Interception Probability Versus Capacity in Wideband Systems: The Benefits of Peaky Signaling

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ABSTRACT Spread-spectrum techniques have found extensive use in broadband communications, both in military and commercial applications, for their low interception probability. However, it has been shown that these techniques prove ineffective on non-coherent fading channels with very large bandwidths since its capacity decreases with the increase of the bandwidth, eventually going to zero as the bandwidth goes to infinity. Peaky frequency-shift keying is a promising alternative modulation technique expected to achieve high data rates while maintaining a low interception probability. The current study explores such modulation techniques and outlines the conditions for which the reliability and capacity of the system increase while reducing the probability of interception compared to typical spread spectrum schemes. We show that peaky frequency-shift keying achieves a considerably higher transmission rate than non-peaky signaling for any given target level of interception probability, especially for outdoor fading scenarios in the low signal-to-noise ratio regime.

INDEX TERMS Direct-sequence spread, peaky frequency-shift keying, probability of interception, wideband channel.

I. INTRODUCTION

The ever-increasing demand for higher data rates coupled with the multitude of new services, ubiquitous coverage, and the shift from personal communications to communications between devices/things are the main driving forces behind new and advanced generations of wireless technologies. Higher data rates are made possible by enhanced transmission techniques and increased bandwidth. The new dynamics introduced by the need for the integration of heterogeneous elements (devices/things) raises various security concerns. Because of the heterogeneity of these elements, systems are more prone to unauthorized interceptions due to their security requirements [1], [2].

Different approaches can ensure security in communications systems. For example, increasing the difficulty of signal interception is a way of improving this security [3]. Direct sequence spread spectrum modulation techniques have been widely used in high data rate communications systems with an add-on feature of providing a low probability of interception/detection (\(P_D\)). This feature arises naturally when the signal power is spread over a frequency band substantially wider than its minimum band required for adequate transmission [4]. Moreover, the signal power spread fulfills the requirements for reliability and secrecy in communications mainly used in military applications.
Time- and frequency-spread signals (e.g., direct sequence spread spectrum, chirp spread spectrum, and frequency-hopping spread spectrum), with the continuous transmission in both domains, are not suitable for non-coherent wideband communications [5], [6], [7], [8]. Therefore, spreading systems operating over multipath channels with no channel information experienced decreased throughput with increasing bandwidth. Particularly, for fixed energy, as the bandwidth increases, the signal energy becomes smaller across the operating band. Detection becomes seriously compromised for the signal falling below the noise level [9]. The authors in [10] and [11] proved that peakey signals in two dimensions achieve the capacity in multipath channels composed of any number of paths.

In [7] and [12], the authors proposed a promising non-coherent low duty cycle frequency-shift keying (FSK) signaling scheme, which achieves the capacity of fading channels at the infinite bandwidth limit. In such a technique, the signal energy is concentrated in time and frequency rather than spread over the entire bandwidth. This scheme is known as Peaky-FSK (PFSK) [12]. In this paper, we pose and answer a new fundamental question: how does the capacity-intercept trade-off of PFSK signaling compare to that of a non-peaky (NP) one? The superior performance of PFSK is already known. But can we just go for it, not knowing how vulnerable the system may be as far as its intercept performance is concerned? And this is an open problem or was. This work is a first attempt to shed light on this challenging subject.

This paper investigates the performance of PFSK and non-peaky FSK (NPFSK) in terms of their probability of interception and rate limit. We assume that a malicious interceptor decides whether a signal is present or absent without any previous knowledge about the transmitted signal. In addition, the interceptor may explore two known spectrum-sensing detection techniques, namely, energy detection [13], [14] and covariance-based detection [15]. These techniques are robust against multipath fading and do not require any a-priori-specific information about the signal, the channel, or the noise power. As already mentioned, the fundamental question concerning the intercept performance of a PFSK has not been previously investigated. Here, we consider the lower limit capacity for the peakey signal and the upper limit capacity for the NP signal. We adopt this procedure for a fair comparison, i.e., using the worst PFSK performance versus the best NP signal performance. We then attain $P_D$ for each detection technique and signaling scheme. The performance evaluation method uses Monte Carlo simulations for both narrowband and wideband scenarios. The performance investigation is thorough and considers the effect of the various system parameters, such as the peakedness of the PFSK scheme, i.e., the duty cycle, observation time, and coherence time, among others.

