# Unified Analysis of Cooperative Spectrum Sensing Over Composite and Generalized Fading Channels

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***Abstract*—In this paper, we investigate the performance of cooperative spectrum sensing (CSS) with multiple-antenna nodes over generalized and composite fading channels. To this end, we approximate the probability density function (pdf) of the signal-to-noise ratio (SNR) of various fading channels using the mixture Gamma (MG) distribution. Based on this, we derive an exact closed-form expression and a generic infinite series representation for the corresponding probability of energy detection, along with a finite upper bound for the involved truncation error. Both expressions have a relatively simple algebraic form that gives them convenience in handling both analytically and numerically. Furthermore, the composite effect of multipath fading and shadowing scenarios in CSS is mitigated by applying an optimal fusion rule that minimizes the total error rate (TER), where the optimal number of nodes is derived under the Bayesian criterion, assuming erroneous feedback channels. We also extend the derived average detection probability to include diversity reception techniques, namely, maximal-ratio combining, square-law combining, and square-law selection (SLS). For the SLS, we demonstrate the existence of an error rate floor as the number of antennas of the cognitive radio nodes increases in erroneous decision feedback channels. Accordingly, we derive the optimal rule for the number of antennas that minimizes the TER in the SLS framework. Monte Carlo simulations are presented to corroborate the analytical results and to provide illustrative performance comparisons and insights between different composite fading channels.**

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## I. Introduction

THE need for an efficient utilization of the available spectrum resources has become a fundamental requirement in modern wireless networks, which is mainly due to the currently witnessed spectrum scarcity and the ever-increasing demand for higher data rate applications and Internet services [1]. In this context, cognitive radio (CR) networks are a particularly interesting framework that has been proposed to mitigate the spectrum scarcity by adapting their transmission parameters according to the environment [2]. To this end, CRs have been shown to be highly efficient in maximizing spectrum utilization due to their inherent spectrum sensing capability. In a CR network environment, users are categorized as either primary users (PUs) or secondary users (SUs). The former are those that have been typically assigned spectrum slots, and hence, have higher priority, whereas the latter are those allowed to access vacant frequency bands opportunistically.

Numerous spectrum sensing techniques have been proposed over the past decade and can be classified into three main categories, namely, energy detection (ED), matched filter detection, and cyclostationary or feature detection. Moreover, one of the earliest methods is the likelihood ratio test [3], whose exploitation is rather limited and impractical as it requires exact knowledge of the signal-to-noise ratio (SNR) distributions as well as the corresponding channel information [4], although the same has been considered optimal. In matched filter detection techniques [5], [6], accurate synchronization and exact information about the transmitted signal waveform, such as its bandwidth and modulation type, are required. Likewise, cyclostationary detection [7] uses the statistical properties of the transmitted signals to enhance the probability of detection. On the contrary, ED is the most common detection method and has received considerable attention due to its low computational and implementation complexity. In ED, the presence of a PU signal is simply detected by comparing the output of the energy detector with a predetermined energy threshold that depends on the *a priori* knowledge of the noise power level [8]. Therefore, poor knowledge of the noise power level results in a high probability of false alarm and an SNR floor. Based on this, several analyses have been proposed for resolving this issue by estimating the noise power level, e.g., see [5], [9], and [10] and the references therein. For instance, Olivieri *et al.* in [10] proposed an iterative algorithm that optimizes the decision threshold for fulfilling the false-alarm probability requirement.

Unlike the conventional ED-based spectrum sensing, methods that rely on the statistical covariances of the received signal do not require knowledge of the noise power level, since their operation relies on the fact that statistical covariance matrices of the received signal and the noise are different. Recently, several advanced spectrum sensing techniques have been proposed, such as statistical-covariance-based sensing techniques and filter-based sensing techniques [8]. For instance, Zeng and Liang [11] proposed sensing techniques based on two eigenvalue statistics, namely, the ratio of the maximum eigenvalue to the minimum eigenvalue and the ratio of the average eigenvalue to the minimum eigenvalue. Based on some latest random matrix theories, the distributions of the two statistics are quantified, and subsequently, the expressions of the probability of detection and false alarm are derived. In [12], assuming that CRs are equipped with spectrum analyzers, a variety of filter banks are proposed for spectral estimation. It is worth mentioning that it was shown in [12] that the well-known multitaper method [13] can be considered as a filter bank spectral estimator with multiple filter banks [14], [15].

It has been also extensively shown that fading phenomena create detrimental effects on the performance of conventional and emerging wireless communications, including CR systems. In this context, the ED performance over multipath fading channels, such as Rayleigh, Rician, and Nakagami-$m$, was analyzed in [16] and [17], respectively, whereas the corresponding performance over the more generalized $\kappa - \mu$ and $\kappa - \mu$ extreme fading channels was investigated in [18]. However, in addition to multipath fading, in most scenarios, the received signal is also degraded by shadowing effects, as it has been shown that multipath and shadowing effects typically occur simultaneously [19]. Therefore, it is evident that there is undoubted necessity to quantify and analyze the CR performance over composite multipath/shadowing fading channels [20]. Nevertheless, it has been shown that such an analysis is particularly tedious, since composite fading models can only be represented by cumbersome, if not intractable, infinite integrals. For example, the probability of detection of the ED-based spectrum sensing over Nakagami-lognormal (NL) fading channels was addressed in [19]; however, the offered solution is semianalytic, as it is not represented in closed form, whereas the impact of fading and shadowing effects is numerically evaluated. Based on this, several alternative models that characterize the composite fading channels have been shown to provide a simplified performance analysis for the CR networks. For example, in the analyses of [21]–[25], the $\mathcal{K}$ distribution [26] is utilized to study the ED performance over Rayleigh-lognormal (RL) channels. The energy detector performance for mixture of Gaussian distribution [27] is derived in [28]. In [29], the sufficiency and optimality of cooperative wireless sensor networks that are based on ED is analyzed over non-line-of-sight (NLOS) fading environments, where zero-mean Gaussian mixtures are assumed as a viable model for NLOS fading channels. A unified and versatile analysis over the ED performance can be made feasible through the use of more recent generalized composite fading models, such as $\kappa - \mu$/Inverse-Gaussian [30], $\eta - \mu$/Inverse-Gaussian [31], $\kappa - \mu$/gamma [32]–[34], and $\eta - \mu$/gamma [32], [35], [36] fading channels.

One of the most efficient techniques to mitigate the effect of fading is cooperative spectrum sensing (CSS), where $N$ users sense the spectrum independently and send their decisions, through an imperfect feedback channel, to a fusion center (FC) for determining a global decision [37]. In CSS, there are two main decision combining schemes, namely, soft-decision combining, where the SUs send their local observations to the FC, and hard-decision combining, where the SUs send their local decisions to the FC.[1] In [38], CSS optimization over the Rayleigh fading channel has been studied assuming a perfect feedback channel. In [39], Quan *et al.* studied the performance of CSS under the Bayesian criterion, which accounts for the costs of probabilities of missed detection and false alarm. However, the feedback channel is assumed to be perfect, and the study is limited to Rayleigh and Suzuki fading channels. In [40], Lee studied the performance of CSS over Rayleigh fading assuming imperfect feedback channels. Recently, CSS over $\kappa - \mu$ fading channels has been studied in [41]; nevertheless, this model does not represent composite fading channels, and the authors considered only the OR fusion rule with a perfect feedback channel. In [42], the optimal fusion rule and the optimal number of antennas in centralized CSS have been studied over a Rayleigh fading channel.

Although CSS has been extensively investigated in the literature, none of the reported analyses have addressed CSS optimization over composite and generalized fading channels. However, it is noted here that analyzing the performance of ED over generalized and composite fading channels for a single node is neither sufficient nor practical. Moreover, even if CSS is applied to the analysis as in [43], using the conventional OR rule does not result in optimal performance. Moreover, incorporating diversity reception schemes, such as square-law combining (SLC) and square-law selection (SLS), further improves the performance and decreases the associated detection errors.

