Sensing-based Opportunistic Channel Access

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Abstract

Enabled by regulatory initiatives and advanced radio technology, more flexible opportunistic spectrum access has great potential to alleviate the spectrum scarcity. In this paper, we study the channel selection issue of secondary users in spectrum-agile communication systems. We focus on the sensing-based approach because it is simple and has low infrastructure requirements. We propose a two-step approach for channel selection. The first step is to determine whether or not a channel is idle and thus accessible to secondary users. We propose three algorithms to perform the accessibility check based on measurements of primary signals. Then we address the question whether an accessible channel is a good opportunity for a secondary user.

I. Introduction

Wireless communication faces constant challenges from the ever-increasing demand for wireless services requiring additional spectrum. Historically, spectrum licensing and access have been static, leading to a low spectral efficiency as shown in a number of studies, e.g., [16]. Since a large amount of white space (unused or lightly occupied spectrum) exists in time, space, and frequency, it is often the absence of dynamic channel **access** instead of the true spectral scarcity that limits the growth of wireless communications systems. With this realization, the Federal Communications Commission (FCC) has taken important initiatives towards flexible and dynamic spectrum policies, including regulation recommendations [7], secondary market spectrum leasing rulings [11], [8], and technical model proposals [6], [5]. At the same time, advanced semiconductor and Radio Frequency (RF) technologies have produced devices that are more intelligent and less expensive with stronger sensing and signal processing capability. Driven by necessity and enabled by new technological advances, now is the perfect time to develop spectrum agile cognitive radio networks.

Focusing on a specific aspect of spectrum-agile wireless networks, we study sensing-based opportunistic access. We consider two types of users. **Primary** users are the rightful owners and have strict priority on spectrum access. They may be motivated by monitory or regulatory benefits to share spectrum with others under certain protections. **Secondary** users are cognitive devices that can sense the environment and adapt to appropriate frequency, power, and transmission schemes. They can opportunistically access unused spectrum vacated by idle primaries. Primary users are conventional legacy users whose hardware and protocols should not be required to retrofit secondary user access needs. Therefore, secondary networks should be *non-intrusive* and pose minimum disruption to the primary network users.

Consider an **illustrative scenario:** a set of spectrum-agile communication devices sense the channel collaboratively. By measuring the signal strength of primary users, the devices choose channels to communicate on and appropriate transmission formats. We focus on the channel selection issue and consider a two-step approach.

- In the first step, a secondary user has to determine whether or not a channel can be considered as "idle" or "accessible" by measuring the ambient signal strength of primaries. A channel is accessible to secondary users if the transmission of a secondary user will not cause significant interference to co-channel primary users (potentially far away).
- The second step is for a secondary user to decide whether an accessible channel is a good opportunity based on channel sensing statistics obtained from the first step. In particular, a secondary user prefers a channel where it can finish its transmission before primary users return.

Channel selection is a specific, yet important, problem in spectrum-agile communications. Primary networks are not required to change their behaviors, although their performance, e.g. capacity and delay, will be nonetheless affected by secondary users. First, transmissions from secondary users may cause outage to co-channel primary users. Second, a newly activated primary user will force some secondary users to evacuate the channel. Primary users experience interference and access delay during evacuation. On the other hand, the performance metrics for secondary users are the channel capacity and delay due to channel reallocation. There are contradicting needs between primary and secondary users. These concerns are common to most non-intrusive spectrum-agile radio networks. To understand such tradeoffs and to propose appropriate approaches are the focal points of the paper.

The paper is organized as follows. We discuss the system model in Section II. In Section III, we focus on accessibility study. We propose algorithms to determine channel accessibility based on sensing information and the outage requirement of primary users. Based on the proposed channel sensing results obtained in Section III, we focus on channel opportunity study in Section IV. We then conclude the paper in Section V.

II. System Model

In this paper, we consider secondary users that can sense activities of primary transmitters in order to determine the presence and the level of primary user transmissions. Note that other approaches to spectral agile networking have been proposed, including those relying on user geo-location and centralized database registry. While acknowledging the advantages of different secondary networks, we advocate the non-intrusive, sensing-based network design that allows secondary users to be backward compatible with any existing wireless primary networks. Without requiring primary users to alter their behaviors, non-intrusive secondary network designs make integration with primary networks much simpler and less disruptive. It requires less system/infrastructure support at the cost of some capacity. Still, in the beginning stage of study on spectrum-agile communications, the goal is to reap the "lower-hanging fruits." Hence, simplicity and compatibility are desirable attributes. Furthermore, sensing-based approach can also be integrated with other approaches as a complementary technique.

We make the following assumptions in the paper:

- Primary users are the spectrum owners that have strict priority over secondary users on spectrum usage. These users can be legacy devices operating in a conventional manner. Only secondary users are agile, i.e., equipped with spectrum-agile devices to yield to primary users.
- Secondary users have built-in channel sensing capabilities and may adapt to the changes in the environment by selecting communication channels, transmission power level, modulation and coding schemes, and other settings. We do not assume that secondary users have GPS devices.
- Both primary and secondary users use omni-directional antennas.

We do not impose specific requirements on the architecture of primary networks. Primary users could be broadcasters such as TV stations or point-to-point communication pairs such as microwave links. Secondary users may form a WLAN or an ad-hoc network. They could potentially have their own default channel, such as the 2.4G ISM band. Our focus is to understand when and how a secondary user can select a (primary) channel based on channel sensing information and statistics.

Secondary users are equipped with important power-sensing capability to measure the background activity level prior to entering a new channel. We assume that sensing devices have enough sensitivity. For instance, a spectrum-agile device operating on TV-band should have much higher sensitivity than that of a regular TV receiver. Thus, if a secondary user fails to detect a primary user, then we assume that the primary user is sufficiently apart and effectively absent. In other words, a TV receiver nearby will not be able to receive TV signals even in the absence of secondary users.

Furthermore, we assume that the transmission power of primary users is either known or bounded. This is a reasonable and necessary assumption. The information can be obtained when negotiating with primary networks for the setup of spectrum agile secondary systems. In general, there may be multiple primary users at different locations and experience interference from secondary users. As a starting point, we study the case of a single (set of) secondary user(s) and a single (set of) primary user(s). One possible scenario is that the access point of a wireless LAN is a smart-device. It can capture a spectrum opportunity and thus inform all its associated stations to explore the opportunity. Conceptually, we can consider this WLAN as one secondary user. We do not consider the potential cumulative impact of secondary users. For cases with multiple primary users, we essentially limit the focus on the most vulnerable primary transmission.

III. SENSING-BASED CHANNEL ACCESSIBILITY STUDY

In this section, we study the feasibility of secondary wireless connectivity based on power-sensing and the resulting capacity-interference tradeoff between primaries and secondaries. To elaborate, when probing a channel, secondary users measure the ambient signal strength of primaries to decide whether the channel is accessible (to secondary users). Due to uncertainties in wireless propagation environment, transmission from secondary users could pose excessive interference to primary users. The objective for the accessibility check is to satisfy the performance requirement of primaries while maximizing the channel access probability of secondary users.

We assume that primary receivers can tolerate a maximum desired-to-undesired (D/U) power ratio, noted as D_u. As defined in [12], D/U is the ratio of the received power of the primary transmitter to that of the secondary one at the primary receiver. If the required D/U is violated, we say that an outage occurs. The primaries require that the outage probability be lower than a certain threshold $(1 - P_{th})$. Both D_u and P_{th} are predefined by primaries or spectrum regulators and are given to secondary users as the metric for non-intrusiveness. The lower the value of D_u and the higher the value of P_{th}, the better the protection of primary users, and the less the opportunity of secondary users, and vice versa. We should note that D/U may be affected by the access scheme of primary users. For instance, for CDMA-based primary systems, processing gain may be cooperated into D/U requirements. However, secondary users only need to be informed of D/U instead of the details of the access scheme of primaries.

The challenge stems from the random path loss in the RF propagation. Suppose the transmission powers of both primary and secondary users are given. Randomness occurs when secondary users probe the signal strength of primaries. Furthermore, randomness also occurs when the secondary user transmits and its randomly propagated signal is considered as interference at a primary receiver. Thus, random RF propagation loss introduces outage probability for primary users due to transmissions of secondary users. Note that additional randomness may occur in the existence of multiple secondary users without collaboration. Their transmission causes cumulative interference at the primaries. However, in this paper, we ignore such issues and focus on one (set of) primary user and one (set of) secondary user.