The simulation results reveal that PFSK signals show a clear advantage over NP signaling according to $P_D$ and achievable rates by using a suitable duty cycle setting that maximizes the capacity, achieving rate increments of up to $10^3$ times for a given target level of $P_D$ in wideband scenarios or low signal-to-noise ratio (SNR) regimes. Importantly, we show that there is a duty-cycle range that should be avoided since it causes PFSK to be more likely intercepted than the NP scheme under the covariance-based detection. The maximum-capacity duty cycle is out of the mentioned range. Additionally, simulations demonstrate that coherence time, observation time, or coherence band considerably impact the $P_D$ in both signaling schemes for frequency-selective channels.

The rest of the paper is organized as follows. Section II describes the system model of the wideband fading channel and the investigated signaling schemes. Section III describes the two non-coherent detection mechanisms employed. In Section IV, we introduce the expressions for the lower-bound capacity of the PFSK signaling and the upper-bound capacity of NP signaling. In Section V, we present some simulation results and discuss the insights. Finally, Section VI provides concluding remarks.

Throughout this paper, $I_n$ represent the identity matrix of size $n$; $\{s_i\}_{i=1}^n$ denotes an indexed series (e.g., $\{s_i\}_{i=1}^n = \{s_1, s_2, \ldots, s_n\}$); $E[-]$ and $Pr(\cdot)$ are the expectation and probability, respectively.

II. SYSTEM MODEL

A. CHANNEL MODEL

We consider a rich scattering, frequency selective wideband fading channel with gain $h(t)\{1\leq t\leq L\}$ and delay $d(t)\{0\leq t\leq L\}, L$ being the number of propagation paths. In this case, the output $y(t)$ of a multipath fading channel with input $x(t)$ is given by

$$y(t) = \sqrt{P} \sum_{i=0}^{L-1} h_i(t)x(t - d_i(t)) + z(t), \quad (1)$$

where $z(t)$ is complex white Gaussian noise with power spectral density $\frac{N_0}{2}$ and $P$ denotes the average received signal power. Let $T_s, T_c$ and $T_d$ be the symbol time, the coherence time and the delay spread, respectively. We consider a frequency-selective block-fading channel model [12]. In other words, the symbol time is smaller than the coherence time of the channel (i.e., $T_s < T_c$) and greater than the delay spread (i.e., $T_s > T_d$). Thus, the path gains and delays remain constant over $T_c$. For simplicity, we will drop the time index within each coherence time so that $h_i(t) = h_i$ and $d_i(t) = d_i$. These gains and delays change independently from block to block.

B. SIGNALING MODEL

1) PEAKY FREQUENCY-SHIFT KEYING SIGNALING

We investigate the low duty-cycle FSK scheme introduced in [16]. In this scheme, each symbol is represented by a single-frequency signal, selected from a large set of frequencies, using a low duty cycle $\delta \in (0, 1]$ and a high-peak-power. Hence, the transmitter is active only for a fraction $\delta$ of time with boosted signal power $P/\delta$ followed by the $(1 - \delta)$
signal is given by
\[ M = B T \]

where \( H \) is a hypothesis testing problem (P and covariance-based detection, which are used to obtain the detection (spectrum sensing) mechanisms, energy detection (ED), and variance-based detection, respectively, \( n \) is the sample index, both \( H_0 \) and \( H_1 \) refer to the two hypotheses of no signal transmitted and signal transmitted, respectively, and \( z(n) \) are complex Gaussian noise samples with zero mean and variance \( \sigma_z^2 = N_0 B, i.e., z(n) \sim N(0, N_0 B) \).

A. ENERGY DETECTION (ED)

For ED, a bandpass filter process the received signal. Next, the result is squared and integrated over the observation time \( T_{obs} \), producing \( y_{ED} \) that is the energy of the received waveform. By using the sampling theorem representation for bandlimited signals, we can write the decision metric for ED as
\[
y_{ED} = \sum_{n=0}^{N_s} |y(n)|^2 ,
\]
where \( N_s \) is the size of the observation vector. From the binary hypothesis testing defined in (5), \( P_D \) (or probability of interception) and the probability of false alarm (\( P_{FA} \)) are given by
\[
P_D = \Pr (y_{ED} > \lambda_E | H_1)
\]
\[
P_{FA} = \Pr (y_{ED} > \lambda_E | H_0).
\]
where \( \lambda_E \) is a decision threshold. Based on the statistics of \( y_{ED} \), \( P_{FA} \) can be calculated as [17]
\[
P_{FA} = Q \left( \frac{\lambda_E - N \sigma_z^2}{\sqrt{2N \sigma_z^2}} \right).
\]