Motivated by this, in this paper, we consider the generic and versatile MG model to derive new exact expressions for the probability of detection over generalized and composite fading channels. Specifically, we derive a simple series representation that is valid for all values of the involved parameters along with a closed-form upper bound for the associated truncation error. In addition, a rather simple closed-form expression is derived for the case of integer values of the involved scale parameter $\beta_k$. It is recalled that the MG distribution [43], [44] has been proposed as an alternative model to various generalized and composite fading channels, namely, lognormal, Weibull, RL, NL, $\mathcal{K}$, $\mathcal{K}_G$, $\eta - \mu$, $\kappa - \mu$, Hoyt, and Rician channels. This model is both accurate and flexible in representing all of the aforementioned fading channels, and thus, it constitutes a generic unified fading model. It is also noted that the probability of detection of the MG distribution has been derived in [43]. However, the solution provided therein is limited to integer values of the $\beta_k$ parameter of the MG model. In this paper, the derived average detection probability is also extended to show the effect of diversity reception by employing the maximal-ratio combining (MRC), SLC, and SLS techniques. Moreover, we derive the optimal fusion rule, where the optimal number of nodes is analytically derived under the Bayesian criterion. In the underlying scenario, for the SLS

[1] This paper considers the hard-decision combining scheme.

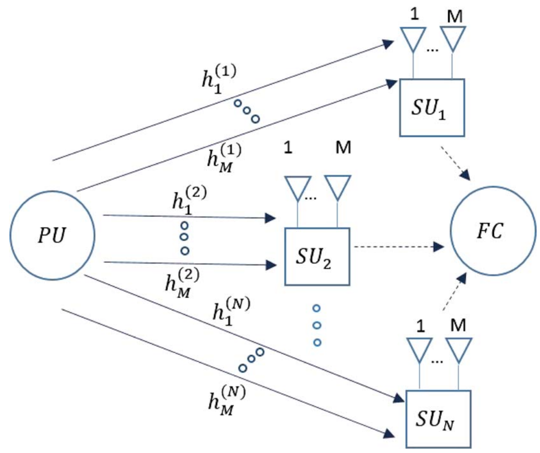


Fig. 1. CSS network configuration.

scheme, we further demonstrate that there exists a total error rate (TER) floor, whereby increasing the number of antennas beyond this floor would not reduce the corresponding TER. To this effect, we derive the optimal number of antennas that achieves the corresponding optimal performance. Notably, this derivation incorporates both cooperative sensing and diversity reception, assuming erroneous feedback channels. Specifically, the contributions of this paper are summarized as follows.

- We derive a generic exact infinite series representation and a closed-form expression for the average detection probability over generalized and composite fading conditions using the MG distribution.
- A tight closed-form upper bound is derived for the truncation error of the derived infinite series.
- The offered analytic results are subsequently extended to the case of diversity reception, including MRC, SLC, and SLS combining schemes.
- We derive a simple analytical solution to the optimal fusion rule in a CSS environment over generalized and composite fading channels. We also demonstrate the importance of applying the optimal fusion rule by comparing it with the conventional AND and OR rules.
- For the SLS scheme, we demonstrate the existence of a TER floor as the number of antennas of the CR node increases. Accordingly, we derive the optimal rule for the number of antennas that minimizes the TER, which, in turn, reduces implementation cost and power consumption.

The remainder of this paper is organized as follows: Section II provides a detailed description of the system model, whereas Section III is devoted to the derivation of the probability of detection using the MG distribution for both single-channel and multichannel systems. The optimal fusion rule and the optimal number of antennas over MG-based fading channels are presented in Section IV, whereas closing remarks are provided in Section V.

## II. System Model

We consider the CSS network configuration shown in Fig. 1. The configuration consists of one PU and $N$ SU nodes, each equipped with $M$ antennas. The SU nodes report their hard decisions via imperfect feedback channels to an FC, which may represent a base station or a cell site. We assume that the channel gains $h_j^{(i)}$ are independent and identically distributed (i.i.d.) and are modeled using the generalized MG distribution, where $i = 1, \ldots, N$, and $j = 1, \ldots, M$.

The received signal copies at the $i$th SU node and the $j$th antenna can have two possible hypotheses, which are modeled as

$$\mathcal{H}_0 : y_j^{(i)}(t) = v_j^{(i)}(t) \tag{1}$$

$$\mathcal{H}_1 : y_j^{(i)}(t) = h_j^{(i)}(t) s_j^{(i)}(t) + v_j^{(i)}(t) \tag{2}$$

where $\mathcal{H}_0$ and $\mathcal{H}_1$ represent the absence and the presence of the PU, respectively; $s(t)$ corresponds to the transmitted signal from the PU, with energy $E_s = \mathbb{E}[|s(t)|^2]$; and $v_j^{(i)}(t) \sim \mathcal{CN}(0, \sigma_n^2)$ is the circularly symmetrical complex additive white Gaussian noise (AWGN), where $\mathbb{E}\{.\}$ is the statistical expectation operator. Each $i$th SU node uses an energy detector for the amplitudes $|y_j^{(i)}|_{j=1}^{M}$ of the received signal and compares it with a threshold $\lambda$. Therefore, the output of this process for each antenna can be written as

$$Z_j^{(i)} = \left| y_j^{(i)} \right|^2 \underset{H_0}{\overset{H_1}{\gtrless}} \lambda \tag{3}$$

where the time index $t$ has been omitted for the sake of notational simplicity.

Based on the given setup, the CSS scheme performs the following steps.

- Each $i$th SU calculates the decision statistic for all $M$ antennas and employs a diversity combining technique to decide on the presence or absence of a PU.
- The binary hard decision of each SU is sent to the FC via a practically erroneous feedback channel.
- The FC applies a fusion rule to the binary decisions received from all SUs, and a final decision is made.

The conditional probabilities of detection and false alarm are determined with the aid of [16], i.e.,

$$P_d = Q_u\left(\sqrt{2\gamma_j}, \sqrt{\lambda_n}\right) \tag{4}$$

$$P_f = \frac{\Gamma\left(u, \frac{\lambda_n}{2}\right)}{\Gamma(u)} \tag{5}$$

where $u$ is the time–bandwidth product, $Q_u(\cdot,\cdot)$ is the generalized Marcum-Q function of order $u$ [45], $\Gamma(\cdot,\cdot)$ is the upper incomplete gamma function [46, eq. (8.35)], $\Gamma(\cdot)$ is the standard gamma function [46, eq. (8.31)], $\lambda_n = \lambda/{\sigma_n}^2$ is the normalized threshold, and $\gamma_j^{(i)} = |h_j^{(i)}|^2 E_s/2\sigma_n^2$ is the instantaneous SNR of the $i$th PU–SU link.

It is recalled that the probability of false alarm is based on the null hypothesis; it remains the same regardless of the involved fading conditions. As a result, in the following sections, we shall focus on the derivation of the probability of detection over the MG distribution both with and without diversity reception.

## III. Probability of Detection Over Composite Fading Channels

### A. Single-Channel Scenario

It is recalled that the MG distribution is a generic and versatile fading model since it has been shown capable of providing accurate representation of several generalized and composite fading models. The corresponding probability density function (pdf) can be expressed as [27]

$$f_\gamma(x) = \sum_{k=1}^{C} \frac{\alpha_k}{\gamma_0}\left(\frac{x}{\gamma_0}\right)^{\beta_k - 1} \exp\left(-\frac{\zeta_k x}{\gamma_0}\right) \tag{6}$$

where the scale and shape parameters of the $k$th component are denoted by $\beta_k$ and $\zeta_k$, respectively. The number of mixture components is denoted by $C$, whereas the mixing coefficient of the $k$th component is denoted by $\alpha_k$, having the constraints $0 \leq \alpha_k \Gamma(\beta_k)/\zeta_k^{\beta_k} \leq 1$ and $\sum_{k=1}^{C} \alpha_k \Gamma(\beta_k)/\zeta_k^{\beta_k} = 1$. To this effect, the average probability of detection for the case of MG distribution can be written as

$$P_{d,\mathrm{MG}} = \sum_{k=1}^{C} \frac{\alpha_k}{\gamma_0} \int_0^\infty Q_u\left(\sqrt{2x}, \sqrt{\lambda_n}\right)\left(\frac{x}{\gamma_0}\right)^{\beta_k - 1} e^{-\frac{\zeta_k x}{\gamma_0}} dx. \tag{7}$$