From a primary user's perspective, secondary users are potential interference sources whose transmission leads to possible outage. From a secondary user's perspective, aggressive access implies more capacity. Thus, there exists a tradeoff between the capacity of secondary users and the outage probability at primary users and its our objective to maintain a balance between them.

There are two communication scenarios of the primary users: broadcasting with effective receiving range as shown in Figure 1 and duplex point-to-point communications as shown in Figure 2.

In the first case, we use a TV station as an example of broadcasters. Assuming known transmission power of the TV station, effective receivers usually requires a certain minimum signal to noise ratio. For example, TV receivers within the dashed circle centered at the TV station are considered as effective receivers in Figure 1. The objective is to provide a probabilistic outage guarantee for effective broadcaster receivers. In other words, if a receiver obtains an SNR that is higher than the required threshold in the absence of secondary users, then the total interference power from the transmission of secondary users should not cause outage of primaries with probability P_{th}. On the other hand, outside the effective receiving range of the TV station, the interference caused by secondary users is **inconsequential**, since the primary (broadcast) receivers are unable to function properly even without secondary users. A secondary user measures the signal strength of possible TV stations. Based on such measurements, the secondary user decides whether or not to transmit.

The second case we consider is when primaries perform duplex point-to-point communications, as illustrated in Figure 2. In the case, terminals A and B are primary users, while terminals C and D (away from A $\&$ B) are non-intrusive secondaries seeking a channel. The received signal strength of the primary users at C $\&$ D are obtained through power sensing. The varying channel characteristics are taken into account. The objective is to keep the outage probability of primary users below $1 - P_{th}$. Given the measurements at C $\&$ D, we must determine whether they can communicate at given transmission powers. We use the broadcasting case to illustrate our algorithms, and then discuss the extension to the point-to-point communication case.

A. Broadcasting Primary Users

When a non-intrusive secondary user wishes to transmit in a given channel (band), it must first undergo an "accessibility" check. In other words, a secondary user probes the channel and decides whether its transmission will violate the required D/U of a potential primary receiver given the transmission power of the TV station. If the answer is yes, the secondary user is not eligible to use the channel. There are two outage scenarios. When the secondary user transmits within the effective receiving range (i.e, the dashed circle), an outage occurs. Second, when the secondary user transmits outside the effective receiving range, if its transmission causes the D/U requirement to be violated for a receiver within the effective receiving range, then we consider it as an outage. The objective is to provide a probabilistic outage guarantee based on power sensing information obtained at the secondary user. This is called an accessibility check.

We define the effective receiving range, R, as follows. When only distance-based path loss is considered for primary transmissions and if background noise is at a fixed level, then the effective receiving area of a TV station is a disk with radius $R \propto P_{TV}^{1/\alpha}$, which is a function of the primary transmission power P_{TV} and the path-loss parameter α, as illustrated by the dashed circle in Figure 1. Such information of a TV station is publicly available. For instance, the analog TV station at channel 4, KRON-TV at San Francisco area [9], has a transmission power of 100KW and an effective radius of 120km (based on its service contour map (47dBμ) in [10]).

We consider a set of K measurements on the primary signal strength at the secondary users, denoted as $Y = \{Y_1, \cdots, Y_K\}^T$, where Y_i is the ith measurement of the received signal strength. We assume that $\{Y_i\}$ are independent measurements. They can be obtained by K secondary users at different but nearby locations or by a secondary user at K different instants. We have $Y_i = X_0 + n_i$, where X_0 is the deterministic distance-based signal strength at the secondary user, and n_i be the uncertainty caused by fading in the random propagation environment, such as shadowing and fast fading. The accessibility problem can be stated as follows: given the estimate, Y, the secondary user estimates the outage probability of its transmission at power P_s. If the outage probability is larger than the threshold C_{th}, the secondary user is not eligible to transmit.

The problem can be formulated as to estimate the outage probability, P_o,

$$P_o = \begin{cases} P\left(10\log_{10}\frac{P_{TV}}{P_s} + 10\alpha\log_{10}\frac{(d-R)}{R} + n \leq D_U\right), & \text{if } d \geq R \\ 1 \quad \text{if } d < R, \end{cases} \tag{1}$$

where d is the distance of the secondary user from the TV station, which is unknown but can be estimated from the measurements $Y = \{Y_1, \cdots, Y_K\}^T$, R is the effective receiving range, $(d - R)$ is the shortest distance from the secondary user to an effective TV receiver, and n is the random factor in the propagation environment. If $P_o \geq 1 - P_{th}$, then the user is not eligible to transmit and vice versa.

A natural idea is to take a two-step approach: to estimate the distance and then to estimate the outage probability. The challenge stems from the randomness in the estimation of d and its combination with the randomness in the transmission from the secondary user to a potential primary receiver. In other words, the two steps are closely coupled in determining P_o.

Our approach is motivated by the following observation: we need to make a conservative estimation in terms of the distance d so that we avoid the situation where the secondary user transmits within the effective receiving range. If the estimation on distance is conservative enough, it is unlikely that the transmission of a secondary user to cause outage at primaries. Based on such intuition, we present the following problem formulation and algorithms.

B. Proposed Algorithms

We define the restricted range through the following equation:

$$\frac{P_{TV}R^{-\alpha}}{P_s(R_r - R)^{-\alpha}} = D_U, \tag{2}$$

where P_{TV} is the transmission power of the TV station, P_s is that of a secondary user, α is the path-loss component, and D_U is the D/U requirement, and R is the effective receiving range, and $(R_r - R)$ is the minimum distance between an effective receiver and the secondary user that is transmitting at distance R_r. The LHS is the ratio of the received TV transmission power to that of the secondary transmission at that TV receiver. Only deterministic distance-related path-loss is taken into account in this equation. The intuition is that a secondary user transmitting in the restricted range will cause outage to a receiver in the effective receiving range when only distance-related path-loss is considered. In other words, the restricted range, $R_r > R$, can be considered as an additional precaution that a secondary user takes to protect the performance of primary TV receivers. It worths mentioning that an adaptive factor can be included in R_r to reflect the fading environment and the estimation accuracy at secondary users. This will be discussed at the end of the section. In summary, a secondary user should not transmit within the restricted range. It makes such a decision based on channel probing information, which is discussed next.

Recall that $Y = \{Y_1, \cdots, Y_K\}$ is the measurement (in dB) and $Y_i = X_0 + n_i$ where X_0 is a deterministic function of the distance between the secondary user and the TV station, which is the parameter to be estimated. Let $X(R_r)$ be the signal strength at distance R_r where only distance-based loss has been considered. If $X_0 \geq X(R_r)$, then the secondary user is within the restricted range (higher signal strength implies shorter distance). Our objective is to determine whether the secondary user is within the restricted range given the measured signal strength. In particular, we obtain an estimate $\hat{X}$ of X_0 given Y. A secondary user consider the channel accessible if $\hat{X} < X(R_r)$ and not if $\hat{X} \geq X(R_r)$. Thus, our objective is to obtain a (conservative) estimate $\hat{X}$ such that

$$P(\hat{X} \geq X_0) \geq P_{th}, \tag{3}$$

where P_{th} is the pre-determined threshold, depending on the requirement of the primaries. Note that the system experiences the highest "miss" probability when $X_0 = X(R_r)$. On the other hand, we want to minimize the estimate $E(\hat{X})$ so that a secondary user is more likely to use a potential free channel.

Note that our objective is not to obtain a "best" estimate of the distance/location, where the "best" can be quantified as minimum-mean square error, etc. Rather, we need a conservative estimate where the conservativeness is defined by P_{th}. Because of different objectives, algorithms for location and distance estimations (e.g., [4], [13], [21], [1], [3], [18], [19], [2], [17], [20], [15]) cannot be directly applied. The intuition here is to provide sufficient protection in range so that outage is unlikely to happen. To quantify such sufficient protection, we propose the following three algorithms.

- Linear estimator. It is defined as

$$\hat{X}_l = \frac{\sum_{i=1}^{K} Y_i}{K} + B_l,$$

  where B_l is a parameter to be determined by the outage requirement in Eq. (3).