While the analytical framework for calculating \( P_D \) in AWGN or slow-fading channels is well known in the literature [14], [18], it is not the case for the fast-fading channel, which intrinsically makes the analytical investigation impracticable. Monte Carlo simulation is a handy tool that gives useful insights in cases like this, and this shall be the approach here. The choice of the detection threshold \( \lambda_E \) is based on the required \( P_{FA} \) [15].

B. COVARIANCE-BASED DETECTION

We provide a short description of the covariance-based detection algorithm for self-containment. (The reader is referred to [15] for a detailed explanation of this method.) Let us define the statistical covariance matrices of the received signal as
\[
R_s = E \left[ s(n)s^T(n) \right] \tag{10}
\]
\[
R_y = E \left[ y(n)y^T(n) \right], \tag{11}
\]
where \( s(n) \) and \( y(n) \) are vectors composed of the \( F \) consecutive samples of the noiseless and noisy version of the received
signal, respectively. (Parameter $F$ is called the smoothing factor.) Note that the vector $s(n)$ considers the transmitted signal and the effects of channel strength. We can also write the covariance matrix of the received signal as

$$R_y = R_s + \sigma^2 I_F.$$  \hspace{1cm} (12)

Observe that, in the absence of the signal $s(n)$, $R_s = 0$, the off-diagonal elements of $R_y$ are all zero. Now, in the presence of the signal, $s(n)$ and the signal samples are correlated, some of the off-diagonal elements of $R_y$ should be nonzero. Hence, this detection method uses the following two decision variables:

$$T_1 = \frac{1}{F} \sum_{n=1}^{F} \sum_{m=1}^{F} |r_{nm}|$$ \hspace{1cm} (13)

$$T_2 = \frac{1}{F} \sum_{n=1}^{F} |r_{nm}|,$$ \hspace{1cm} (14)

where $r_{nm}$ denotes the element of the matrix $R_y$ at the $n$th row and $m$th column. Because, in the absence of signal $T_1/T_2 = 1$ and the presence of signal $T_1/T_2 > 1$, the ratio $T_1/T_2$ is an effective metric for signal detection.

Due to the limited number of signal samples in practice, the statistical covariance matrix is approximated by the sample covariance matrix, which can be expressed as

$$\hat{R}_y(N_s) = \begin{bmatrix} \phi(0) & \phi(1) & \cdots & \phi(F - 1) \\ \phi(1) & \phi(2) & \cdots & \phi(F - 2) \\ \vdots & \vdots & \vdots & \vdots \\ \phi(F - 1) & \phi(F - 2) & \cdots & \phi(0) \end{bmatrix},$$ \hspace{1cm} (15)

where $\phi(j)$ is the sample autocorrelations of the received signal and is given as follows:

$$\phi(j) = \frac{1}{N_s} \sum_{m=0}^{N_s - 1} x(m)x(m - j), \hspace{0.5cm} j = 0, 1, \ldots, F - 1.$$ \hspace{1cm} (16)

Based on the sample covariance matrix, we use the following signal detection method:

1) COVARIANCE ABSOLUTE VALUE (CAV) DETECTION ALGORITHM [15]

- Sample the received signal.
- Chose a smoothing factor $F$ and the threshold $\lambda_C$. The decision threshold must be determined to comply with a target $P_{FA}$.
- Compute the sample covariance matrix (15).
- Calculate the decision variables $T_1(N_s)$ and $T_2(N_s)$ using the expressions in (13) and (14), and considering $r_{nm} = r_{nm}(N_s)$, where $r_{nm}(N_s)$ are the elements of a sample covariance matrix $\hat{R}_y(N_s)$.
- Detect the signal’s presence by comparing the decision metric $y_{cov} = T_1(N_s)/T_2(N_s)$ against a threshold $\lambda_C$. The $P_D$ and the $P_{FA}$ are given by

$$P_D = \Pr \left( y_{cov} > \lambda_C \mid H_1 \right)$$ \hspace{1cm} (17)

$$P_{FA} = \Pr \left( y_{cov} > \lambda_C \mid H_0 \right).$$ \hspace{1cm} (18)

An approximation of $P_{FA}$ for the CAV algorithm is obtained in [15] as

$$P_{FA} \approx 1 - Q \left( \frac{1}{\sqrt{2/F}} \left( 1 + \left( F - 1 \right) \sqrt{\frac{2}{N_s \pi}} \right) \right).$$ \hspace{1cm} (19)

Here again, we compute $P_D$ by means of simulation.