With the aid of Lemma 1 in [48, eq. (8)] and after some simplifications, (7) is evaluated in terms of the following exact infinite series representation:

$$P_{d,\mathrm{MG}} = \sum_{l=0}^{\infty}\sum_{k=1}^{C} \frac{\alpha_k}{\gamma_0^{\beta_k}} \frac{\Gamma(\beta_k + l)\Gamma\left(u + l, \frac{\lambda_n}{2}\right)}{l!\Gamma(u+l)\left(1 + \frac{\zeta_k}{\gamma_0}\right)^{\beta_k + l}}. \tag{8}$$

It is noted that the given series converges after relatively few terms while it is generic as the involved parameters are not subject to any validity restrictions [48]. However, to determine the exact number of terms that correspond to a certain truncation error, it is essential to derive an accurate expression for (8). To this end and following [48, Lemma 2], a closed-form upper bound for the involved truncation error, i.e., $\epsilon_t$, can be deduced as follows:

$$\epsilon_t \leq \sum_{k=1}^{C} \alpha_k \Gamma(\beta_k)\zeta_k^{-\beta_k} - \sum_{k=1}^{C}\sum_{l=0}^{n_0} \frac{\alpha_k}{\gamma_0^{\beta_k}} \frac{\Gamma(\beta_k + l)\Gamma\left(u + l, \frac{\lambda_n}{2}\right)}{l!\Gamma(u+l)\left(1 + \frac{\zeta_k}{\gamma_0}\right)^{\beta_k + l}}. \tag{9}$$

In addition, an exact closed-form expression is also derived for the special case that $\beta_k \in \mathbb{N}$. This is realized with the aid of Theorem 1 in [48, eq. (3)] and by carrying out some long but basic algebraic simplifications, yielding

$$P_{d,\mathrm{MG}}^{\mathrm{int}} = \sum_{k=1}^{C} \frac{\alpha_k \Gamma(\beta_k)\Gamma\left(u, \frac{\lambda_n}{2}\right)}{\Gamma(u)\zeta_k^{\beta_k}} + \sum_{k=1}^{C}\sum_{l=0}^{\beta_k - 1} \frac{\alpha_k \Gamma(\beta_k)}{\gamma_0^{\beta_k}} \frac{\left(\frac{\lambda_n}{2}\right)^u {}_1\mathcal{F}_1\left(l+1, u+1, \frac{\frac{\lambda_n}{2}}{1+1\frac{\zeta_k}{\gamma_0}}\right)}{u!\left(\frac{\zeta_k}{\gamma_0}\right)^{\beta_k - l}\left(1 + \frac{\zeta_k}{\gamma_0}\right)^{l+1} \exp\left(\frac{\lambda_n}{2}\right)} \tag{10}$$

where ${}_1\mathcal{F}_1(.,.,.)$ is the confluent hypergeometric function [46, eq. (9.210.1)]. It is noted here that the given expression has a relatively simple algebraic representation that renders it convenience in handling both analytically and numerically since ${}_1\mathcal{F}_1(.,.,.)$ is included as built-in function in popular software packages, such as MATLAB, MAPLE, and MATHEMATICA.

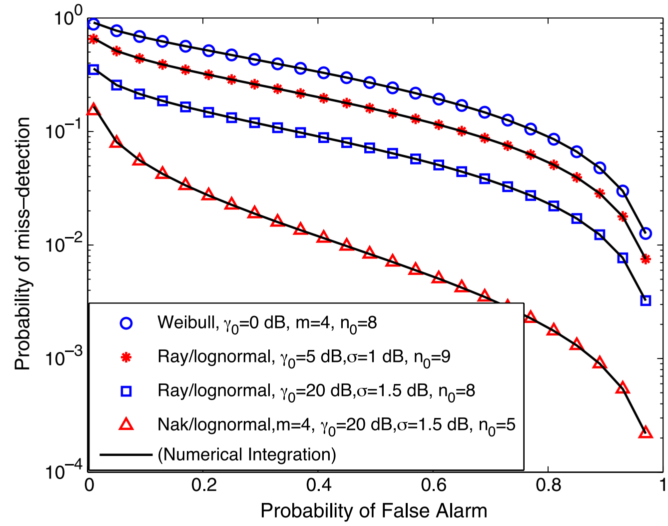


Fig. 2. Complementary ROC for a single SU over various fading channels.

In Fig. 2, the complementary receiver operating characteristic (ROC) curves over various fading scenarios are plotted using (8). The involved infinite series in (8) is truncated after $n_0$ terms, as specified correspondingly in the legend so that the level of the corresponding relative error is $\epsilon_t^2 \leq 10^{-5}$. The term ‘Numerical Integration’ refers to numerically integrating (7) via the trapezoidal integration routine in MATLAB. It can be observed that there is a perfect match between results from the analytic expression form derived in (8) and the respective computer simulation results, where, as shown, the curves span a wide average SNR range. The addressed scenarios were all approximated by two mixture components, i.e., $C = 2$.

Table I provides a brief comparison between simulation and analytical values of the probability of missed detection over different channels, whereas the probability of false alarm is 0.1. It can be deduced from the table that the difference between simulation and analytical values is practically negligible, as they seem fully identical in Fig. 2.

It is worth noting that (8) coincides with the expressions offered in [14] and [15], after setting the following parameters in (8) for the case of Rayleigh fading, namely, $\alpha_k = 1$, $\beta_k = 0$, and $1/\zeta_k = 1$. Fig. 3 shows the ROC curves over Rayleigh fading using (8), [16, eq. (9)], and [17, eq. (5)]. It is clearly shown that in spite of the difference between these mathematical solutions for the same fading conditions, there is a perfect match between our generalized solution in (8), after choosing the corresponding parameters, and Nakagami-$m$ solution with $m = 1$, which also represents a Rayleigh fading channel, and the specific analytical solution for Rayleigh fading derived in [16].

## *B. Diversity Reception*

*1) MRC:* Under MRC, the received signal copies are coherently weighted and summed up to maximize the instantaneous output SNR. Although MRC is the optimal spatial combining strategy, it still requires channel estimation. However, in the context of ED, this is not a practical assumption since the essence of ED of unknown signals has no *a priori* knowledge of the signal. Moreover, other more accurate detection schemes

TABLE I
COMPARISON OF SIMULATION AND ANALYTICAL VALUES OF $P_{md}$ OVER DIFFERENT CHANNELS AND SNRS, WITH $P_f = 0.1$

| Channel | Probability of missed detection (Simulation) | Probability of missed detection (Analytical) |
|---|---|---|
| Nakagami-m/lognormal,m=4 SNR=20dB | 0.02511886431 | 0.02494708915 |
| Rayleigh/lognormal SNR=20dB | 0.12589254117 | 0.1273503081 |
| Rayleigh/lognormal SNR=5dB | 0.28183829312 | 0.27925438412 |
| Weibull SNR=0dB | 0.44668359215 | 0.44357044735 |

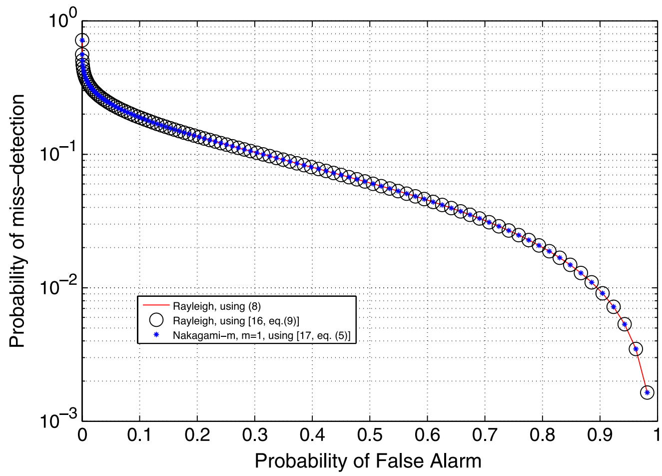


Fig. 3. Complementary ROC over a Rayleigh fading channel.

could be employed to harness the knowledge of the channel, as explained in Section I. Nevertheless, MRC can be considered as a benchmark since it practically resembles an upper bound on the performance of other diversity schemes, as also discussed thereafter. To this effect, it is recalled that the total instantaneous SNR at the output of the MRC method is given by

$$\gamma_{\mathrm{MRC}} = \sum_{l=1}^{M} \gamma_l \tag{11}$$

where $M$ denotes the number of antennas at each SU node. To evaluate the corresponding average detection probability, one needs to derive the pdf of $\gamma_{\mathrm{MRC}}$. Unfortunately, in this case, it seems cumbersome to derive a closed-form expression for the pdf of $\gamma_{\mathrm{MRC}}$ in (11), since it involves $M$ integrals of set convolution. In what follows, we derive the useful, yet extendable, special cases for $M = 2$ and $M = 3$.