- Extreme estimator. It is defined as

$$\hat{X}_m = \max_{i=1,\cdots,K} Y_i + B_m,$$

  where B_m is a parameter to be determined by the outage requirement in Eq. (3). The subscript m stands for maximum.

- Confidence interval estimator: Let $\hat{X}_{ub}$ be the confidence interval estimator. It is built upon the concept of confidence interval from estimation and detection theory. We first obtain a maximum likelihood estimation. Consider y as a continuous random variable with probability density function $f(y; X_0)$ where X_0 is the unknown parameter. The likelihood function with K independent data sets is given by $L(y_1, \cdots, y_K) = \prod_{i=1}^{K} f(y_i; X_0)$. A maximum likelihood estimate (MLE) of X_0 is the value that maximizes $\ln(L(y_1, \cdots, y_K))$. In general, MLE estimates of the parameters are asymptotically normal. Thus, if $\hat{X}_{ML}$ is the MLE estimate for X_0, obtained from a large sample, then it can be approximated by a Gaussian distribution. Given the one sided confidence interval $P(X_0 \leq C_u) = P_{th}$, we set the estimator $\hat{X}_{ub}$ as

$$\hat{X}_{ub} = C_u \approx \hat{X}_{ML} + Q^{-1}(P_{th})\sqrt{Var(\hat{X}_{ML})},$$

where $Q(x) = (2\pi)^{-1/2}\int_{-\infty}^{x} e^{-\frac{x^2}{2}}dx$. The intuition is that X_0 is likely to be bounded by the one-sided confidence interval C_u given a large sample set.

C. Parameter Estimations

We have estimated the parameters evolved in the afore-mentioned three algorithms under the following fading scenarios: 1) log-normal shadowing only; 2) Rayleigh fading only; and 3) combined shadowing and Rayleigh fading. We report the following results and include the details in the Appendix.

a) Shadowing: Shadowing is due to cumulative effects of different objects in the propagation path. When the number of such objects become large, the distribution of the cumulative effects is often modelled as log-normal shadowing. Let σ^2 be the variance of the log-normal shadowing. A typical range for σ^2 is between 4dB to 12dB. We have the following results: 1) For the linear estimator, $B_l = Q^{-1}(P_{th})\sqrt{\sigma^2/K}$; 2) For the extreme estimator, $B_m = -\sigma \times Q^{-1}\left((1-P_{th})^{1/K}\right)$; and 3) The confidence interval estimator is the same as the linear estimator. Numerical results show that all estimators maintain the desired outage probability. Furthermore, the linear estimator performs better than that of the extreme estimator in terms of the capacity gain. The conjecture is that the variance of the linear estimator is smaller than that of the extreme estimator.

b) Rayleigh Fading: Rayleigh fading is due to the interference caused to the main signal by the same signal arriving over many different paths, resulting in out-of-phase components at the receiver. Let $r_i = 10\log_{10} v$, where v follows Rayleigh distribution with probability density function $f_v(v) = v/s^2 e^{-v^2/2s^2}$. The results are as follows: 1) For the linear case, we have the following approximation $B_l \approx Q^{-1}(P_{th})\sqrt{\frac{Var(r_i)}{K}} - E(r_i)$; 2) For the extreme estimator, we have $B_m = -5\log_{10} 2s^2[-\ln(1-(1-P_{th})^{1/K})]$; 3) The confidence interval estimate is $\hat{X}_c \approx 5 \times \log_{10}\left(\hat{\hat{X}}^2_{ML} + Q^{-1}(P_{th})\frac{\hat{\hat{X}}^2_{ML}}{\sqrt{K}}\right)$. Note that in both the linear and confidence interval estimates, approximations are involved and they work well when the number of independent samples is large. When the number of samples is small, the extreme estimator is more accurate in maintaining the desired outage probability.

c) Combined Shadowing and Rayleigh Fading: To consider the cumulative effects, we approximate the linear estimator as follows: $B_l = Q^{-1}(P_{th})\sqrt{\frac{\sigma^2+Var(r_i)}{K}} - E(r_i)$. An accurate closed-form solution is difficult to find due to the complexities in the joint distribution function.

D. Numerical Results

The performance of the proposed estimation algorithm is evaluated numerically. Due to space limitation, we report the result of the linear estimator under log-normal shadowing when $K = 1$. The following parameters are used in the numerical results. The analog TV station at channel 4, KRON-TV at San Francisco area [9], has a transmission power of 100KW and an effective radius of 120km (based on its service contour map (47dBμ) in [10]). FCC's recommendation for D/U for an analog TV station is 34dB [12]. Let the maximum transmission power of a secondary user, P_s, be 100mW. In this case, we can calculate that $R_r = 1.22R$.

We consider two metrics: the probability a secondary user tests the channel as accessible, and the outage probability. As discussed earlier, there are two possible outage when a secondary user transmits. First, the secondary user is within the effective receiving range. Second, the secondary user is outside the effective receiving range, but its transmission causes the D/U requirement to be violated for a receiver within the effective receiving range (probabilistically). We consider the receiver that is closest to the secondary user.

Figures 3 and 4 show the performance of the proposed linear algorithm when $P_{th} = 0.99$ and 0.9, respectively, for various degrees of shadowing. In both figures, the x-axis is the normalized distance between the secondary user and the TV station normalized over the effective receiving range (R). In other words, $x = 1$ is the maximum distance of an effective receiver, and $x = 1.22$ is the restricted range when no fading is considered. The probability of sensing an accessible channel is plotted in the upper figures, and the probability of outage is plotted in the lower figures. When the distance between the secondary user and the TV station increases, the probability of deciding an idle channel increases. When the shadowing is low, the curve is more steep, as illustrated in Figure 4. Note that the restricted range is an auxiliary concept and we do not use it as a performance criterion. However, we do notice that the maximum outage probability occurs at the edge of the restricted range. In both figures, we see that the outage probability of primary receivers is under control using our proposed algorithm.

The numerical results are provided in the case of TV broadcasting because regulatory data is currently available in this case. We should note that the proposed algorithm is not limited to this special case. Extension to point-to-point communication scenarios is discussed in Section III-E. Furthermore, the proposed algorithms can be applied to scenarios where multiple wireless networks co-exist. For instance, a wireless network operates in a certain geographic area. Another wireless network that begins operations later can yield the operation rights of the first-arrived network when selecting its spectrum using the proposed algorithm. In this case, the operation parameter may be less stringent (e.g., allowing a larger value of outage probability) to increase spectrum efficiency. Another example is the co-existence of heterogeneous wireless networks. In IEEE 802.15.2, Bluetooth devices yield the operation of WLAN devices. In this case, Bluetooth devices can apply the algorithms similarly as the secondary users.

E. Point-to-point Communication

We can extend the result from the broadcast case to the point-to-point communication case as follows. We define the effective receiving range for each primary user as the distance between the transmitter and the receiver. We then define the restricted range for each primary user similarly as in Eq. (2). When the radius of the inner circle (receiving range) is much smaller than that of the outer circle (restricted range), the overall effect is approximated as a big circle. A secondary user performs the accessibility check for both primary users. The channel is accessible if the user passes both checks. To further investigate the case of point-to-point communication is a future research topic.

F. Discussions

In all three algorithms (and others), we note that the number of independent measurements is an important factor in the estimation accuracy. The larger the number of measurements, the more accurate and less conservative the estimate is, the higher the chance a secondary user passes an accessibility check. In practice, we may or may not be able to obtain a large number of independent measurements. In particular, when shadowing is considered, measurements from close locations are likely to be correlated. On the other hand, Rayleigh fading happens in a small scale and it might be easier to obtain multiple independent measurements. We note that when the number of measurements is small, the accessibility check is more conservative. An interesting byproduct is that a secondary user is unlikely to cause outage given a conservative estimate on its location. In Section III-D, we show that a secondary user will not violate the outage requirement of primaries if it passes the accessibility test when the number of measurements is small.