IV. RATE LIMITS

This section introduces the theoretical limits for the considered signaling schemes.

A. LOWER BOUND CAPACITY FOR PFSK

In [19], the lower bound of the achievable rate in a wideband non-coherent channel with i.i.d fading channels, using a peaky signal with duty cycle $\delta \in (0, 1]$ was introduced as

$$R_{LB, PFSK} = \frac{P}{N_0} \left[ 1 - \frac{P_k}{2B N_0} \right] - \frac{\delta B}{B_c T_c} \log \left( 1 + \frac{P}{2B N_0 B_c T_c} \right),$$ \hspace{1cm} (20)

where $\kappa$ is the kurtosis of the fading coefficients, for Rayleigh fading equals $\kappa = 2$. The maximum of the capacity lower bound $R_{LB, PFSK}$, here denoted with *, is obtained by approximating the optimal function of the product $\delta B$ for any finite $B_c T_c$ as

$$(\delta B)^* = \frac{P}{N_0} \left[ \frac{B_c T_c \kappa}{\log (B_c T_c)} + o \left( \frac{B_c T_c}{\log (B_c T_c)} \right) \right].$$ \hspace{1cm} (21)

$$R_{LB, PFSK} \geq \frac{P}{N_0} \left[ 1 - \sqrt{\frac{(1 + \log (B_c T_c)) \kappa \log \pi}{B_c T_c}} \right] - o \left( \frac{\log (B_c T_c)}{B_c T_c} \right).$$ \hspace{1cm} (22)

For details, the reader is referred to [19].

B. UPPER BOUND CAPACITY FOR NON-PEAKY SIGNALING

In order to derive the upper bound of the achievable rate in a wideband non-coherent channel with i.i.d Rayleigh-faded taps, the authors in [20] model the channel as a tapped delay line with its number of taps calculated as $L = [B T_d]$. Let $\left\{ h_{\ell} \right\}_{\ell=0}^{L-1}$ be the tap gains during a time coherence interval, and $g_\ell = E \left[ | h_{\ell} |^2 \right]$ be the average power of the $\ell$th tap satisfying $\sum_{\ell=0}^{L-1} g_\ell = 1$. For no-sparse channel, $g_\ell > 0 \forall \ell$. Thus, the upper bound of the achievable rate using NP signaling can be
estimated as [20, Eq. 48]

$$R_{NP}^{UB} \leq B \log_2 \left( 1 + \frac{P}{N_0 B} \right) - \frac{B}{B_c T_c} \sum_{\ell = 0}^{L-1} \log_2 \left( 1 + \frac{P}{N_0 B} B_c T_c \cdot L g_\ell \right). \tag{23}$$

For large $B$, $\tilde{L} = BT_\delta$. For more details on this, please refer to [20].

V. SAMPLE CASES AND INTERPRETATION

In this section, we assess the detection performance and the achievable rate of the investigated schemes by Monte Carlo simulations and the expressions presented in Sections III and IV. We employ the probability of misdetection $P_{MD}$ (detection failure) as an intercept metric. Thus, $P_{MD} = 1 - P_s$. Furthermore, we explore two representative scenarios, indoor narrowband and outdoor wideband systems.

In the indoor narrowband case, the system is chosen to operate in a bandwidth used by a current IoT scheme [21]. In the outdoor wideband case, the settings are chosen as in [20], in which the performance of NP signals is explored. These cases shall be analyzed in the next sections. Although our main interest is to assess the detectability performance of these signaling schemes in a wideband regime, the narrowband scenario serves as a benchmark, allowing for a more flexible, speedy, and detailed evaluation since the complexity and the computational load of the simulations increase rapidly with the increase of the bandwidth. Interestingly, after many independent runs, we maintain that the detection behavior in both scenarios is relatively similar. The most significant difference, as expected, concerns the required SNR and the achieved transmission rate for equivalent performance.

