Optimal Cooperative Spectrum Sensing over Composite Fading Channels

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***Abstract*—In this paper, we study cooperative spectrum sensing over composite fading channels. First, we consider the Mixture of Gaussian distribution to model the composite channel statistics and derive a simple generic approximation for the average probability of detection which can be efficiently applied to any composite fading channel. Second, we derive the optimal voting rule for hard combining in cooperative spectrum sensing over composite fading channels. In particular, we derive an exact closed form expression for the optimal decision fusion rule (*k*-out-of-*N*) that minimizes the total sensing error in cognitive radio networks (CRNs). This expression enjoys both simplicity and generality, making it applicable to any CRN, regardless of the channel considered. Numerical results validate the proposed analysis and show that the proposed combining rule efficiently minimizes the CRN's total error and significantly outperforms the AND, OR and majority rules that are usually considered.**

***Index Terms*—Composite fading channels, cooperative spectrum sensing, probability of detection, hard combining, optimal voting rule.**

I. Introduction

Cognitive radio (CR) is a promising technology that can enhance the performance of wireless communications [1]. The basic concept behind opportunistic CR, is that a secondary user (SU) is allowed to use the spectrum, which is assigned to a licensed primary user (PU), when the channel is idle [2]. The CR users perform spectrum sensing, in order to identify idle spectrum, via energy detection which is the most common sensing technique due to its low implementation complexity and no requirements for knowledge of the sensed signal [3].

In a typical mobile radio environment, the received signal presents small scale power fluctuations, due to the multipath propagation, superimposed on large signal power fluctuations – also known as shadowing – due to the presence of large obstacles between the transmitter and receiver. The small scale fading results in very rapid fluctuations around the mean signal level, while shadowing gives rise to relatively slow variations of the mean signal level [4]. For example, this is the scenario in congested downtown areas with slow-moving pedestrians and vehicles [5].

The Spectrum sensing performance of a CR system is highly dependent upon the severity of fading of the PU signal, making it very challenging for a single SU to efficiently sense the spectrum. Cooperative sensing strategies have been studied to combat the wireless fading, improve the detection performance and potentially allow the network to overcome the *hidden terminal* problem, which is due to shadowing. In cooperative spectrum sensing (CSS) multiple SUs perform independent sensing of the licensed primary channel and report of their initial detection results to the fusion center (FC) [6]. The SU can report the measured energy, known as soft combining, or send an one bit decision to the FC for hard combining. Nevertheless, this cooperation may also introduce overhead and some performance degradation [7], which justifies the need for optimization of such networks. In [8] and [9], optimal fusion rules for hard combining in CSS have been derived. In the former, the authors consider an approximation to derive the optimal voting rule that minimizes the network's total sensing error, whereas in the later the optimal voting rule is obtained by applying convex minimization to an objective function.

Several studies have been devoted to the analysis of the performance of energy detection-based spectrum sensing for different communication and fading scenarios [10]. The probability of detection, P_d, is an important performance metric for cognitive radio networks (CRNs), since it measures the probability that the PU is detected. Expressions for P_d over Rayleigh, Rician, and Nakagami-*m* fading channels were derived in [11], for Weibull channel in [12], and for generalized $\kappa-\mu$ as well as extreme $\kappa-\mu$ fading channels in [13]. In [14], a mixture of gamma distribution is proposed to model the signal to noise ratio (SNR) of wireless channels and a generalized expression for the probability of detection was presented.

The contribution of this paper is twofold. First, we consider spectrum sensing over composite fading channels and derive a generalized closed form approximation for P_d. We use the Mixture of Gaussian (MoG) distribution to model different channels' statistics. Second, we consider hard combining CSS and derive an exact closed form expression for the optimal *decision fusion* or *voting rule* (*k*-out-of-*N*) at the FC. For any N SUs, the optimal k that minimizes the total error of the system can be evaluated using the derived expression. Note, that this expression can be efficiently applied to any fading scenario but in this paper we focus on composite fading channels.

The rest of this paper is organized as follows. In section II, the CRN system model considered is described and the local and cooperative probability of detection over composite fading channels is derived. The optimal voting rule for hard combining CSS is derived in section III and numerical results are presented in section IV. Finally, section V provides concluding remarks.