On the other hand, if the estimate of distance (or equivalently X_0) is very accurate, (e.g., from a GPS device), we need to introduce an adjust factor into R_r. The idea of the adjust factor is to take into account the fading effect from the secondary user to primaries. For instance, suppose d is given accurately, the adjust factor β can be calculated as follows assuming log-normal shadowing. Let βR_r be the distance from the TV station where a secondary user has the probability of outage $1 - P_{th}$. We have

$$P_{th} = P\left(10\log_{10}\frac{P_{TV}}{P_s} + 10\alpha\log_{10}\frac{(\beta R_r - R)}{R} + n \leq D_U\right), \quad (4)$$

and thus

$$\beta = \frac{R}{R_r}\left(10^{c_1} + 1\right),$$

where

$$c_1 = \frac{1}{10\alpha}\left(D_U - 10\log_{10}\frac{P_{TV}}{P_s} - \sigma Q^{-1}(P_{th})\right).$$

In this case, the accessibility test much simpler since the distance is known. To elaborate, the channel is accessible if $d \geq \beta R_r$ and not otherwise.

In general, the value of β depends on the accuracy of the position estimation. We show that in the numerical results, when the number of measurements is small, $\beta = 1$ suffice. We also show the extreme case where the location is known. In general, the value of β is in between.

A practical challenge is for a user to decide a channel model and appropriate parameters for the chosen model. For instance, a user needs to know whether a Rayleigh fading channel is appropriate. In general, information on the operation environment may help a user choose an appropriate channel model. For instance, urban and suburban areas may apply different channel models. Different urban areas may have different values on path loss factor. In addition, if a user experiences dramatic small scale channel quality fluctuation, e.g., by measuring the signal strength of a beacon signal from an AP or the pilot from a BS, a fast Rayleigh fading channel could be assumed. We plan to further study the issue and the impact of imperfect channel model in the future.

In the paper, we assume that a user can make its decision in each time instance. For fast fading channels, a user experiences independent fading at different time instances. Therefore, measurements at different times of a user can be used as independent measurements and enhance the measurement quality. In this case, there exists a tradeoff between time and conservativeness in the decision. A user that is willing to tolerate longer delay can get better estimations. The time scale of fast fading is on the order of milliseconds. On the other hand, in the case of shadowing, a stationary user is unlikely to have independent measurements at different time instance. (We can obtain independent measurements through collaborative sensing by users at different locations.) In this case, time will not help and a user can make instantaneous decisions with little performance loss.

In this paper, we consider one secondary and one primary user. If there are multiple primary users, the channel is accessible to a secondary user if and only if the secondary user will not cause outage to any of the primary users. Therefore, the secondary user can apply the algorithm to all primary users. On the other hand, the problem is more challenging when there are multiple secondary users (potentially unaware of each other). In this case, the interference at a primary user accumulates. It is shown that an additional protection on distance is needed under certain propagation models and without fading [14]. We plan to extend the results to our scenarios. Note that limitations on sensitivity and power scaling are also discussed in [14].

IV. Channel Opportunity Study and the Optimal Sensing Protocol

So far, we answer the question whether or not a channel can be considered accessible or idle at a given time instance. The second step is for a secondary user to decide whether an accessible channel is a good opportunity based on channel sensing statistics obtained from the first step. In particular, a secondary user prefers a channel where it can finish the transmission before the primary users return. Determining whether the channel is idle or not poses a serious challenge, particularly in the context of available estimation and detection algorithms, in the design of agile radio, but there have been studies indicating the use of sensors whose prime function is to update a central server. An agile radio uses its position and accesses this central server to determine if the particular channel is idle or not. Whether sensors are used or not, the following simple algorithm is useful in estimating the white spaces of the spectrum [22].

The secondary wireless network would determine that a particular channel is an opportunity if it can find an idle time in that channel that is greater than T_{opp}, where T_{opp} is the requirement in time and stems from the applications running in the secondary wireless network such as video, audio, data etc. In order to use a particular primary channel whose idle times are greater than T_{opp}, we need a sensing scheme that would determine if the particular channel is an opportunity or not. The occupancy in a particular channel is defined as the probability that the physical layer signatures of the current primaries are present. Using simple correlation or feature detection techniques one can easily determine the presence of the primary. Let us now consider important aspects in designing a sensing protocol. A secondary wireless network has a requirement in terms of time or bandwidth (bits/sec) when it is looking for opportunities or white spaces in the spectrum to transmit its data. If the bandwidth requirement is in bits/sec, it is translated to a time requirement based on the physical transmission rate that the wireless system is currently using.

As indicated above, let a secondary wireless system look for a spectral opportunity equal to T_{opp}. This is different from the channel occupancy, T_{on}, of the primary. The channel occupancy represents the actual occupancy of the channel by the primary. A secondary wireless network occupies that particular channel if and only if it determines that channel is a spectral opportunity which is given by the following equation:

$$T_{off} \geq \alpha T_{opp}, \quad \alpha > 1, \tag{5}$$

where T_{off} represents the time that a particular channel is not occupied by the primary. The intuition behind Eqn.(5) is to reduce the probability of collision with the primary. α is a design parameter and smaller values of α make the probability of collision with the primary higher. Reducing the collision probability has a negative effect of lowering the spectrum utilization. This would mean that the secondary wireless network is very conservative in determining that the channel is an opportunity. On the other hand, a non-conservative approach would increase the chance of colliding with primary. So one needs to choose α in optimal way that maximizes the spectrum utilization for a given probability of collision. Currently all primary channels have their value of $\alpha = \infty$ implying that the secondary wireless network cannot access this channel. The value of α is chosen to be 2 in this paper for simplicity. It should be noted that designing the right value of α is out of scope of this paper.

Once the sampling rate is determined, the secondary wireless network senses that channel and collects information about that channel. The results of the sampling are updated in the database maintained by the individual station or the central controller, such as access point or base station, for possible switching in the future. The initial requirement of sampling requirement comes from the secondary wireless network applications that require an opportunity of T_{opp}. Initially it is fixed at:

$$T_{sample} = \frac{T_{opp}}{2}, \tag{6}$$

where T_{sample} represents the sampling interval and this will determine if the channel is a spectral opportunity for this secondary wireless network. This sampling interval is also called as the Nyquist opportunity determination rate as this represents the maximum rate that will be used by the secondary wireless network to determine the availability of the channel. This rate can construct the original occupancy of the channel if that channel has $E[T_{off}] = T_{opp}$. This sampling rate may not be optimal, as it may spend more time in sampling the spectral opportunity and thus increase the sampling overhead and power consumption.

We outline a technique to find the optimal sampling frequency. Let X_t be a stochastic process denoting whether the channel is occupied or not at time t. X_t represents the indicator random variable. Then the fraction of time the channel is busy in an interval $[0, \tau]$ is given by:

$$O_{\tau} = \frac{1}{\tau} \int_{0}^{\tau} X_t dt, \tag{7}$$

where O_τ is actual occupancy of the channel that is currently sensed and is a random process whose realizations are different at different instants of time. The above equation represents the continuous process. As mentioned we will be sampling the channel for regular interval given by T_{sample} whose optimal value has to be determined. Based on the sampled process, the best prediction of the channel occupancy is given by:

$$\hat{O}_\tau = \frac{1}{n}\sum_{i=1}^{n} X_{iT_{sample}} \tag{8}$$

Here $n = \frac{1}{T_{sample}}$. Under continuity conditions of the process X_t, the process $\hat{O}_\tau \to O_\tau$ as $T_{sample} \to 0$. This would mean that the secondary wireless network is continuously sensing a particular channel and so the measurement results would yield the occupancy and availability times exactly. From $X_{iT_{sample}}$ collected over the entire measure interval, one can easily determine the $E[T_{on}]$ and $E[T_{off}]$ of the channel by noting the number of consecutive ones and zeros and looking into the transitions from 0s to 1s and vice versa. One of the most important goals is to verify reliability of the sampling process by determining the variance of the estimator. The variance of the sampled process, $\hat{O}_\tau$ is given by:

$$Var\{\hat{O}_\tau\} = Var\left\{\frac{1}{1/T_{sample}}\sum_{i=1}^{n} X_{iT_{sample}}\right\} = \left(\frac{1}{T_{sample}}\right)^2 \sum_{1\le i,j\le n} Cov(X_{iT_{sample}}, X_{jT_{sample}}) \tag{9}$$

If T_{sample} is small compared to the expected ON period, $E[T_{on}]$, of the channel, the measurements will be dependent. Hence one needs to determine the off diagonal elements of the covariance matrix. If the process were stationary, one can replace the $Cov(X_{iT_{sample}}, X_{jT_{sample}})$ by a function f with one argument, that is given by the difference in time between $(X_{jT_{sample}} - X_{iT_{sample}})$. Thus we can re-write Eqn. (9) as:

$$Var\left\{\hat{O}_\tau\right\} = n^2 \sum_{1\le i,j\le n} f((i-j)T_{sample}) \tag{10}$$

If the duration T_{sample} is not zero and has very large value, the variance of the measurement will be maximum and is equal to $\rho(1-\rho)$, where ρ represents the occupancy utilization of the channel by the primary.