We assume an environment with one source, one destination, and one observer/interceptor. Communication is established between source and destination using a defined setting, i.e., duty cycle and transmission rate. At the same time, the observer/interceptor attempts to determine whether or not the transmission is taking place. We locate the observer/interceptor closer to the source (far from the destination), aiming to have a received energy level $P_{obs}$ at the observer much higher than the received energy level $P_R$ at the destination. This difference in power levels must be considered because the observer does not know the transmitted signal and must deal with the noise of the entire scanned bandwidth. Therefore, the observer requires a very high $P_{obs}/N_0$ to obtain a $P_D$ large enough to be analyzed. We avoid the scenario where the interceptor and the destination are co-located and therefore have the same SNR levels. In this scenario, the power levels are so high that they would force the system to leave the low-SNR regime, and the capacity expressions (20), (22) and (23) are no longer valid.

Concerning security application requirements, we are more interested in $P_{MD}$ rather than in $P_{FA}$. On the other hand, it is essential to set a maximum permitted $P_{FA}$ to find an adequate threshold to perform the detection. This setting avoids the arbitrary selection of a very low detection threshold, which may cause the interceptor to detect all transmissions without distinguishing between actual transmission and noise. Hence, the choice of the said parameter is paramount.

A. INDOOR NARROWBAND CASE

Consider an indoor system at $f_c = 1$ GHz. Assume a velocity $v = 5$ km/h, corresponding to $T_c = c/(2f_c v) = 0.10$ s, and a typical delay spread $T_\delta = 8$ µs, leading to $B_c = 125$ kHz. Altogether, $B_c T_c = 13.5 \times 10^3$. We assume a $B = 125$ kHz and $T_{obs} = 100T_s$ and $T_{obs} = 500T_s$, with $T_s = 1$ ms being the symbol duration. This results in $M = 125$ possible frequencies. We set the target $P_{FA} = 0.01$ following the results reported in [15] and chose $F = 10$ for the covariance-based detection.

Figs. 3 and 4 show the simulation results for this case considering the observation times 100$T_s$ and 500$T_s$, respectively. Figs. 3a and 4a illustrate $P_{MD}$ of the candidate signals schemes NPFSK (continuous red curves) and PFSK (dashed black curves), using the detection mechanisms ED and CAV while varying the observer/interceptor average SNR$_{obs}$, where SNR$_{obs} \triangleq P_{obs}/(BN_0)$. We simulate different $\delta$ values for the PFSK scheme and the optimal $\delta$ set that approximates the optimal relation ($\delta B$)* in the equation (21). This set is composed of a $\delta$ value for each transmitted $P_{R}/N_0$ and determines the maximum capacity lower bound $R_{LB}$ in (22). Furthermore, in Figs. 3b and 4b, we illustrate $P_{MD}$ versus the achievable rate between the source and the destination, applying the foregoing analytical expressions for the limit rates of the signaling schemes, considering a $-14$ dB $< P_{R}/N_0 < 20$ dB for both observation time cases. These figures show the upper bound capacity for NP and the lower bound capacity for PFSK using $\delta = 1$ and the optimal $\delta$ set. The following can be observed from the curves.

1) INTERCEPTION PERFORMANCE OF THE NP SIGNALING

In both investigated cases, $T_{obs} = 100T_s$ and $T_{obs} = 500T_s$ and through all of the several other simulation runs, the NPFSK signals with ED achieve a lower $P_{MD}$ than those with CAV. It suggests that ED is the most appropriate mechanism for detecting this type of signal because of its low computational and implementation complexity.

Notice that, for the ED approach, the average energy is the only signal attribute that matters. Therefore, the observations drawn here for NPFSK can be extended to all NP signaling.
2) IMPACT OF FADING ON THE INTERCEPTION PERFORMANCE

In Fig. 3a, which illustrates the scenario with $T_{\text{obs}} < T_c$, a higher $P_{\text{MD}}$ can be observed for the considered SNR range, as compared to that achieved in Fig. 4a that illustrates the scenario $T_{\text{obs}} > T_c$. This is because when $T_{\text{obs}} < T_c$, all the received signal samples are affected by a single fading coefficient, $\alpha_1$ in Fig. 1. Therefore, the entire signal may go below the minimum required value for detection under a deep fade. On the other hand, in scenario $T_{\text{obs}} > T_c$, the received signal samples experience a time diversity of the fading channel, $\alpha_1, \ldots, \alpha_i$ in Fig. 1, preventing the signal from being fully attenuated.