II. System Model

Consider a CRN, presented in Fig. 1, consisted of N SUs, which perform spectrum sensing using energy detection. The sensing channels with real gains, h_i, $i = 1, 2, ..., N$, are independent but not necessarily identically distributed composite fading channels. Each SU takes a binary local decision on the activity of the PU and sends the one bit decision to a predefined FC in the network. The last combines the data received from all nodes and takes a global decision on the considered spectrum's state. The decision hypotheses is either H_0, when the spectrum is idle, or H_1 when a PU is active.

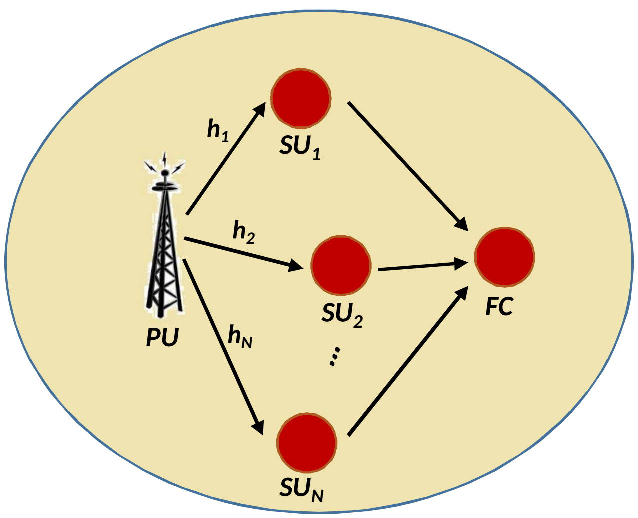

Fig. 1. Cooperative Spectrum sensing in CRNs

A. Local Spectrum Sensing

An energy detector is largely characterized by a predefined energy threshold, λ. This threshold is particularly critical in the decision process and is associated with the following three metrics, that evaluate the overall performance of the detector:
1) The probability of detection, $P_d = \Pr(Y > \lambda | H_1)$: The probability that the signal is sensed when the PU is active.
2) The probability of false alarm, $P_f = \Pr(Y > \lambda | H_0)$: The probability that the signal is detected when the PU is idle.
3) The probability of missed detection, $P_m = \Pr(Y < \lambda | H_1)$: The probability that the signal is not detected when the PU is active.

Above, Y denotes the output of the energy detector and acts as the test statistics in order to test the hypotheses H_0 and H_1. The aforementioned metrics can be evaluated over Additive White Gaussian Noise (AWGN) channel as [15]

$$P_d = Q_u\left(\sqrt{2\gamma}, \sqrt{\lambda}\right), \quad (1)$$

$$P_f = \frac{\Gamma\left(u, \frac{\lambda}{2}\right)}{\Gamma\left(u\right)}, \quad (2)$$

$$P_m = 1 - P_d \quad (3)$$

where $Q_u(.,.)$ is the generalized Marcum-Q function [16], $\Gamma(.,.)$ is the incomplete gamma function [17], $\Gamma(.)$ is the gamma function [17], λ is a predefined energy detection threshold, u is the time bandwidth product which corresponds to the number of samples of either the in-phase (I) or the quadrature (Q) component. The received SNR is defined as $\gamma \triangleq \frac{\alpha^2 E_s}{N_0}$, where E_s is the signal energy, N_0 the one-sided noise power spectral density, and α the channel gain where $\alpha = 1$ for AWGN channel.

The probability of false alarm, P_f, is constant regardless of the fading channel, since it is considered for the case of no signal transmission and hence it is independent of the SNR statistics. On the other hand, the average detection probability, $\overline{P_d}$, at each SU is evaluated by averaging (1) over the probability density function (pdf) of the SNR, for the considered fading channel [11].

B. Spectrum Sensing in Composite Fading Channels

As mentioned above, a composite multipath/shadowed fading environment consists of multipath fading superimposed on shadowing. A popular example of such a channel is the Nakagami/Lognormal (NL). In this case, the pdf $f_\gamma(\gamma)$, is obtained by averaging the instantaneous Nakagami-*m* fading average power over the conditional pdf of the log-normal shadowing, resulting in a complicated pdf that has no closed form expression [5].