*Theorem 1:* For $\beta_i,\ \beta_j,\ \beta_l\ \in \mathbb{N}$, the pdf expressions for $\gamma_{\mathrm{MRC}}$ for $M = 2$ are given by

$$f^{(2)}_{\gamma_{\mathrm{MRC}}}\Big|_{(\zeta_i=\zeta_j)} = \sum_{i=1}^{C}\sum_{j=1}^{C} \frac{\alpha_i\alpha_j}{\gamma_0{}^{\beta_i+\beta_j}} \frac{\Gamma(\beta_i)\Gamma(\beta_j)}{\Gamma(\beta_i+\beta_j)} e^{-\frac{\zeta_j}{\gamma_0}\gamma}\gamma^{\beta_i+\beta_j-1} \tag{12}$$

$$\begin{aligned} f^{(2)}_{\gamma_{\mathrm{MRC}}}\Big|_{(\zeta_i\neq\zeta_j)} =& \sum_{i=1}^{C}\sum_{j=1}^{C}\sum_{l=0}^{\beta_j-1} \binom{\beta_j-1}{l} \\ &\times \frac{(-1)^l\alpha_i\alpha_j}{\gamma_0{}^{\beta_j-l}(\zeta_i-\zeta_j)^{\beta_i+l}}\gamma^{\beta_j-l-1}e^{-\frac{\zeta_j}{\gamma_0}\gamma}\Gamma(\beta_i+l) \\ &\times \left(1-e^{-\frac{\gamma(\zeta_i-\zeta_j)}{\gamma_0}}\sum_{t=0}^{\beta_i+l-1}\frac{\left(\frac{\gamma(\zeta_i-\zeta_j)}{\gamma_0}\right)^t}{t!}\right) \end{aligned} \tag{13}$$

$$\begin{aligned} f^{(3)}_{\gamma_{\mathrm{MRC}}}\Big|_{(\zeta_i=\zeta_j=\zeta_k)} =& \sum_{i=1}^{C}\sum_{j=1}^{C}\left[\frac{\alpha_i\alpha_j\alpha_k}{\gamma_0{}^{\beta_i+\beta_j+\beta_k}}\frac{\Gamma(\beta_i)\Gamma(\beta_j)\Gamma(\beta_k)}{\Gamma(\beta_i+\beta_j+\beta_k)}\right. \\ &\left.\times\, e^{-\frac{\zeta_k}{\gamma_0}\gamma}\gamma^{\beta_i+\beta_j+\beta_k-1}\right] \end{aligned} \tag{14}$$

and for the case of $M = 3$ and $(\zeta_i \neq \zeta_j \neq \zeta_k)$, we have (15), shown at the bottom of the page, while $f^{(x)}_{\gamma_{\mathrm{MRC}}} = f^{(x)}_{\gamma_{\mathrm{MRC}}}|_{(\zeta_i=\zeta_j)} + f^{(x)}_{\gamma_{\mathrm{MRC}}}|_{(\zeta_i\neq\zeta_j)}$.

*Proof:* For the case of M = 2, the pdf of $\gamma_{\mathrm{MRC}}$ can be obtained by evaluating the following integral:

$$\begin{aligned} f^{(2)}_{\gamma_{\mathrm{MRC}}} =& \int_0^{\gamma} f_{\gamma_1}(x)f(\gamma-x)dx = \sum_{i=1}^{C}\sum_{j=1}^{C}\frac{\alpha_i\alpha_j}{\gamma_0^{\beta_i+\beta_j}} \\ &\times\int_0^{\gamma} x^{\beta_i-1}e^{-\frac{\zeta_i}{\gamma_0}x}(\gamma-x)^{\beta_j-1}e^{-\frac{\zeta_j}{\gamma_0}(\gamma-x)}dx. \end{aligned} \tag{16}$$

$$\begin{aligned} f^{(3)}_{\gamma_{\mathrm{MRC}}}\Big|_{(\zeta_i\neq\zeta_j\neq\zeta_k)} =& \sum_{i=0}^{C}\sum_{j=0}^{C}\sum_{k=0}^{C}\sum_{l=0}^{\beta_j-1}\sum_{r=0}^{\beta_k-1}\frac{\alpha_i\alpha_j\alpha_k}{\gamma_0{}^{\beta_k-r}}\binom{\beta_j-1}{l}\binom{\beta_k-1}{r}\frac{(-1)^{\beta_j}\Gamma(l+\beta_i)}{(\zeta_i-\zeta_j)^{l+\beta_i}\zeta_k^{r+\beta_j-l}}\frac{\gamma^{\beta_k-r-1}}{e^{\frac{\gamma}{\gamma_0}(\zeta_k+\zeta_j)}\gamma\left(b_j+r-l,-\frac{\zeta_k\gamma}{\gamma_0}\right)} \\ &-\sum_{i=0}^{C}\sum_{j=0}^{C}\sum_{k=0}^{C}\sum_{l=0}^{\beta_j-1}\sum_{t=0}^{\beta_i+l-1}\sum_{r=0}^{\beta_k-1}(-1)^{l+r}\frac{\alpha_i\alpha_j\alpha_k}{\gamma_0{}^{\beta_k-r}}\binom{\beta_j-1}{l}\binom{\beta_k-1}{r} \\ &\times\frac{\Gamma(l+\beta_i)(\zeta_i-\zeta_j)^{t-l-\beta_i}}{t!(\zeta_i-\zeta_j-\zeta_k)^{r+t+\beta_j-l}}\gamma^{\beta_k-r-1}e^{-\frac{\gamma}{\gamma_0}(\zeta_k+\zeta_j)}\gamma\left(b_j+r+t-l,\frac{\gamma(\zeta_i-\zeta_j-\zeta_k)}{\gamma_0}\right) \end{aligned} \tag{15}$$

To solve (16), we split the solution into two scenarios, namely, when $\zeta_i = \zeta_j$ and $\zeta_i \neq \zeta_j$. In the former scenario, (16) reduces to the following integral:

$$f^{(2)}_{\gamma_{\rm MRC}}\Big|_{(\zeta_i=\zeta_j)} = \sum_{i=1}^{C}\sum_{j=1}^{C} \frac{\alpha_i}{{\gamma_0}^{\beta_i}}\frac{\alpha_j}{{\gamma_0}^{\beta_j}} e^{-\frac{\zeta_j}{\gamma_0}\gamma} \times \int_0^{\gamma} x^{\beta_i-1}(\gamma-x)^{\beta_j-1}dx. \quad (17)$$

By performing the change in variables $u = x/\gamma$ and with the aid of [46, eq. (8.380)] and the functional relation in [46, eq. (8.384)], we obtain the closed-form solution in (12).