Now to determine the optimal sampling interval once the mean's of ON, OFF and the variance of the OFF periods are determined is to double the sampling interval until the measured variance of the newly measured variance is greater than the original variance using the Nyquist rate by certain bound. The bound is also dependent on how far the mean ON and OFF periods vary from the true ON and OFF period that was determined by the initial sampling interval. The above new sampling periods obtained from Eqn.(6) may not be optimal in terms of resource power utilizations. Hence, determination of the optimal number of sampling points is mandatory that characterizes the ON and OFF periods efficiently while conserving the wireless resources. Having obtained the mean and variance of the ON and OFF periods using T_{sample}, we will determine the optimal number of samples that are required to capture the characteristics of the channel. From the central limit theorem of random samples, we know that as the sample size is large with the number of samples, $n \rightarrow \infty$, the average of the sampled data approaches the original mean regardless of the distribution. This is expressed by the following equation:

$$P\left\{\left|\frac{O-\hat{O}}{O}\right| > \varepsilon\right\} \approx 2\left(1-\phi\left(\frac{\varepsilon\mu\sqrt{n}}{\sigma}\right)\right) \leq \eta \tag{11}$$

In the above equation, ε and η are the design parameters and μ and σ denote the sample mean and sample standard deviation using T_{sample} as the sample duration. From the above equation we can easily calculate the optimal number of samples and this is given by:

$$n \geq n_{optimal} = \left[\frac{\phi^{-1}\left(1-\frac{\eta}{2}\right)\sigma}{\varepsilon\mu}\right]^2 \tag{12}$$

Figure 5 shows the optimal number of samples required using the approximation of Eqn.(12). It is clear that the number of samples required to estimate the channel occupancy increases if the channel availability is very small and decreases as this time increases. The plot is for the exponential channel availability time and can be done for different distributions that have the second moment. In this numerical analysis, the value of η was set to 0.01.

A. *Implementation of the Sampling function in practical networks*

Consider the case of infrastructure networks, wherein the Access Point (AP) or Base Station (BS) is the central controller that is responsible for the wireless resources. The AP/BS initiates a measurement request to the clients who in turn measure a particular channel and report the activity to the access point. The secondary wireless network first tunes to a particular channel and will listen to the channel for 1 second to calculate the mean ON and OFF periods of the channel. In a distributed Adhoc network, this sensing is periodic for a channel and may happen once in every few minutes. All devices agree upon the periodicity and sense the channel. It may turn out that they may dedicate users who take turns to sense a particular channel for the 1 second period. In case of infrastructure networks, the central controller may dedicate some wireless devices to periodically visit the channel to collect the information that is then updated in its database. After determining the mean ON and OFF periods of the channel it will then use Eqn.(12) to sample that channel for a duration of $T_{duration}$. In the existing protocols like IEEE 802.11, IEEE 802.16 and IEEE 802.15, the AP/BS collectively chooses a channel and scans the channel for information for 1 second and then estimate the mean ON and OFF periods first. Then it will scan the channel at the optimal sampling rate using the estimated mean and variance by disseminating the optimal n to all the individual wireless stations. The other way is to disseminate the $^{n}/_{x}$ instead of n. Here x represents the number of clients associated with that AP/BS. Since the value of n is obtained based on the characteristics of the particular channel it represents the sampling rate of a particular channel in order to reconstruct the occupancy properties of that channel. Hence distributing the new sampling frequency improves the radio resource usage resulting in more data traffic transmissions. In the case of Adhoc networks, there is complexity on the individual clients to calculate the value n and a dissemination protocol has to be designed that will propagate this information so that wireless clients can use radio resources efficiently.

V. Conclusion

Preliminary studies as well as general observations indicate the presence of a significant amount of white space in radio spectrum, varying based on time, frequency, and geographic locations. Thus, it is likely that spectrum access, instead of true spectrum scarcity, is the limiting factor of potential growth of wireless services. Enabled by regulatory changes and radio technologies advances, opportunistic usage of white space may significantly mitigate the spectrum scarcity. In this paper, we study channel selection using sensing-based approaches.

Channel selection is a specific, yet important, problem in spectrum-agile communications and the sensing-based approach has the advantage of simplicity and low infrastructure requirements. We propose a two-step approach. The first step is to decide whether or not a channel can be considered as "idle" or "accessible" by measuring the ambient signal strength of primaries. A channel is accessible to secondary users if the transmission of a secondary user will not violate the outage requirement of the primary users. We have developed three algorithms that provide statistic outage guarantee to primary users. The second step is to examine whether an accessible channel is a good opportunity. In particular, a secondary user prefers a channel where it can finish the transmission before the primary users return. We have developed and evaluated a sensing scheme for the purpose.

We consider the paper as a first step to fully understand the feasibility and performance of sensing-based spectrum-agile communication system. Further research is needed to handle more sophisticated situations, such as the co-existence of multiple primary and secondary networks, different traffic characteristics of primary users. In addition, the performance tradeoff of primary and secondary users, such as capacity, outage, collision probability, and the delay associated with collision, should be analyzed.

VI. Appendix

In the appendix, we calculate the parameters evolved in the three algorithms proposed in Section III-B.

1) Shadowing: The measurement is given by $Y_i = X_0 + n_i$, where n_i follows a zero-mean normal distribution with variance σ^2, modelling shadowing effects. In the linear estimator, we have

$$\hat{X}_l = \frac{\sum Y_i}{K} + B_l,$$

where B_l is a parameter to be determined by the requirement for outage protection $P(\hat{X}_l \geq X_0) = P_{th}$ given $X_0 = X(R_r)$. We have

$$P(\hat{X}_l \geq X_0) = P\left(\frac{\sum n_i}{K} + B_l \leq 0\right) = P\left(\frac{\sum n_i}{K} \leq -B_l\right) \overset{(a)}{=} P\left(n_0 \leq -B_l/\sqrt{\sigma^2/K}\right) \tag{13}$$

where $n_0 \sim N(0,1)$, and (a) holds because $n_i \sim N(0, \sigma^2)$, and $\sum n_i/K \sim N(0, \sigma^2/K)$. Because $P(\hat{X}_l \geq X_0) = P_{th}$, we have

$$B_l = Q^{-1}(P_{th})\sqrt{\sigma^2/K}.$$

The extreme estimator is expressed as follows:

$$\hat{X}_m = \max_i Y_i + B_m,$$

where B_m is to be determined by the outage requirement $P(\hat{X}_l \geq X_0) = P_{th}$ given $X_0 = X(R_r)$. Thus,

$$\begin{aligned} P(\hat{X}_m \geq X_0) &= P(\max_i X_0 + n_i + B_m \geq X_0) = P(\max_i n_i \geq -B_m) \\ &= 1 - \prod_i P(n_i < -B_m) = 1 - (Q(-B_m/\sigma))^K = P_{th} \end{aligned} \tag{14}$$

Therefore, we have

$$B_m = -\sigma \times Q^{-1}\left((1 - P_{th})^{1/K}\right).$$

Last, we study the confidence interval estimator. The maximum likelihood estimation of X_0 is given by $\hat{X}_{ML} = \sum_i Y_i/K$. We also have $\hat{X}_{ML} \sim N(X_0, \frac{\sigma^2}{K})$. Thus, in this case, the upper one-sided bound, i.e., the confidence interval estimator $\hat{X}_c$ is

$$\hat{X}_c = \frac{\sum_i Y_i}{K} + \sqrt{\frac{\sigma^2}{K}} Q^{-1}((1 - P_{th}) = \hat{X}_l. \tag{15}$$

We have $\hat{X}_c = \hat{X}_l$ because of the noise term n_i follows Gaussian distribution.