An alternative approach to model the envelope of a composite fading channel by the MoG distribution, was proposed in [18]. This approximation method is based on the expectation-maximization (EM) algorithm, which was coined by Dempster et al. in their seminal paper [19]. The EM algorithm is essentially a set of algorithms exceptionally useful for finding the maximum likelihood estimator (MLE) of any distribution in the exponential family [20], and widely used for the missing data problem (i.e., Modeling a mixture distribution). In this work, we consider the MoG distribution to approximate the channel statistics of any composite fading channel. In fact, the pdf of the envelope of the signal can be approximated using the MoG as [18]

$$f_\alpha(x) \simeq \sum_{i=1}^{G} \frac{\omega_i}{\sqrt{2\pi}\sigma_i} \exp\left(-\frac{(x-\mu_i)^2}{2\sigma_i^2}\right), \quad (4)$$

and the pdf of the SNR can be expressed as

$$f_\gamma(\gamma) \simeq \sum_{i=1}^{G} \frac{\omega_i}{\sqrt{8\pi\overline{\gamma}}\sigma_i} \frac{1}{\sqrt{\gamma}} \exp\left(-\frac{\left(\sqrt{\frac{\gamma}{\overline{\gamma}}}-\mu_i\right)^2}{2\sigma_i^2}\right) \quad (5)$$

In (5), G is the number of Gaussian components considered for the approximation and the parameters ω_i, σ_i^2, and μ_i represent the weight, variance, and mean of the ith weighted Gaussian pdf which can be evaluated in the beginning of the communication process evaluated using the EM algorithm. The average SNR is defined as [5]

$$\overline{\gamma} \triangleq \int_0^\infty \gamma p_\gamma(\gamma) d\gamma,$$

where γ is a random variable representing the instantaneous SNR and $p_\gamma(\gamma)$ denotes the pdf of γ.

The generalized expression for the average detection probability over composite fading channels can be derived by averaging (1) over (5) as follows

$$\overline{P_d} = \int\limits_0^\infty Q_u(\sqrt{2\gamma}, \sqrt{\lambda}) f_\gamma(\gamma) d\gamma, \tag{6}$$

where the Marcum Q-function can be expressed as [21]

$$Q_u(\sqrt{2\gamma}, \sqrt{\lambda}) = e^{-\gamma} \sum_{n=0}^{\infty} \frac{\gamma^n}{n!} \frac{\Gamma(u+n, \frac{\lambda}{2})}{\Gamma(u+n)}. \tag{7}$$

By substituting (5) and (7) in (6), we obtain

$$\overline{P_d} \simeq \sum_{i=1}^{G} \frac{w_i e^{-\frac{\mu_i{}^2}{2\sigma_i{}^2}(1-\frac{1}{4\overline{\gamma}\sigma_i^2+2})}}{\sqrt{2\pi\overline{\gamma}}\sigma_i} \Bigg(\sum_{n=0}^{\infty} \frac{\Gamma(u+n, \frac{\lambda}{2})\Gamma(2n+1)}{n!\Gamma(u+n)} \times \left(\frac{2\overline{\gamma}\sigma_i^2+1}{\overline{\gamma}\sigma_i^2}\right)^{-\frac{2n+1}{2}} D_{-(2n+1)}\left(\frac{-\mu_i}{\sigma_i\sqrt{2\overline{\gamma}\sigma_i^2+1}}\right)\Bigg), \tag{8}$$

where $D_n(i)$ is the parabolic cylinder function [17].

C. Cooperative Spectrum Sensing

Next, we assume that the network performs hard combining, in which each cooperative partner i makes a binary decision based on its local observation and then forwards its one-bit decision d_i ($d_i = 1$ stands for the presence of the PU, and $d_i = 0$ stands for the absence of the PU) to the FC. The FC combines all local decisions and makes a final decision obtained as [22]

$$Y = \sum_{i=1}^{N} d_i \begin{cases} \geq k & H_1 \\ < k & H_0 \end{cases}, \tag{9}$$

where the threshold k ($1 \leq k \leq N$) is an integer that corresponds to the k-out-of-N voting rule. This means that if k users or more detect the PU signal, the network decides that the PU is active and does not use the considered frequency band. Some well known voting rules are the AND, OR and the majority rule, where the AND rule corresponds to the case, $k = N$, the OR rule to the case, $k = 1$, and finally, the majority rule to the case, $k = \lceil \frac{N}{2} \rceil$.

