estimate of the two parameters is then set to be the pair $(\hat{\theta}_0, \hat{\theta}_1)$ for which the value of $L(\theta_0, \theta_1)$ is maximized. This is an analytically intractable problem. Hence, a suboptimal estimation is adopted. First, u is estimated using

$$\hat{u} = \frac{1}{m} . \sum_{i=1}^{m} z_i. \quad (26)$$

Then observing that $\theta_1 = \frac{(1-u)\theta_0}{u}$, the likelihood function is rewritten as

$$\begin{aligned} L(\theta_0) &= u^{z_1}(1-u)^{1-z_1} \prod_{i=2}^{m} (u^{z_i}(1-u)^{1-z_i} \\ &\quad + (-1)^{z_i+z_{i-1}} u^{1-z_{i-1}} (1-u)^{z_{i-1}} e^{-\theta_0 \Delta t_i/u}). \end{aligned} \quad (27)$$

θ_0 is then estimated to be the value for which $L(\theta_0)$ is maximum. We use the *Golden Section Search* method to find the estimation of θ_0 [15].

V. Experiment Setup

A. Testbed

We have implemented RIBS for an Orthogonal Frequency Division Multiplex (OFDM) system on a testbed shown in Figure 2. The testbed has two rack-mounted host servers and four USRP N210 software-defined radios connected in a full mesh topology through an RF channel emulator. Each host servers have 12 core CPUs and 64GB memory and run CentOS linux 2.6.32. The SBX daughterboards on the USRP can operate in the frequency range of 400 MHz to 4400 MHz. The protocol stack is implemented in GNU Radio 3.6.5.

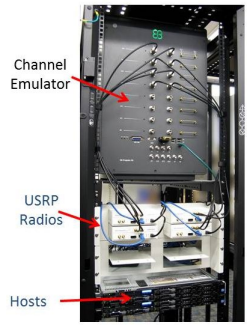

Fig. 2. Testbed used for our Experiments

B. Configurations

Two radios are used as PU sender and receiver whereas the other two act as SU sender and receiver. The OFDM signal has a bandwidth of 1 MHz comprising of 512 subcarriers, of which the center 240 subcarriers are used for communication. The center 240 subcarriers are divided into four channels, each channel containing 60 contiguous subcarriers. One channel is dedicated as the control channel and the other three are used for data. The single physical pair of PU radios emulates three pairs of PUs using one data channel each, and each with its own ON-OFF traffic over its respective channel. RIBS is applied to each channel, i.e., the maximum duration of transmission of the SU over a given channel is computed based on the PU traffic on the channel and the disruption QoS constraint. The PU and SU senders transmit with a power density of -100 dBm/Hz and -110 dBm/Hz, respectively, using Binary Phase Shift keying (BPSK) subcarrier modulation. A fixed path loss of 20.8 dB is applied to all links. The PU and SU senders are assumed to always have at least one packet for transmission, and all packets are of size 50 bytes.

1) Configuration-A: In this configuration, we generate synthetic PU traffic on each of the three data channels, exponentially distributed with mean idle periods of $10, 5$ and 4 seconds. Mean busy periods are the same as the respective idle periods. Thus, in this configuration, the SUs know the PU traffic parameters and use them to compute the maximum duration of transmission over each channel.

2) Configuration-B: The parameters for this configuration are exactly the same as that of Configuration-A. However, even though the PU traffic on each channel is generated synthetically, the SUs operate as though they do not know the PU traffic parameters. Hence, they use the parameter estimation method described in Section IV to estimate PU traffic parameters on the fly. The most recent 400 sensing results are used for parameter estimation. Parameters are dynamically estimated when the utilization of the channel changes by more than 0.01 and then the corresponding maximum transmission duration (y_{max}) is recomputed. The system performance in this configuration is expected to be comparable to that of Configuration-A, which should be a validation of parameter estimation method used in our implementation.

3) Configuration-C: For this configuration, we captured one hour worth of WiFi traffic in an office building on three different days. In each of the traffic captures, idle periods which were more than 400 ms were marked as idle periods and all other periods were marked as busy periods. These produced three profiles for ON-OFF PU traffic that are used to generate the PU traffic on the three data channels. The SU transmitter assumes the ON-OFF traffic on each channel to be exponentially distributed, uses the parameter estimation method to compute their parameters, and then computes the maximum transmission duration (y_{max}) for each channel. Similar to Configuration-B, parameter estimates are updated when utilization of a given channel changes by more than 0.01.