Next, we compare the numerical results from the three (two) estimators. In the simulation, we set $X_0 = -1$dB and run 10000 estimates for each set of parameters (P_{th} and K) in the figure. We compare the performance of the linear (confidence interval) and the extreme estimators. Figure 6 shows the success probability compared to that of the threshold. If $\hat{X} \geq X_0$, it is considered a success. In all situations, both estimators achieve the desired probability P_{th}. In the figure, the four sets of lines from bottom to top represents $P_{th} = [0.9, 0.95, 0.99, 0.999]$. The solid and dashed lines represent the linear and extreme estimators, respectively. Figure 7 shows the average estimated values of X_0 of the two estimators. We note that the average of the linear estimator is closer to that of the true value ($X_0 = -1$dB), and thus implies better capacity gain for secondary users.

2) Rayleigh Fading: In Rayleigh fading, the observations are given by $Y_i = X_0 + r_i$, where $r_i = 10\log_{10} v$ and v follows Rayleigh distribution with probability density function

$$f_v(v) = \frac{v}{s^2} e^{-\frac{v^2}{2s^2}}.$$

In the case of the linear estimator, B_l is the parameter to be determined. We approximate $\sum Y_i/K$ as a Gaussian distributed random variable with mean $X_0 + E(r_i)$ and variance $\sigma_z^2 = Var(r)/K$. Thus, we have

$$\begin{aligned} P(\hat{X}_l \geq X_0) &= P\left(\frac{\hat{X}_l - X_0 - E(r_i) - B_l}{\sigma_z} \geq \frac{X_0 - X_0 - E(r_i) - B_l}{\sigma_z}\right) \\ &\approx P(n_0 \leq \frac{E(r_i) + B_l}{\sigma_z}) \approx Q\left(\frac{E(r_i) + B_l}{\sigma_z}\right) = P_{th}. \end{aligned} \tag{16}$$

Thus, we have

$$B_l \approx Q^{-1}(P_{th})\sqrt{\frac{Var(r_i)}{K}} - E(r_i).$$

Next, we calculate the parameter B_m used in the extreme estimator. We have

$$P(\hat{X}_m \geq X_0) = P(\max_i X_0 + r_i + B_m \geq X_0) = 1 - \prod_i P(r_i < -B_m) \tag{17}$$

We have

$$P(r_i < -B_m) = P(10\log_{10} v \leq -B_m) = P(v \leq 10^{-B_m/10}) = 1 - \exp(-\frac{10^{-B_m/5}}{2s^2}). \tag{18}$$

Thus, we have

$$P(\hat{X}_m \geq X_0) = 1 - \left(1 - \exp(-\frac{10^{-B_m/5}}{2s^2})\right)^K = P_{th} \tag{19}$$

Thus, we have

$$B_m = -5\log_{10} 2s^2(-\ln 1 - (1 - P_{th})^{1/K}).$$

Last, we study the confidence interval estimator. We start with the maximum likelihood estimator. Let $\bar{X} = (X_0/10)^{10}$. We first obtain a maximum-likelihood estimator of $\bar{X}$. Let $\bar{Y} = v\bar{X}$. We have $f_y(\bar{Y}; \bar{X}) = f_v(y/\bar{X})/\bar{X}$. The likelihood function is $L = \prod_i f_v(y; \bar{X})/\bar{X}$, and

$$\ln L = \sum_i \left(-\ln \bar{X} + \ln \bar{Y}_i - \ln s^2 - \ln \bar{X} - \frac{\bar{Y}_i^2}{2s^2\bar{X}^2}\right) = -2K\ln \bar{X} + \sum_i \ln \bar{Y}_i - \sum_i \frac{\bar{Y}_i^2}{2s^2\bar{X}^2}. \tag{20}$$

Taking derivatives with respect to $\bar{X}$, we have

$$\hat{\bar{X}}_{ML}^2 = \frac{\sum_i \bar{Y}_i^2}{2Ks^2}. \tag{21}$$

Further, we have

$$E(\hat{\bar{X}}_{ML}^2) = \frac{E(\sum_i \bar{Y}_i^2)}{2Ks^2} = \frac{K\bar{X}^2 E(v^2)}{2Ks^2} = \bar{X}^2.$$

and $Var(\hat{\bar{X}}_{ML}^2) = \bar{X}^4/K$. The upper one-sided confidence bound on $\bar{X}^2$ is given by

$$\bar{X}^2 \leq \hat{\bar{X}}_{ML}^2 + Q^{-1}(P_{th})\sqrt{Var(\hat{\bar{X}}_{ML}^2)} = \hat{\bar{X}}_{ML}^2 + Q^{-1}(P_{th})\frac{\bar{X}^2}{\sqrt{K}}. \tag{22}$$

Because $\bar{X}^2$ is unknown, we use $\hat{\bar{X}}_{ML}^2$ to replace it. Thus, we have

$$\hat{X}_c = 5 \times \log_{10}\left(\hat{\bar{X}}_{ML}^2 + Q^{-1}(P_{th})\frac{\hat{\bar{X}}_{ML}^2}{\sqrt{K}}\right).$$

Figure 8 shows the success probability on the estimate (an estimate is successful if it is larger than the value of X_0). It shows that the extreme estimator can maintain the desired success ratio while the linear case cannot especially for a small value of K. This is due to the fact that an approximation is involved in the linear estimator. When K is larger, the approximation is better. Figure 9 shows the average estimates for the linear and extreme estimators. Note that when P_{th} is large, say 0.999, the estimator has to be very conservative, i.e., a very large value of B_m for small K. This is due to the fact that the logarithm of a random variable with Rayleigh distribution has a heavier tail than that of a Gaussian distribution.

Figure 10 shows the success ratio on the estimate for the confidence interval estimator. It shows the performance of the ideal case where X is known and where X_{ML} is used instead. It is not surprising that the ideal case gives very good performance. Recall that X is actually on the right hand side of the equation. However, when the MLE is used instead, the performance degrades dramatically. This is due to the fact that the approximation as a Gaussian distribution is less accurate and the MLE is less accurate. The performance improves as K increases. Figure 11 shows the average estimated value of $\hat{X}$.

3) Combined Shadowing and Rayleigh Fading: In this case, the observation is given by $Y_i = X_0 + n_i + r_i$, where $n_i \sim N(0, \sigma^2)$, and $r_i = 10\log_{10} v$, where v follows Rayleigh distribution. We can only use the linear estimator in this case due to the complexity in the combined distribution. We have $\hat{X}_l = \frac{\sum Y_i}{K} + B_l$, where B_l is a parameter to be determined by the outage requirement. We approximate $\sum Y_i/K$ as a Gaussian distributed random variable with mean $X_0 + E(r_i)$ and variance $\sigma_z^2 = (\sigma^2 + Var(r_i))/K$. Thus, we have

$$\begin{aligned} P(\hat{X}_l \geq X_0) &= P\left(\frac{\hat{X}_l - X_0 - E(r_i) - B_l}{\sigma_z} \geq \frac{X_0 - X_0 - E(r_i) - B_l}{\sigma_z}\right) \\ &\approx P(n_0 \leq \frac{E(r_i) + B_l}{\sigma_z}) \approx Q\left(\frac{E(r_i) + B_l}{\sigma_z}\right) = P_{th}. \end{aligned} \tag{23}$$

Thus, we have

$$B_l = Q^{-1}(P_{th})\sqrt{\frac{\sigma^2 + Var(r_i)}{K}} - E(r_i).$$

Figure 12 shows the average estimates and the success ratio of the linear estimator with the Gaussian approximation. The linear estimator can approximate the threshold. It is more difficult to use the extreme estimator and the confidence interval estimator because the distribution function of $n_i + r_i$ is difficulty to find.