For the sake of simplicity, we consider that the reporting channels between the SUs and the FC are perfect, but this work can be easily extended to binary symmetric channels, with probability of error, q, by using

$$\overline{P_d}_{BSC} = \overline{P_d}(1-q) + q(1-\overline{P_d})$$

and

$$P_{fBSC} = P_f(1-q) + q(1-P_f).$$

Moreover, it is assumed that all SUs experience independent and identically distributed fading and all nodes use the same threshold λ. In this case, $\overline{P_{d,i}}$ and $P_{f,i}$ are equal for each node i. Hence, the CSS joint probability of detection, Q_d, the false alarm probability Q_f, and the miss detection probability Q_m, are given, respectively, as [8]

$$Q_d = \Pr\{H_1|H_1\} = \sum_{l=k}^{N} \binom{N}{l} \overline{P_d}^l (1-\overline{P_d})^{N-l}, \tag{10}$$

$$Q_f = \Pr\{H_1|H_0\} = \sum_{l=k}^{N} \binom{N}{l} P_f^l (1-P_f)^{N-l}, \tag{11}$$

$$Q_m = \Pr\{H_0|H_1\} = 1 - \sum_{l=k}^{N} \binom{N}{l} \overline{P_d}^l (1-\overline{P_d})^{N-l}, \tag{12}$$

where k corresponds to the adopted voting rule. It should be noted here that these expressions can be evaluated for any sensing channel, by providing a local value or expression for $\overline{P_d}$ and P_f. Next, we define the total sensing error of the system as

$$Q_t = Q_m + Q_f,$$

where Q_m is a missed detection by the system which can result in a transmission when a PU is active and interference to the PUs, and Q_f is a false detection of the PU signal that is associated with a waste of resources and a degradation of the CR system's performance.

III. Optimal Voting Rule

In this section, we derive the optimal voting rule for hard decision fusion CSS over composite fading channels. It is worth noting that the derived expression can be applied to any fading channel.

Suppose that the FC knows $\overline{P_d}$ and P_f. The problem of choosing the voting rule (k-out-of-N) that minimizes the total error probability Q_t is considered, where

$$Q_t = 1 - \sum_{l=k}^{N} \binom{N}{l} \overline{P_d}^l (1-\overline{P_d})^{N-l} + \sum_{l=k}^{N} \binom{N}{l} P_f^l (1-P_f)^{N-l}. \tag{13}$$

Lemma 1. *For $a, b \in \Re$, $N \in \mathbb{N}$ and $\forall\, 0 < l < N$, if $a > b$, then there is a $t \in \mathbb{Z}^+$ for which holds*

$$a^l(1-a)^{N-l} < b^l(1-b)^{N-l}, \quad l < t$$

and

$$a^l(1-a)^{N-l} > b^l(1-b)^{N-l}, \quad l > t. \qquad \square$$

Proof. Let the function

$$f(l) = a^l(1-a)^{N-l} - b^l(1-b)^{N-l}. \tag{14}$$

For $a,\, b\,\epsilon\,[0,1]$, it can be easily proved that

$$f(0) = (1-a)^N - (1-b)^N < 0$$

and

$$f(N) = a^N - b^N > 0. \tag{15}$$

Since $f(l)$ is a continuous and monotonic function, according to Boltzano's Theorem, $f(l)$ has a unique root in the interval $[0, N]$. □

This root can be found from

$$f(t) = a^t(1-a)^{N-t} - b^t(1-b)^{N-t} = 0, \tag{16}$$

or

$$t = \left\lceil \frac{-n \log\left[\frac{1-b}{1-a}\right]}{\log\left[\frac{(1-a)b}{(1-b)a}\right]} \right\rceil, \tag{17}$$

where $\lceil . \rceil$ is the ceiling function.

Theorem 1. *Given N, the optimal fusion rule that minimizes the total error Q_t in CSS systems is*

$$k_{opt} = \left\lceil \frac{-N \log\left[\frac{1-P_f}{1-\overline{P_d}}\right]}{\log\left[\frac{(1-\overline{P_d})P_f}{(1-P_f)\overline{P_d}}\right]} \right\rceil. \tag{18}$$

□

Proof. The summation terms on the right hand side of (13) are those of a Binomial pdf

$$\sum_{l=0}^{N} \binom{N}{l} \overline{P_d}^l (1-\overline{P_d})^{N-l} = \sum_{l=0}^{N} \binom{N}{l} P_f^l (1-P_f)^{N-l} = 1. \tag{19}$$

Hence Q_t can be written as

$$Q_t = \sum_{l=0}^{k-1} \binom{N}{l} \overline{P_d}^l (1-\overline{P_d})^{N-l} + \sum_{l=k}^{N} \binom{N}{l} P_f^l (1-P_f)^{N-l}. \tag{20}$$