For the latter scenario, i.e., $\zeta_i \neq \zeta_j$, and under the assumption that $\beta_j \in \mathbb{N}$, (16) is solved with the aid of the binomial theorem in [46, eq. (1.111)]. To this effect, the representation in (16) can be equivalently rewritten as follows:

$$f^{(2)}_{\gamma_{\rm MRC}}\Big|_{(\zeta_i\neq\zeta_j)} = \sum_{i=1}^{C}\sum_{j=1}^{C}\sum_{l=0}^{\beta_j-1}\binom{\beta_j-1}{l} \times (-1)^l \frac{\alpha_i}{{\gamma_0}^{\beta_i}}\frac{\alpha_j}{{\gamma_0}^{\beta_j}}\gamma^{\beta_j-l-1}e^{-\frac{\zeta_j}{\gamma_0}\gamma} \times \int_0^{\gamma} x^{\beta_i+l-1}e^{-\frac{x}{\gamma_0}(\zeta_i-\zeta_j)}dx. \quad (18)$$

Evidently, the given integral can be expressed in closed form with the aid of [46, eq. (8.350.1)], yielding

$$f^{(2)}_{\gamma_{\rm MRC}}\Big|_{(\zeta_i\neq\zeta_j)} = \sum_{i=1}^{C}\sum_{j=1}^{C}\sum_{l=0}^{\beta_j-1}\binom{\beta_j-1}{l} \times \frac{(-1)^l\alpha_i\alpha_j}{{\gamma_0}^{\beta_j-l}(\zeta_i-\zeta_j)^{\beta_i+l}}\gamma^{\beta_j-l-1}e^{-\frac{\zeta_j}{\gamma_0}\gamma} \times \gamma\left(\beta_i+l, \frac{\gamma(\zeta_i-\zeta_j)}{\gamma_0}\right) \quad (19)$$

where $\gamma(a,x) \triangleq \int_0^x t^{a-1}e^{-t}dt$ denotes the lower incomplete gamma function. Thus, by expressing the $\gamma(a,x)$ function according to [46, eq. (8.352.6)], one obtains the closed-form expression in (13). By following the same methodology, a similar expression can be obtained for $f^{(3)}_{\gamma_{\rm MRC}}$, which completes the proof. ■

It is noted here that the given methodology allows the derivation of similar expressions for $f^{(4)}_{\gamma_{\rm MRC}}$ and $f^{(5)}_{\gamma_{\rm MRC}}$.

Based on the given expressions, the average detection probability is readily obtained by

$$\overline{P}^{(M)}_{d,{\rm MRC}} = \int_0^{\infty} Q_u\left(\sqrt{2\gamma_{\rm MRC}}, \sqrt{\lambda}\right) f^{(M)}_{\gamma_{\rm MRC}}(\gamma_{\rm MRC})\, d\gamma_{\rm MRC}. \quad (20)$$

For the case of $M = 2$ and by inserting (12) and (13) in (20), it follows that

$$\overline{P}^{(2)}_{d,{\rm MRC}}\Big|_{(\zeta_i=\zeta_j)} = \sum_{i=1}^{C}\sum_{j=1}^{C}\frac{\alpha_i\alpha_j}{{\gamma_0}^{\beta_i+\beta_j}}\frac{\Gamma(\beta_i)\Gamma(\beta_j)}{\Gamma(\beta_i+\beta_j)} \times \int_0^{\infty} Q_u\left(\sqrt{2\gamma_\Sigma}, \sqrt{\lambda}\right) e^{-\frac{\zeta_j}{\gamma_0}\gamma}\gamma^{\beta_i+\beta_j-1}\, d\gamma \quad (21)$$

and for the case of $(\zeta_i \neq \zeta_j)$, we have (22), shown at the bottom of the page. Notably, the three integrals in (21) and (22) have the same algebraic representation as (7). Therefore, by utilizing Theorem 1 in [48, eq. (3)] and after some algebraic manipulations, one obtains the following closed-form expressions:

$$\overline{P}^{(2)}_{d,{\rm MRC}}\Big|_{(\zeta_i=\zeta_j)} = \sum_{i=1}^{C}\sum_{j=1}^{C}\alpha_i\alpha_j\Gamma(\beta_i)\Gamma(\beta_j)\frac{\Gamma\left(u,\frac{\lambda}{2}\right)}{\zeta_j^{\beta_i+\beta_j}\Gamma(u)} + \sum_{n=0}^{\beta_i+\beta_j-1}\frac{{\gamma_0}^{-n}\left(\frac{\lambda}{2}\right)^u {}_1\mathcal{F}_1\left(n+1, u+1, \frac{\frac{\lambda}{2}}{1+\frac{\zeta_j}{\gamma_0}}\right)}{u!(\zeta_j)^{\beta_i+\beta_j-n}\left(1+\frac{\zeta_j}{\gamma_0}\right)^{n+1}\exp\left(\frac{\lambda}{2}\right)} \quad (23)$$

and for the case of $(\zeta_i \neq \zeta_j)$, we have (24), shown at the bottom of the next page.

In the same context, by following a similar methodology, one can obtain the average detection probability for a large number of diversity branches while the probability of false alarm remains unchanged, i.e., $P_{f,{\rm MRC}} = P_f$ as in (5).

*2) SLC:* Under SLC, the received signals from each branch are integrated, squared, and then summed up. It is recalled that SLC is very similar to MRC in the sense that the total instantaneous SNR at the output of the combiner is equivalent to that in MRC, i.e., $\gamma_{\rm SLC} = \sum_{l=1}^{M}\gamma_l$. Nevertheless, SLC does not require *a priori* knowledge of the channel [49]. As a result, the conditional detection and false alarm probabilities would follow (4) and (5), with $u$ replaced by $Mu$. Therefore, the corresponding average detection probability, i.e., $P^{(M)}_{d,{\rm SLC}}$, becomes equivalent to $P^{(M)}_{d,{\rm MRC}}$, with $u$ replaced by $Mu$. Finally, $P_{f,{\rm MRC}}$ is the same as $P_f$ in (5) with the replacement of $u$ by $Mu$.

$$\overline{P}^{(2)}_{d,{\rm MRC}}\Big|_{(\zeta_i\neq\zeta_j)} = \sum_{i=1}^{C}\sum_{j=1}^{C}\sum_{l=0}^{\beta_j-1}\binom{\beta_j-1}{l}\frac{(-1)^l\alpha_i\alpha_j\Gamma(\beta_i+l)}{{\gamma_0}^{\beta_j-l}(\zeta_i-\zeta_j)^{\beta_i+l}}\int_0^{\infty}\frac{Q_u\left(\sqrt{2\gamma_\Sigma},\sqrt{\lambda}\right)\gamma^{\beta_j-l-1}}{e^{\frac{\zeta_j}{\gamma_0}\gamma}}d\gamma - \sum_{i=1}^{C}\sum_{j=1}^{C}\sum_{l=0}^{\beta_j-1}\sum_{t=0}^{\beta_i+l-1}\left[\binom{\beta_j-1}{l}\frac{(-1)^l\alpha_i\alpha_j\Gamma(\beta_i+l)}{t!{\gamma_0}^{\beta_j-l+t}(\zeta_i-\zeta_j)^{\beta_i+l-t}}\right]\int_0^{\infty}\frac{Q_u\left(\sqrt{2\gamma_\Sigma},\sqrt{\lambda}\right)\gamma^{\beta_j+t-l-1}}{e^{\frac{\zeta_i}{\gamma_0}\gamma}}d\gamma \quad (22)$$

*3) SLS:* In the SLS scheme, for each $i$th SU node, the branch with the maximum $\gamma_j$ is selected as follows [16]:

$$\gamma_{\mathrm{SLS}} = \max_{j=1,\ldots,M}(\gamma_j). \tag{25}$$

Under $\mathcal{H}_0$, the probability of false alarm for the SLS scheme can be expressed as

$$P_{f,\mathrm{SLS}} = 1 - \Pr(\gamma_{\mathrm{SLS}} < \lambda_n|\mathcal{H}_0). \tag{26}$$

Substituting (25) in (26), we obtain

$$P_{f,\mathrm{SLS}} = 1 - \Pr\left(\max(\gamma_1, \gamma_2, \ldots, \gamma_M) < \lambda_n|\mathcal{H}_0\right) \tag{27}$$

which translates to [47]

$$P_{f,\mathrm{SLS}} = 1 - [1 - P_f]^M. \tag{28}$$

Similarly, the unconditional probability of detection over the AWGN channel is obtained by

$$P_{d,\mathrm{SLS}} = 1 - \prod_{j=1}^{M}\left[1 - Q_u\left(\sqrt{2\gamma_j}, \sqrt{\lambda_n}\right)\right]. \tag{29}$$