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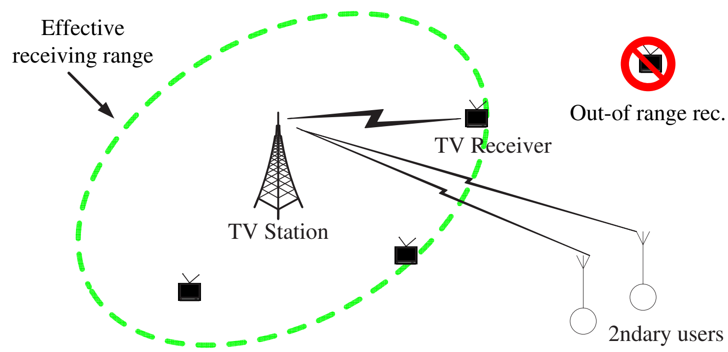

Fig. 1. Broadcasting case

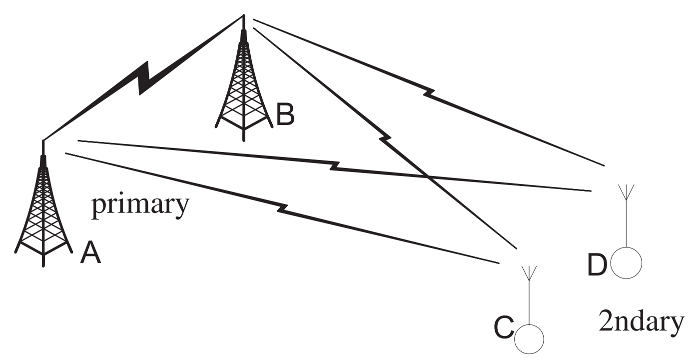

Fig. 2. Point-to-point case

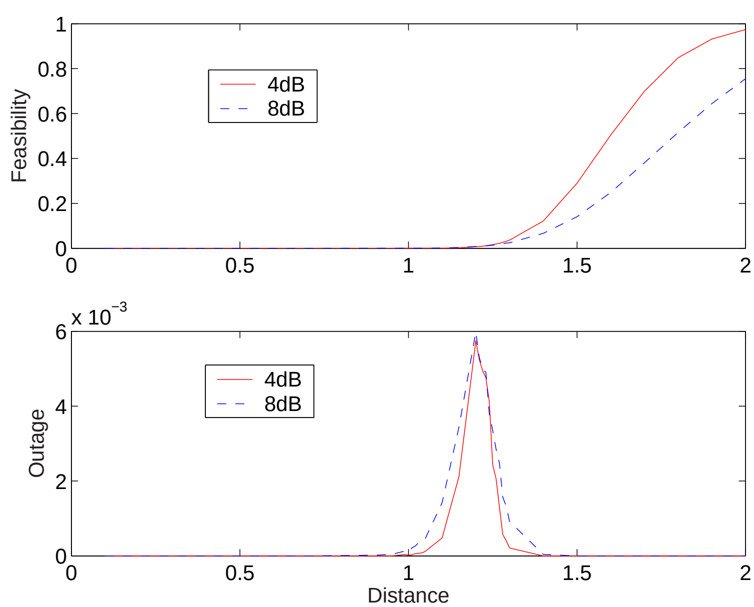

Fig. 3. Outage probability when P_{th}=0.99; i.e., the threshold for outage is 0.01.

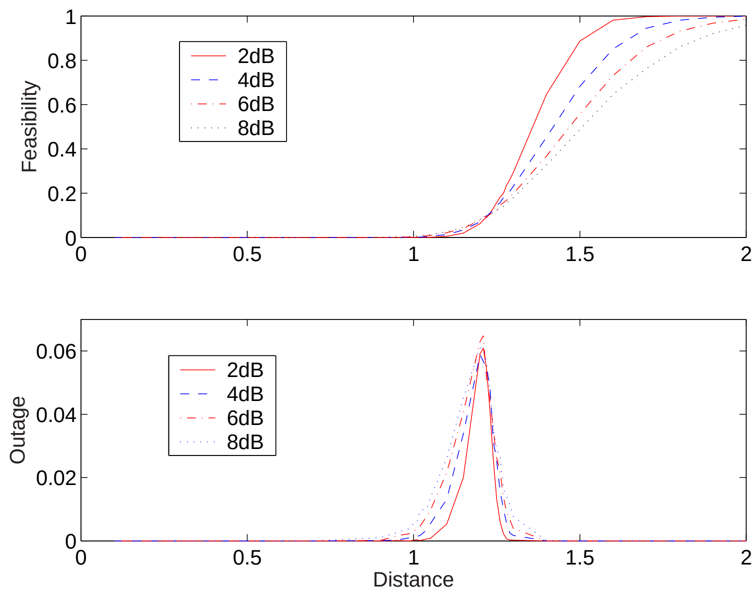

Fig. 4. Outage probability when P_{th}=0.9; i.e., the threshold for outage is 0.1.

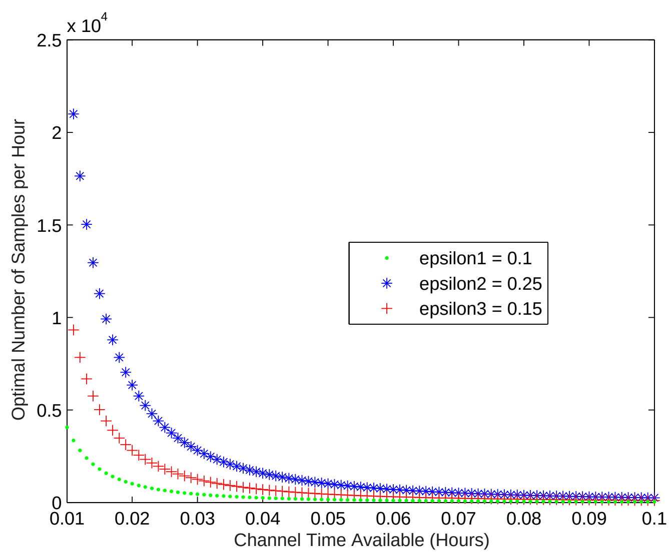

Fig. 5. Optimal number of samples as a function of exponential channel occupancy. The value of η is fixed at 0.01 and the three values of ϵ are 0.1, 0.15 and 0.25.

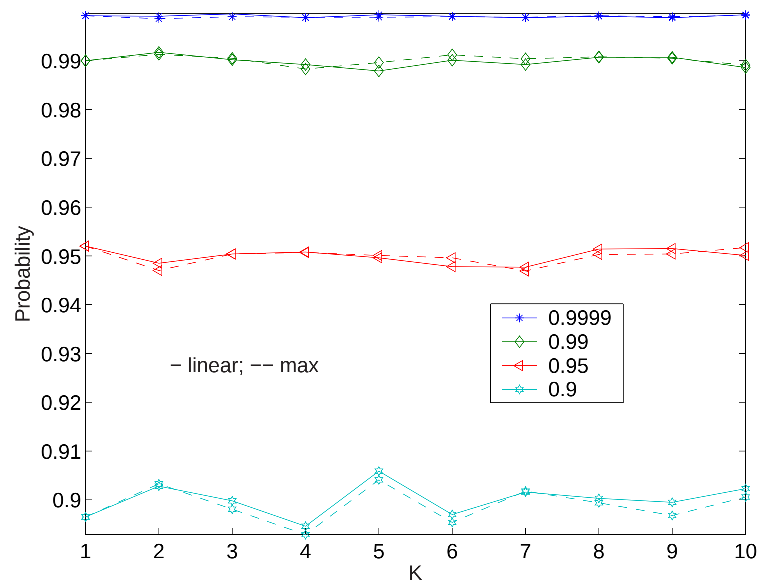

Fig. 6. Success probability under shadowing.

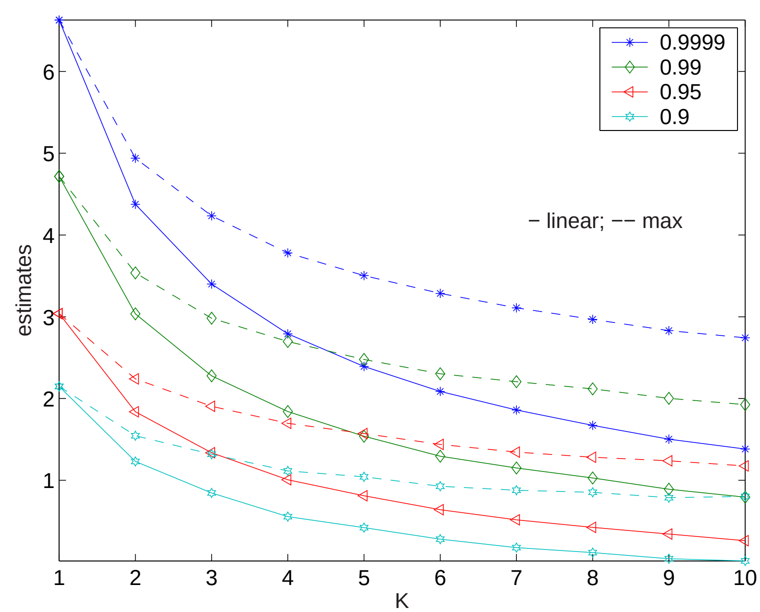

Fig. 7. Average estimate under shadowing.