According to Lemma 1, Since $P_d > P_f$ if $l < t$, then

$$\binom{N}{l} \overline{P_d}^l (1-\overline{P_d})^{N-l} < \binom{N}{l} P_f^l (1-P_f)^{N-l},$$

and if $l > t$, holds

$$\binom{N}{l} \overline{P_d}^l (1-\overline{P_d})^{N-l} > \binom{N}{l} P_f^l (1-P_f)^{N-l}. \tag{21}$$

This follows that the value that minimizes Q_t is $k_{opt} = t$. Substituting $a = \overline{P_d}$ and $b = P_f$ in (17), k_{opt} is obtained as in (18). □

It should be noted that a similar result has been reported in [8], where the authors considered an approximation to reach a value for k that minimizes Q_t. However, in this work an alternative approach is used to prove that k_{opt}, given by (18), effectively minimizes the total error.

IV. Numerical and Simulation Results

In this section, we evaluate the validity of the proposed approximation for $\overline{P_d}$, as well as the optimal voting rule through simulations. The number of components in the MoG distribution is set to $G = 10$ and we consider only the first 60 terms in the infinite sum in (8). The corresponding parameters for the MoG pdf are given in Table I and Table II.

First, in Fig. 2 we compare the complementary ROC curves (P_m versus P_f) obtained from (8) to the theoretical expression from (6). We consider a single user performing spectrum sensing over NL channel where m is the Nakagami-m fading parameter which is inversely proportional to multipath fading severity i.e., as ($m \to \infty$) multipath severity diminishes. Note that the Rayleigh/Lognormal distribution is a special case of NL distribution, that is when $m = 1$. Moreover, ζ^2, measured in dB, is the variance of the Gaussian random variable defined by $V = 10\log_{10}(\eta)$, where η corresponds to the Lognormal shadowing. The parameters for the MoG distribution are calculated via the EM algorithm and are provided in Appendix A. It can be observed that, for both cases, the approximation is very accurate over all the values of P_f.

Second, a CRN of $N = 10$ users performing CSS over NL sensing channel is considered in Figs. 3 and 4. The users report their respective hard decisions to the FC via the reporting channels. For the sake of simplicity, the sensing channels are considered identically distributed and the reporting channels are assumed to be perfect. We evaluate $\overline{P_d}$ using (8) with the same parameters stated earlier in this section and the total error is calculates using (13). Fig. 3 presents the total error of the system for the different k-out-of-N voting rules. We should notice that the total error of the system is highly dependent upon the considered voting rule . In fact, for $\overline{\gamma} = 10$dB, a voting rule unwisely chosen can result in a total error reaching 0.86 when the optimum k nearly eliminates the sensing error of the network.

It can be easily understood that for low SNR, the PU signal will not be detected by most of the CR nodes and hence the OR ($k = 1$) rule provides the optimal performance, while for large $\overline{\gamma}$, the AND ($k = 10$) rule is optimal. Furthermore, there is always an optimal voting rule, given by (18), that minimizes the total error. This rule is dependent on the system parameters such as the energy detection threshold, the average SNR, the time bandwidth product and the number of CR nodes in the system.

Fig. 4 shows the total error of the system versus P_f at each CR node. Since P_f is determined by u and λ only, fixing u and varying P_f is equivalent to varying the local energy detection threshold at the SUs. It is obvious the proposed optimal k significantly outperforms the well known AND, OR and Majority rules that are usually considered in CSS. Moreover, it can be observed that for high values of P_f at the SU's, the proposed rule has a very low total error compared to the others. In fact, for $P_f = 0.3$, the total error obtained is near to 0 when the AND rule, which has the best performance in that case, provides an error close to 0.1. We can conclude our analysis by highlighting that for a reasonable average SNR ($\overline{\gamma} = 3$dB) and 10 CR nodes, the proposed optimal voting rule nearly eliminates the total error of the CSS for $P_f \leq 0.4$. This means that even over extreme fading and shadowing conditions, CR can be efficiently exploited with low sensing errors providing that the network can optimize the voting rule whenever the sensing conditions are changed.