3) INTERCEPTION PERFORMANCE OF THE PFSK SIGNALING

a: ENERGY DETECTION APPROACH

The PFSK and NP schemes intuitively yield the exact same $P_{\text{MD}}$ using the ED approach since its detector utilizes the reserved energy from an observation time. Therefore, it seems indifferent whether transmission occurs at each $T_s$ or in spaced intervals with the corresponding concentrated energy.

However, the simulations reveal two conditions where this behavior is not observed.

1) Small duty cycles make the signal less susceptible to interception. Given that the PFSK signal transmission only occurs $\delta$ of the time, the decrease of the duty cycle can lead to a temporal sparsity of transmission greater than the observation time, affecting the next observation intervals. Fig. 2 illustrates an example of this situation. Here, a transmission occurs in the first observation period followed by a silent cycle $T_{\text{obs}} = 2T_s$. Therefore, the detector cannot find any transmission in the second observation period, which increases $P_{\text{MD}}$. The curve $\delta = 0.005$ represents this scenario in Fig. 3a. We can observe a considerable increase in $P_{\text{MD}}$ over medium and high SNR ranges and a slight decrease for low SNR. This decrease is because the energy concentration allows a better detection at very low SNRs, in which the detector fails in most time intervals.

2) Low temporal diversity of the fading channel reduces the probability of interception. As previously mentioned, a lower $P_{D}$ is obtained with the decrease of the temporal diversity of fading channel, defined by the relationship $\frac{T_{\text{obs}}}{T_c}$. Small duty cycles can force the
system to have silence cycles greater than \( T_c \), reducing the number of fading coefficients that affect the sample signal. This reduction occurs for \( \delta \)’s smaller than a fixed duty cycle, namely \( \delta_f \), defined as

\[
\delta_f = \frac{T_s}{T_c}.
\]  

(24)

We observe this behavior in Fig. 4a, with \( T_{\text{obs}} > T_c \). Particularly in this scenario, the signal is affected by five fading coefficients \( \alpha_1, \ldots, \alpha_5 \) and has a \( \delta_f = 0.01 \). The signal sample will always be affected by all five coefficients as long as \( \delta > \delta_f \). For \( \delta < \delta_f \), the coefficient number decreases. For instance, the curve of \( \delta = 0.002 \) represents the case of a single transmission during the entire observation time. Different from what is expected, a considerable increment in \( P_{\text{MD}} \) is observed due to the reduction to a single coefficient. This behavior is not presented in the scenario \( T_{\text{obs}} = 100T_s \) in Fig. 3a; since \( T_{\text{obs}} \leq T_c \), the sample signal is always affected by a single channel realization.

**b: COVARIANCE-BASED DETECTION APPROACH**

Unlike the ED mechanism, covariance-based detection performance varies with the duty cycle. For the PFSK scheme, decreasing the delta results in transmissions more spaced in time with a higher power concentration, which increases the sample auto-correlations and, therefore, \( P_{\text{MD}} \). Note that in Figs. 3a and 4a, \( \delta = 0.01 \) achieves the lowest \( P_{\text{MD}} \). These curves show an outperformance of CAV as compared to the ED. \( P_{\text{MD}} \) is progressively increased by using smaller duty cycles than a specific \( \delta \), namely \( \delta_f \). For reasons similar to those previously described for ED, \( \delta_f \) depends on the relation \( T_{\text{obs}}/T_c \) and it is defined in (24). Furthermore, for \( \delta < \delta_f \), the covariance detection method exceeds the performance of ED, especially for low SNR. The explanation given in (i) of the ED approach concerning the low \( P_D \) of PFSK also applies here.