Hence, averaging (29) over (7) yields the unconditional probability of detection under the SLS scheme, i.e., $\bar{P}_{d,\mathrm{SLS}}$, which is given by

$$\bar{P}_{d,\mathrm{SLS}} = 1 - \prod_{j=1}^{M}[1 - P_{d,\mathrm{MG}}]. \tag{30}$$

## IV. Optimal Fusion Rule and Optimal Number of Antennas in Composite Fading Channels

CSS can highly decrease the probability of missed detection in wireless transmission over fading channels. Here, the performance of CSS is analyzed over various fading conditions. Practically, the channel between the SUs and the FC is imperfect. Therefore, the hard decisions sent by each SU node are affected by the quality of the feedback channel. Here, a binary symmetric channel with error probability $q$ is assumed. The probabilities of false alarm and detection over erroneous feedback channels are given by [37]

$$P'_f = (1-q)P_f + q(1-P_f) \tag{31}$$
$$P'_{d,\mathrm{MG}} = (1-q)(P_{d,\mathrm{MG}}) + q(1-P_{d,\mathrm{MG}}). \tag{32}$$

For the SLS diversity reception, we substitute (28) and (30) into (31) and (32), respectively, yielding

$$P'_{f,\mathrm{SLS}} = \left(1-(1-P_f)^M\right)(1-q) + (1-P_f)^M q \tag{33}$$
$$P'_{d,\mathrm{SLS}} = (1-q)\left(1-\prod_{j=1}^{M}(1-P_{d,\mathrm{MG}})\right) + q\prod_{j=1}^{M}(1-P_{d,\mathrm{MG}}). \tag{34}$$

Assuming i.i.d. diversity branches, (34) can be readily expressed as

$$P'_{d,\mathrm{SLS}} = (1-q)\left(1-(1-P_{d,\mathrm{MG}})^M\right) + q(1-P_{d,\mathrm{MG}})^M. \tag{35}$$

Likewise, the same approach is followed for SLC and MRC diversity schemes, i.e.,

$$P'_{d,\mathrm{SLC}} = (1-q)P_{d,\mathrm{SLC}} + q(1-P_{d,\mathrm{SLC}}) \tag{36}$$
$$P'_{d,\mathrm{MRC}} = (1-q)P_{d,\mathrm{MRC}} + q(1-P_{d,\mathrm{MRC}}). \tag{37}$$

Since the optimal fusion rule analysis will be applied to MRC, SLC, and SLS, we let $P'_f = P'_{f,\mathrm{MRC}}$, $P'_{f,\mathrm{SLC}}$, or $P'_{f,\mathrm{SLS}}$, and $P'_d = P'_{d,\mathrm{MRC}}$, $P'_{d,\mathrm{SLC}}$, or $P'_{d,\mathrm{SLS}}$.

The false alarm and detection probabilities, i.e., $Q_f$ and $Q_d$, at the FC using the $k$-out-of-$N$ rule is, thus, given by

$$Q_f = \sum_{n=k}^{N}\binom{N}{n}\left(P'_f\right)^n\left(1-\left(P'_f\right)\right)^{N-n} \tag{38}$$
$$= 1 - \mathrm{B}_F\left(k-1, N, P'_f\right) \tag{39}$$
$$Q_d = \sum_{n=k}^{N}\binom{N}{n}(P'_d)^n(1-(P'_d))^{N-n} \tag{40}$$
$$= 1 - \mathrm{B}_F\left(k-1, N, P'_d\right) \tag{41}$$

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$$\begin{aligned}
\overline{P}^{(2)}_{d,\mathrm{MRC}}\Big|_{(\zeta_i\neq\zeta_j)} &= \sum_{i=1}^{C}\sum_{j=1}^{C}\sum_{l=0}^{\beta_j-1}\binom{\beta_j-1}{l}\frac{(-1)^l\alpha_i\alpha_j\Gamma(\beta_i+l)}{\gamma_0{}^{\beta_j-l}(\zeta_i-\zeta_j)^{\beta_i+l}}\\
&\times\left[\frac{\Gamma(\beta_j-l)\Gamma\left(u,\frac{\lambda}{2}\right)}{\left(\frac{\zeta_j}{\gamma_0}\right)^{\beta_j-l}\Gamma(u)} + \sum_{n=0}^{\beta_j-l-1}\frac{\left(\frac{\lambda}{2}\right)^u\Gamma(\beta_j-l)}{u!\left(\frac{\zeta_j}{\gamma_0}\right)^{\beta_j-l-n}}\frac{{}_1\mathcal{F}_1\left(n+1,u+1,\frac{\frac{\lambda}{2}}{1+\frac{\zeta_j}{\gamma_0}}\right)}{\left(1+\frac{\zeta_j}{\gamma_0}\right)^{n+1}\exp\left(\frac{\lambda}{2}\right)}\right]\\
&-\sum_{i=1}^{C}\sum_{j=1}^{C}\sum_{l=0}^{\beta_j-1}\sum_{t=0}^{\beta_i+l-1}\binom{\beta_j-1}{l}\frac{(-1)^l\alpha_i\alpha_j\Gamma(\beta_i+l)}{t!\gamma_0{}^{\beta_j-l+t}(\zeta_i-\zeta_j)^{\beta_i+l-t}}\\
&\times\left[\frac{\Gamma(\beta_j+t-l)\Gamma\left(u,\frac{\lambda}{2}\right)}{\left(\frac{\zeta_i}{\gamma_0}\right)^{\beta_j+t-l}\Gamma(u)} + \sum_{n=0}^{\beta_j+t-l-1}\frac{\left(\frac{\lambda}{2}\right)^u\Gamma(\beta_j+t-l){}_1\mathcal{F}_1\left(n+1,u+1,\frac{\frac{\lambda}{2}}{1+\frac{\zeta_i}{\gamma_0}}\right)}{u!\left(\frac{\zeta_i}{\gamma_0}\right)^{\beta_j+t-l-n}\left(1+\frac{\zeta_i}{\gamma_0}\right)^{n+1}\exp\left(\frac{\lambda}{2}\right)}\right].
\end{aligned} \tag{24}$$

where $B_F$ is the binomial cumulative distribution function [39]. Since $P_m = 1 - P_d$, the probability of missed detection at the FC becomes

$$Q_m = \sum_{n=k}^{N} \binom{N}{n} (1 - P_d')^n (P_d')^{N-n} \tag{42}$$

$$= \mathrm{B}_F \left(k - 1, N, 1 - P_d'\right). \tag{43}$$

It is noted here that (38)–(43) reduce to the OR rule and the AND rule as a special case when $k = 1$ and $k = N$, respectively.

### A. Optimal Fusion Rule Under Bayesian Criterion

The performance of CSS in generalized and composite fading environments can be improved by applying an optimal fusion rule to decrease the TER. The problem is formulated under the Bayesian criterion, which accounts for the cost of missed detection and false alarm. Such a cost can be set by regulation or based on past experiences, which makes the preceding analysis both practical and widely applicable to any fading channel. To this end, we consider the problem of minimizing the Bayesian risk of CSS, which is given by [33]

$$\min_{1 \le k \le N} R(k) = W_f Q_f + W_m Q_m \tag{44}$$

where the aforementioned $W_m$ and $W_f$ are the cost of missed detection and false alarm, respectively.

*Proposition 1:* If we let $R(k)$ be the cost function whose derivative with respect to (w.r.t.) $k$ exists, then the optimal fusion rule, which minimizes the Bayesian risk, can be determined by

$$k_{\mathrm{opt}} \approx \left\lceil \frac{\ln \left( \frac{W_m}{W_f} \cdot \frac{1-P_f'}{1-P_d'} \right)^N}{\ln \left( \frac{(P_d')(1-P_f')}{(1-P_d')(P_f')} \right)} \right\rceil \tag{45}$$

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

*Proof:* The proof follows from [38, Th. 1] and [39, Section III-B]. ■

It is noted that unlike [38, eq. (9)] that is based on the Neyman–Pearson criterion, (45) is based on the Bayesian criterion, which accounts for the costs of missed detection and false alarm. Moreover, we considered the errors in the feedback channel. It is noted here that unlike the present analysis, the contributions in [38] and [39] assume error-free feedback channels, which is not a practical approach.