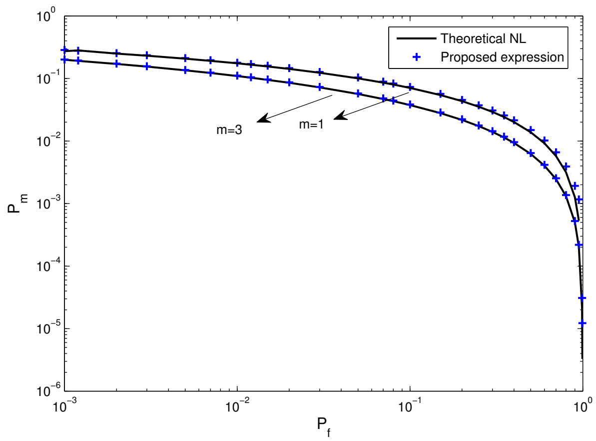

Fig. 2. Complementary ROC curves when $\zeta = 2$, $u = 3$ and $\overline{\gamma} = 5dB$.

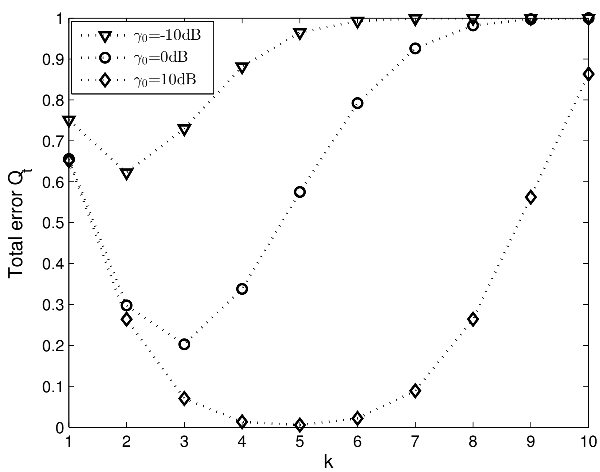

Fig. 3. Q_t versus k in NL sensing channel when $m = 3$, $\zeta = 2$ and $u = 1$.

V. Conclusion

In this paper, cooperative spectrum sensing over composite fading channels was investigated. First, the MoG distribution was considered to model the statistics of composite fading channels and a simple approximation for the average detection probability over generalized composite fading channels was derived. Second, the optimal combining rule for hard decision based cooperative spectrum sensing in cognitive radio networks was investigated and exact expression for the optimal k-out-of-N rule that minimizes the total error of the network was derived.

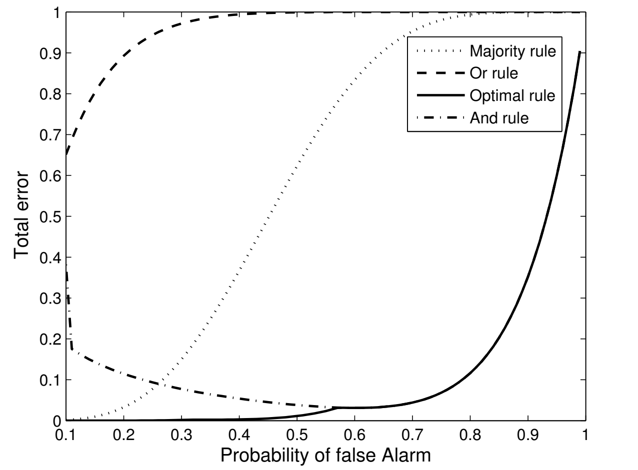

Fig. 4. Q_t versus P_f in NL sensing channel when $m = 1$, $\zeta = 2$, $u = 2$ and $\overline{\gamma} = 3$ dB.

TABLE II
MoG Parameters for NL channel $m = 3$, $\zeta = 2$

i	ω_i	μ_i	σ_i
1	0.0045723	0.054824	0.023214
2	0.018487	0.12622	0.041603
3	0.053141	0.23603	0.068681
4	0.11657	0.39073	0.10468
5	0.23304	0.60606	0.15207
6	0.20138	0.8864	0.18134
7	0.20286	1.1829	0.25922
8	0.13306	1.5772	00.37511
9	0.034063	2.1289	0.53072
10	0.0028262	2.8129	0.81739

Appendix A
MoG Parameters for Selected Scenarios

TABLE I
MoG Parameters NL channel $m = 1$, $\zeta = 2$

i	ω_i	μ_i	σ_i
1	0.018504	0.11388	0.048116
2	0.059575	0.24597	0.81305
3	0.12967	0.44561	0.13128
4	0.18639	0.73547	0.20206
5	0.20342	1.1485	0.30392
6	0.17426	1.7284	0.45023
7	0.12767	2.5859	0.68335
8	0.068447	3.9113	1.061
9	0.026641	6.0376	1.7052
10	0.0054257	9.2445	2.936

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