4) INTERCEPTION PERFORMANCE VERSUS DATA RATE

Figs. 3b and 4b show the achievable rate bounds of the analyzed signaling schemes vs. \( P_{\text{MD}} \), considering the upper bound for the NPFSK signaling (ED and CAV-UB, NPFSK curves), the lower bound for the PFSK signaling for \( \delta = 1 \) (ED and CAV-LB1, PFSK curves) and, the lower bound for PFSK signaling for \( \delta_{\text{opt}} \) (ED and CAV-LBopt, PFSK curves). The lower-bound misdetection of PFSK outperforms the upper-bound misdetection NPFSK, rendering the advantage of the former over the latter technique unambiguous. Despite the slight difference in performance, especially in the scenario \( T_{\text{obs}} = 500T_s \), these results reveal that, even in narrowband regimes, the PFSK scheme can achieve higher rates with a fixed \( P_{\text{MD}} \) regarding NPFSK schemes, especially in low-SNR (equivalent to a high probability of misdetection). From the figures, note that the gap formed by the lower limits for PFSK signaling for \( \delta = 1 \) and \( \delta_{\text{opt}} \) defines an area that can be explored by the PFSK technique depending on the available resources, such as peak power or hardware constraints.

**B. OUTDOOR WIDEBAND CASE**

Consider an outdoor system operating at \( f_c = 2 \) GHz. A velocity of \( v = 250 \) km/h corresponds to \( T_c = c/(2f,cv) = 1.1 \) ms. In turn, a typical delay spread \( T_d = 2 \) \( \mu s \) gives \( B_c = 500 \) kHz [20]. Altogether, \( B_cT_c = 550 \) (Reproduced from [20]). This case is applicable to a high-speed train with \( B = 30 \) MHz as well as the time of observation \( T_{\text{obs}} = 500T_s \) with \( T_s = 100\mu s \) being the symbol duration. This results in \( M = 2640 \) possible frequencies. We set the target \( P_{\text{FA}} = 0.01 \) and chose \( F = 10 \) for the covariance-based detection.

Fig. 5 illustrates the detection performance for this wideband case. The simulations performed here follow those whose curves are presented in Figs. 3 and 4 for the indoor narrowband case. \( P_{\text{MD}} \) in Fig 5a presents the same behavior observed for the narrowband scenario, illustrated in Figs. 3a and 4a. The main observed difference is in the \( \delta_{\text{opt}} \) set curves. Since this set satisfies the relationship \( \delta B \) in (21), when the bandwidth increases, the duty cycle is reduced proportionally (i.e., \( \delta \rightarrow 0 \)), which increases \( P_{\text{MD}} \).

Fig. 5b shows the achievable rate vs. \( P_{\text{MD}} \). It can be observed that unlike narrowband scenarios, in which the use of the PFSK signaling revealed a slight gain regarding the NPFSK signals (Figs. 3 and 4), in wideband scenarios, PFSK vastly outperforms NPFSK if a suitable \( \delta \) configuration is...
used. In particular, PFSK can achieve rates thousands of times higher than NPFSK rates without impacting the $P_{MD}$; i.e., for $P_{MD} = 0.96$, PFSK can achieve a rate $9.15 \times 10^7$ times higher than NPFSK.

The sample cases also reveal that the time-frequency coherence block $B_T$ plays a crucial role. The higher (smaller) $B_T$, the less (more) noticeable the performance advantage of PFSK with respect to NPFSK signaling, as shown in Fig. 4b and Fig. 5b. Note that $B_T$ may increase for multiple reasons, including a lower velocity, a lower carrier frequency, and a more confined propagation scenario (indoor). In particular, this renders PFSK especially advantageous for high-mobility and high-frequency scenarios.

VI. CONCLUSION

This work analyzes and compares the trade-off between achievable transmission rates and the interception probability for a traditional NP wideband modulation technique and the emerging alternative PFSK. Interception behavior is investigated using two non-coherent detection methods: energy detection and a method based on the sample covariance matrix by simulation. Our results revealed that, given any target interception probability, PFSK achieves significantly higher transmission rates than NPFSK or any other NP signaling scheme in wideband regime, especially for outdoor environments. Additionally, our discussions indicate that (i) the (less complex) energy detection technique outperforms the covariance method for NP signals; (ii) there is a small duty-cycle range that should be avoided, since it causes PFSK to be more likely intercepted than the NP scheme under the covariance method; and (iii) the PFSK detection performance is strongly affected by the relationship between observation time and coherence time.

We showed that PFSK signaling arises as a novel benchmark for designing effective wideband communication systems where both capacity and security are paramount. On the other hand, an optimum PFSK receiver is impractical, as it requires a massive number of matched filters (hundreds to thousands). We have been working on practical, suboptimal solutions of reduced complexity but with a marginal performance penalty.

REFERENCES


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