In what follows, we present indicative simulation results for the three fusion rules and the three diversity combining schemes. We adopt the NL with $m = 4$ and the RL fading channels, where they are approximated by the MG distribution with $C = 7$ components.

Fig. 4 shows the TER as a function of the normalized threshold, i.e., $\lambda_n$, over NL and RL composite fading channels using different fusion rules. It is clear that the optimal fusion rule yields the best performance for both fading channels. For example, the minimum TER of the optimal fusion rule ($k = 3$) in the NL channel is $10^{-3.9}$, whereas in the RL channel, it is lower by an order of magnitude, i.e., $10^{-2.9}$. On the contrary, the AND rule exhibits the worst performance, yielding

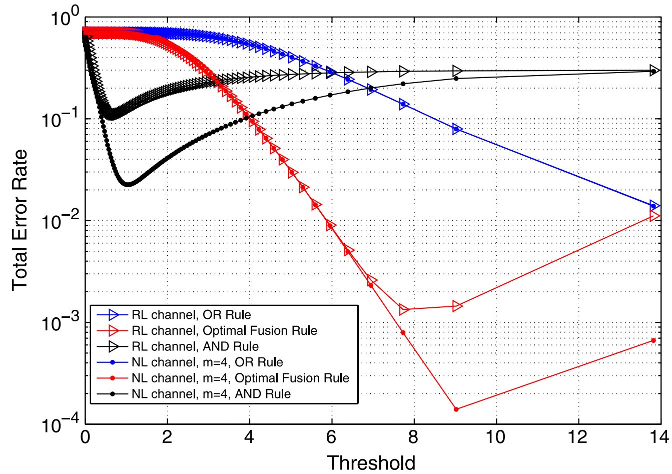


Fig. 4. TER versus normalized detection threshold over the RL and NL fading channels using different fusion rules with no diversity, $\gamma_0 = 10$ dB, $u = 1$, $m = 4$, $\zeta = 0.5$ dB, $M = 1$, $N = 10$, $W_m = 0.3$, $W_f = 0.7$, and $q = 10^{-2}$.

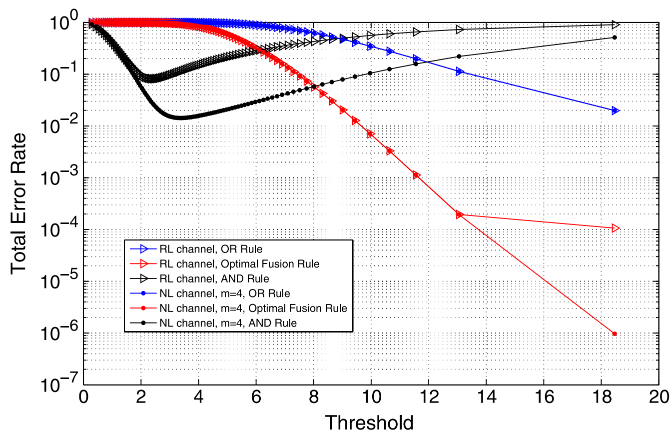


Fig. 5. TER versus normalized detection threshold over the RL and NL fading channels, using different fusion rules with SLC, $\gamma_0 = 10$ dB, $\zeta = 0.5$ dB, $M = 2$, $u = 1$, $N = 10$, $W_m = 0.7$, $W_f = 0.3$, and $q = 10^{-2}$.

a minimum TER of $10^{-1}$ for the RL scenario and $10^{-2}$ for the NL scenario. Interestingly, the OR rule did not improve from RL to NL, where the corresponding minimum TER is $10^{-2}$ for both channels. We have also observed that the OR rule is less sensitive to the change in fading severity since only one user gets to decide on the presence of the PU signal. The AND rule performs poorly because all the SUs have to detect the PU signal in order for the FC to decide on its presence effectively. This is rather hard in such harsh channel conditions where multipath fading and shadowing effects are present. On the other hand, the optimal fusion yields the best performance as it selects the optimal number of users that have to decide on the presence of the PU to achieve a reliable decision at the FC.

In Fig. 5, SLC has been used to the same scenario used in Fig. 4, with having different weights for missed detection and false alarm and $M = 2$. It is shown that the performance of the optimal fusion rule has significantly increased, yielding a minimum TER of $10^{-6}$ and $10^{-4}$ for the NL channel and the RL channel, respectively. The AND rule and the OR rule yield a minimum TER of nearly $10^{-2}$.

Fig. 6 shows the effects of SLS as compared with SLC. As expected, SLS performs worse than SLC in the optimal fusion

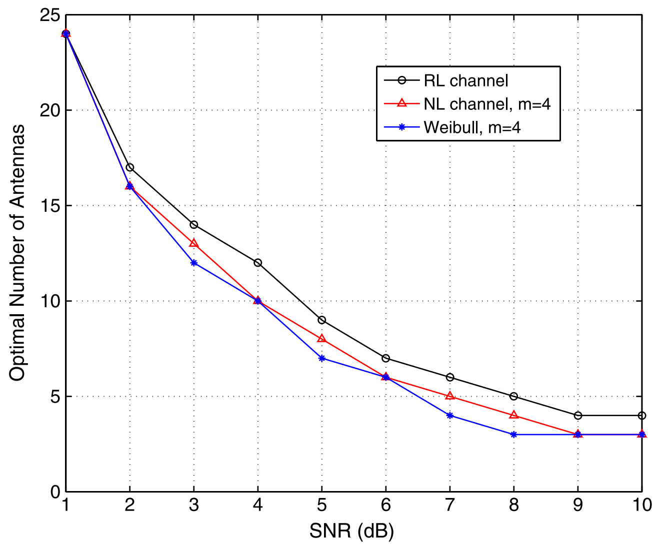


Fig. 6. Optimal number of antennas versus average SNR in various fading channels for SLS with $k = 3$, $N = 10$, $u = 1$, $\lambda_n = 8$, $W_m = 0.7$, $W_f = 0.3$, and $q = 10^{-2}$.

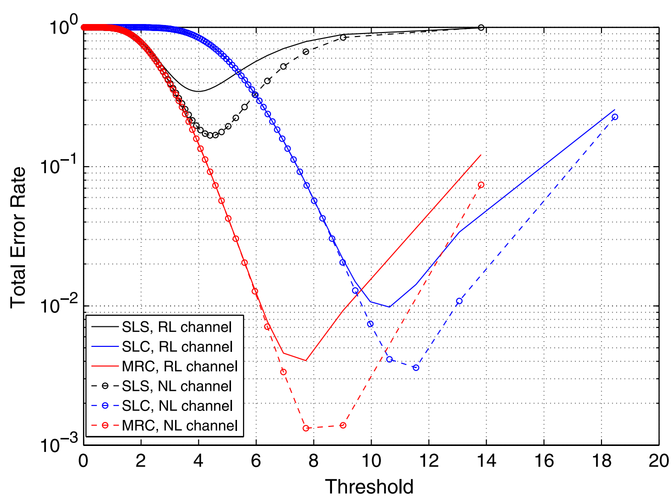


Fig. 7. TER versus normalized detection threshold over the RL and NL fading channels using different diversity reception schemes with $k = k_{\mathrm{opt}}$, $\gamma_0 = 5$ dB, $\zeta = 0.5$ dB, $M = 2$, $u = 1$, $N = 10$, $W_m = 0.7$, $W_f = 0.3$, and $q = 10^{-2}$.

rule case, yielding a minimum TER of $10^{-4.9}$, which is lower by an order of magnitude, as compared with SLC. It can be noticed that also in SLS, the OR rule did not decrease the TER, yielding minimum TERs of around $10^{-2}$.