VI. Experimental Results

A. Results for PIP

The results for PIP are presented in Table I. It can be seen that the measured PIP is below the respective PIP constraints for all the configurations. The PU performance in terms of packet loss ratio and SU performance in terms of goodput more or less match between Configuration A and B. This is a validation that the PU parameter estimation based method gives satisfactory result. When there is no SU transmitting ($\eta_{pip} = 0.0$), the PU packet loss ratio is $11.2\,\%$ for Configuration A and B. This can be attributed to two phenomena. First, to generate exponential traffic on the three data channels, carrier maps of OFDM signal has to be changed frequently. When the transmitter transmitted with a new carrier map, there were packet losses at the beginning of the burst. Second, there is no error correcting code used in the primary or secondary transmissions. So, even with a single bit error in a packet, the packet is considered lost. The difference of PU packet loss when $\eta_{pip} = 0.0$ (no SU) and when η_{pip} is non-zero, is between $2\,\%\ to\ 5\,\%$. This shows that PIP metric can be effective in providing SU access to the spectrum with low impact on PU performance. For Configuration C, the PU packet loss ratio is even higher ($32.2\,\%$) when there is no SU. In Configuration C, the WiFi network was sending out many control packets (e.g., ARP, RARP and DHCP packets) which resulted in much fewer white spaces with shorter duration than Configuration A. This lead to much quicker and a larger number of carrier map transitions in the PU traffic which resulted in a higher number of packet losses. SU goodput in Configuration C is much lower compared to the other two configurations. This is also a manifestation of fewer and shorter white spaces available and too many carrier map transitions for the SUs.

B. Results for FOP

The results for FOP are presented in Table II. Here, as well, we notice that the measured FOP is always below the corresponding FOP constraints for all the configurations. The parameter estimation based method (Configuration-B) performs reasonably well, although the SU goodput is slightly lower than that in Configuration-A. The parameter estimation

Configuration	PIP constraint (η_{pip})	measured PIP (CH1)	measured PIP (CH2)	measured PIP (CH3)	PU packet loss ratio (%)	SU goodput (kb/s)
Config-A	0.0	N/A	N/A	N/A	11.2	N/A
	0.1	0.054	0.069	0.069	13.2	4.14
	0.2	0.136	0.139	0.127	15.5	8.42
Config-B	0.0	N/A	N/A	N/A	11.2	N/A
	0.1	0.038	0.075	0.079	13.3	3.92
	0.2	0.17	0.18	0.125	16.06	7.95
Config-C	0.0	N/A	N/A	N/A	32.2	N/A
	0.1	0.042	0.029	0.039	33.96	0.663
	0.2	0.049	0.037	0.054	35.08	0.944

TABLE I
DISRUPTION QOS METRIC PIP (E[BO]=4.0SEC)

Configuration	FoP Constraint (η_{fop})	measured FoP (CH1)	measured FoP (CH2)	measured FoP (CH3)	PU packet loss ratio (%)	SU goodput (kb/s)
Config-A	0.0	N/A	N/A	N/A	11.2	N/A
	0.03	0.01	0.017	0.016	19.6	19.31
	0.05	0.018	0.033	0.035	23.6	24.67
Config-B	0.0	N/A	N/A	N/A	11.2	N/A
	0.03	0.008	0.014	0.013	18.5	15.83
	0.05	0.016	0.026	0.023	22.44	21.13
Config-C	0.0	N/A	N/A	N/A	32.16	N/A
	0.03	0.006	0.008	0.002	36.89	2.34
	0.05	0.011	0.013	0.005	37.9	3.12

TABLE II
DISRUPTION QOS METRIC FOP (E[BO] = 0.8 SEC)

method used in Configuration-B is more conservative in estimating the parameters leading to shorter transmission duration and hence lower goodput. For Configuration-C, the measured FOP is below the FOP constraint and the SU transmission degrades the PU packet loss ratio by about $5.74\,\%$ for FOP constraint $\eta_{fop} = 0.05$ as compared to the case of $\eta_{fop} = 0.0$ (no SU). Note that, for both the QoS metrics, in Configuration-C, although the distribution of ON-OFF traffic is unknown, assuming the distribution to be exponential and then estimating the parameter seems to work well in terms of honoring the respective QoS constraint.

VII. CONCLUSION AND FUTURE WORK

We presented an implementation of RIBS using GNU Radio 3.6.5 on a software-defined radio testbed which can provide disruption QoS to the PUs. The maximum duration for which an SU can transmit depends on the QoS metric used. In this paper, we introduced two disruption QoS metrics and presented the method to calculate y_{max}, the maximum duration of transmission. We also implemented a maximum likelihood estimation based method to estimate PU traffic parameters. This eliminates the necessity of knowing the traffic characteristics of PUs a priori, which is widely assumed in the literature but may not always be practical. This also enables the system to adapt to changing PU traffic characteristics.

We intend to move our current implementation to GNU Radio 3.7 which is supposed to have a more robust implementation of OFDM for bursty traffic. This, we hope, will partially mitigate the high packet loss seen in our experiments even when there is no SU. The current parameter estimation method assumes that PU traffic is exponential and estimates the parameter of the exponential distribution. For the WiFi traffic trace, this seemed to work well. But a more robust method would be to have a feedback system which will feed observed disruption QoS to the estimator module. If the QoS is violated, then the estimator should be more conservative in estimating the parameter. The current implementation is only for a single SU pair. In the future, we intend to implement a MAC protocol based on RIBS which would allow multiple SU pairs to communicate.

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