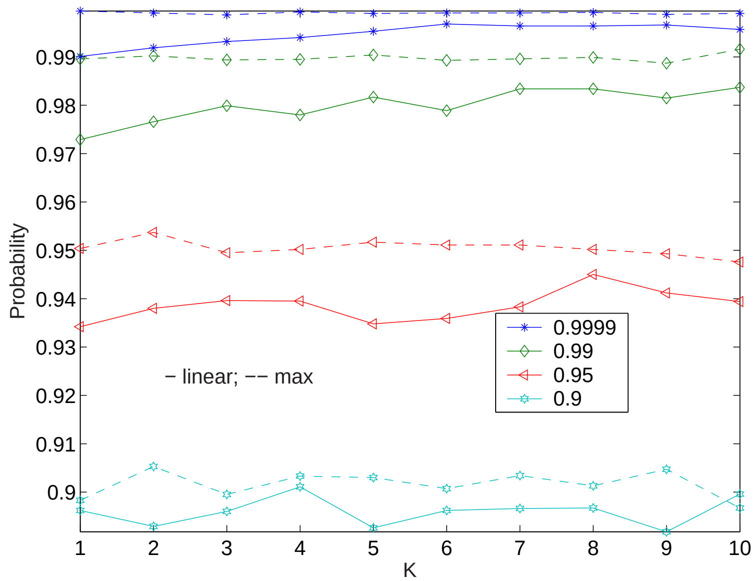

Fig. 8. Success probability under Rayleigh fading using linear and extreme estimators.

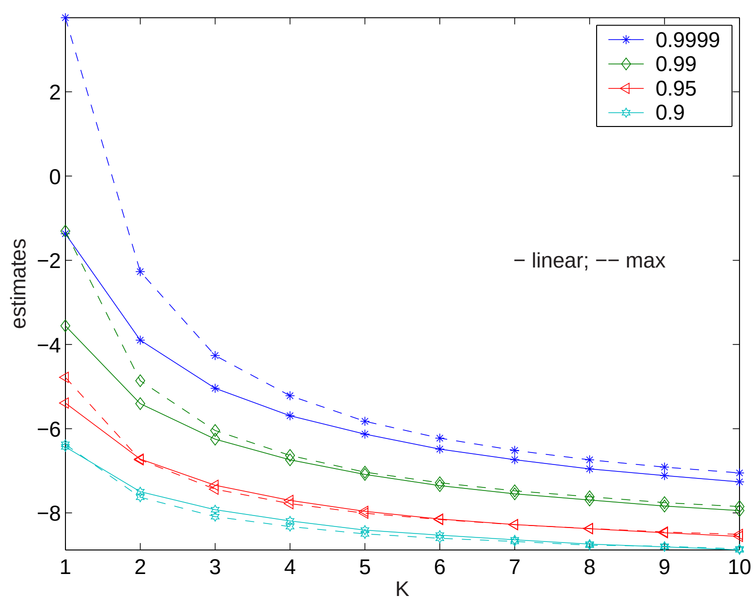

Fig. 9. Average estimate under Rayleigh fading using linear and extreme estimators.

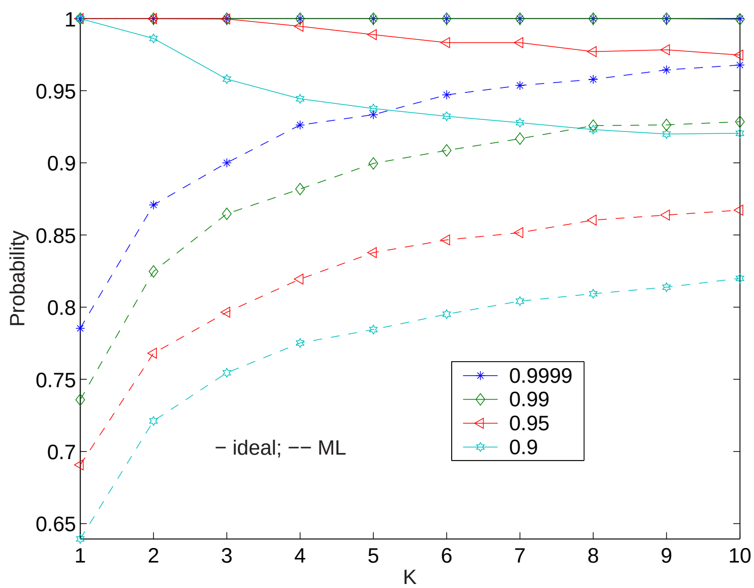

Fig. 10. Success probability under Rayleigh fading using confidence interval estimator.

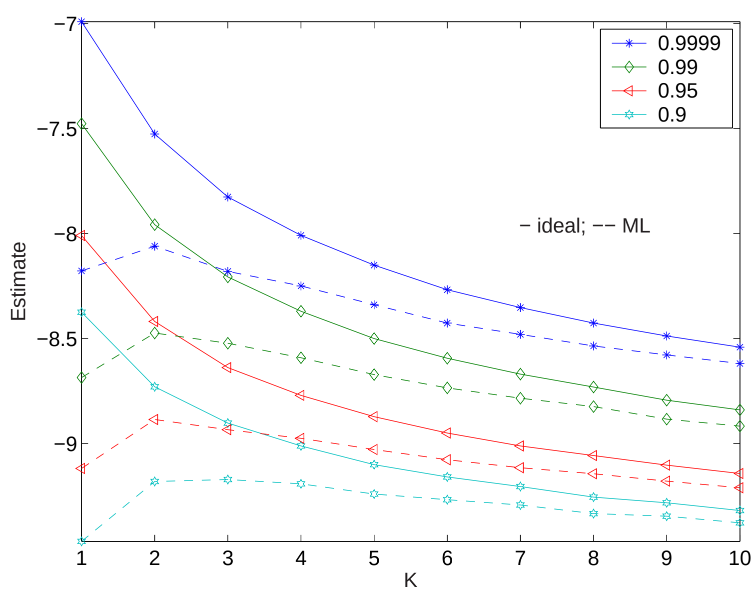

Fig. 11. Average estimate under Rayleigh fading using confidence interval estimator.

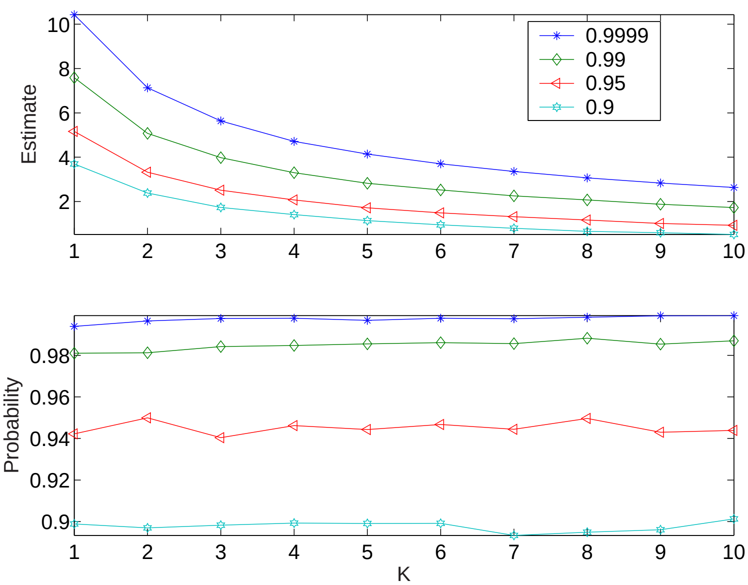

Fig. 12. Average estimate under Rayleigh fading and shadowing using linear estimator.