Fig. 7 shows a comparison between different diversity schemes while using the optimal fusion rule. As expected, MRC outperforms SLC and SLS in both the RL and NL channels. It should be noted that SLC outperforms SLS considerably as the minimum TER in SLS is $10^{-0.92}$ in the NL channel, contrary to the $10^{-2.75}$ value in SLC.

### *B. Optimal Number of Antennas Using the SLS Diversity Scheme*

Here, we investigate the effect of increasing the number of antennas with SLS diversity reception. It is subsequently shown

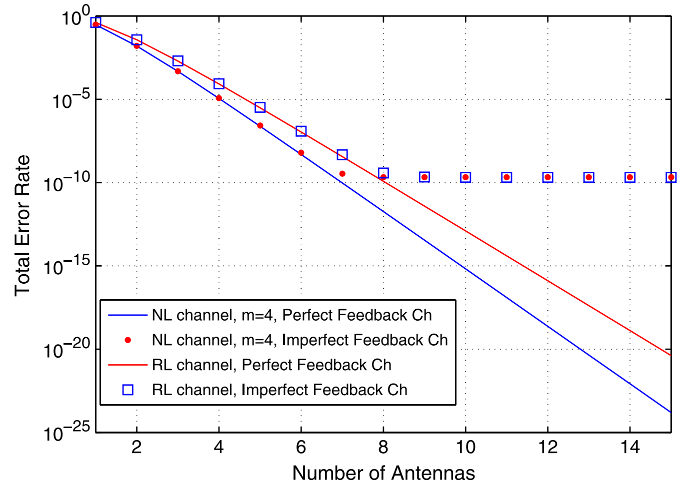


Fig. 8. TER versus number of antennas over perfect and imperfect feedback channels with $\gamma_0 = 5$ dB, $\zeta = 0.5$ dB, $u = 1$, $k = 3$, $N = 10$, $\lambda_n = 8$, $W_m = 0.3$, $W_f = 0.7$, and $q = 10^{-2}$.

in Figs. 4 and 5 that SLS can increase the performance of the CSS remarkably, as compared with single-antenna nodes. In what follows, it is shown that the performance is not monotonically increasing if the feedback channel is erroneous. In Figs. 4 and 6, it has been shown that the SLS scheme can increase the performance of the CSS as compared with the single-antenna case. This behavior is consistent if one assumes ideal feedback channels; increasing the diversity order always improves the TER performance. However, we found out that this is not the case in realistic imperfect feedback channels, where the TER performance does not monotonically improve as the diversity order increases. Fig. 8 shows the effect of the feedback channel errors on the TER while increasing the number of antennas $M$ in various composite fading channels. In the perfect-feedback-channel case, the TER is monotonically decreasing as we increase the number of antennas. However, in the imperfect-feedback-channel case, the TER decreases until a specific lower bound, whereby increasing $M$ afterward is ineffective and inefficient. This is because optimizing the detection performance by selecting the antenna with the best SNR does not necessarily lead to an optimal performance for the feedback channel. Based on this, we consider the problem of minimizing the Bayesian risk of CSS, which is given by

$$\min_{M \geq 1} R(M) = W_f Q_f + W_m Q_m \tag{46}$$

subject to $k = k_{\mathrm{opt}}$ and $q = \delta$, where $\delta$ is the bit error probability of the feedback channel.

*Theorem 2:* Let $R(M)$ be the cost function whose derivative w.r.t. $M$ exists. Accordingly, the optimal number of antennas, i.e., $M^*$, which minimizes the Bayesian risk, can be obtained when

$$\frac{\partial Q_m}{\partial M} + \frac{\partial Q_f}{\partial M} = 0. \tag{47}$$

*Proof:* The partial derivative of $Q_f$ w.r.t. $M$ is given by (48), shown at the top of the next page, and

$$\frac{\partial P'_{f,\mathrm{SLS}}}{\partial M} = (1 - P_f)^M (-1 + 2q) \ln(1 - P_f). \tag{49}$$

$$\begin{aligned}\frac{\partial Q_f}{\partial M} &= \sum_{n=k}^{N} \binom{N}{n} n\left(P'_{f,\mathrm{SLS}}\right)^{n-1} \frac{\partial P'_{f,\mathrm{SLS}}}{\partial M}\left(1-P'_{f,\mathrm{SLS}}\right)^{N-n} \\ &\quad - \sum_{n=k}^{N} \binom{N}{n} \left(P'_{f,\mathrm{SLS}}\right)^{n}(N-n)\left(1-P'_{f,\mathrm{SLS}}\right)^{N-n-1} \frac{\partial P'_{f,\mathrm{SLS}}}{\partial M} \\ &= \frac{\partial P'_{f,\mathrm{SLS}}}{\partial M} \sum_{n=k}^{N} \binom{N}{n} \left(P'_{f,\mathrm{SLS}}\right)^{n-1}\left(1-P'_{f,\mathrm{SLS}}\right)^{N-n}\left[(n-(N-n).\frac{P'_{f,\mathrm{SLS}}}{1-P'_{f,\mathrm{SLS}}}\right] \end{aligned} \tag{48}$$

$$\begin{aligned}\frac{\partial Q_m}{\partial M} &= -\sum_{n=k}^{N} \binom{N}{n} n\left(\bar{P}'_{d,\mathrm{SLS}}\right)^{n-1} \frac{\partial P'_{d,\mathrm{SLS}}}{\partial M}\left(1-P'_{d,\mathrm{SLS}}\right)^{N-n} \\ &\quad + \sum_{n=k}^{N} \binom{N}{n} \left(\bar{P}'_{d,\mathrm{SLS}}\right)^{n}(N-n)\left(1-P'_{d,\mathrm{SLS}}\right)^{N-n-1} \frac{\partial \bar{P}'_{d,\mathrm{SLS}}}{\partial M} \\ &= -\frac{\partial \bar{P}'_{d,\mathrm{SLS}}}{\partial M} \sum_{n=k}^{N} \binom{N}{n} \left(P'_{d,\mathrm{SLS}}\right)^{n-1}\left(1-P'_{d,\mathrm{SLS}}\right)^{N-n}\left[(n-(N-n).\frac{\bar{P}'_{d,\mathrm{SLS}}}{1-P'_{d,\mathrm{SLS}}}\right] \end{aligned} \tag{50}$$

Similarly, the partial derivative of $Q_m$ w.r.t. $M$ is given by (50), shown at the top of the page, and

$$\begin{aligned}\frac{\partial P'_{d,\mathrm{SLS}}}{\partial M} &= (1-P_{d,\mathrm{MG}})^M q \ln(1-P_{d,\mathrm{MG}}) \\ &\quad - (1-P_{d,\mathrm{MG}})^M (1-q)\ln(1-P_f) \end{aligned} \tag{51}$$

$$= (1-P_{d,\mathrm{MG}})^M(-1+2q)\ln(1-P_{d,\mathrm{MG}}). \tag{52}$$

Thus, the optimal number of antennas can be obtained by substituting (49) and (52) in (47) and solving it for $M$ numerically, which completes the proof. ■

Fig. 8 shows the optimal number of antennas as a function of the average SNR under SLS over various generalized and composite fading channels. As expected, the optimal number of antennas is inversely proportional to $\gamma_0$, whereas it is observed that there is a frequent cross between NL and Weibull channels due to the fact that both of them depict moderate fading with $m = 4$ as compared with the RL channel, which requires more antennas than the NL and Weibull channels to reach $M^*$. Therefore, in the presence of both shadowing and multipath fading effects, more antennas are required to reach the optimal performance to compensate for the involved channel imperfections.

## V. Conclusion

We have investigated the performance of CSS over generalized and composite fading channels. A unified MG-based approach has been proposed for the performance analysis of CSS in CR. It was shown that in a composite fading channel, the performance can be remarkably improved by applying an optimal fusion rule, which outperforms AND and OR rules. In addition, in the SLS, it has been found that increasing the number of antennas in a CSS network with an erroneous feedback channel does not decrease the TER monotonically. Based on this observation, the optimal rule for the number of antennas for SLS was numerically determined. Finally, it was shown that the fading severity can highly affect, in practice, the optimal rule for the number of antennas.

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