Spectrum Sensing for Cognitive Maritime VHF Networks

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***Abstract*—The Automatic Identification System (AIS) is used worldwide as a maritime system for identifying and locating vessels by exchanging data in Very High Frequency (VHF) band with other nearby ships, AIS base stations and satellites. It is an important system for safety of navigation to assist collision avoidance and enables marine traffic supervision and management. However, the expanding use of AIS band by other emerging applications and services has caused significant increase on the maritime VHF Data Link (VDL) load, hampering smooth exchange of critical AIS information. Instead of assigning new frequency resources for new marine VDL services, in this paper we present a solution to overcome this spectrum scarcity issue by utilizing Cognitive Radio (CR) technology in maritime AIS VHF network. A preliminary analysis of the performance of such an approach is carried out taking into account the different properties and challenges of marine communication channels due to sea surface movement. The outcome of our study shows how the application of CR techniques to maritime VDL indeed represents an appealing alternative to static spectrum allocation schemes to deal with overloading issues in AIS networks.**

I. Introduction

Operating in the VHF maritime band, the Automatic Identification System (AIS) [1] enables wireless data exchange among ships as well as between ships and costal authorities to automatically identify, locate and track vessels for collision avoidance and safety of navigation purposes. Developed in the early 90s, AIS has nowadays become a widespread communication system, enforced by the IMO for international voyaging vessels with gross tonnage of 300 or more, and all passenger vessels. The AIS is composed of several substandards called *types* that specify individual service types. Even though several *types* are foreseen in the standard for different data services, AIS Class-A and Class-B are the most critical ones, being devoted to the exchange of vessel position information.

These services are implemented in two channels, centered at 161.975MHz and 162.025MHz, and operate at the link layer following a distributed scheduling solution. In particular, frames of one-minute duration and composed of 2250 slots repeat over time, and each ship is allowed to transmit AIS messages only over slots that are not already occupied by others. This is achieved by means of a Self-Organized Time Division Multiple Access (SOTDMA) protocol, which provides a high level of coordination among vessels within each other's coverage range, avoiding interference and collisions and ensuring good reception quality for exchanged messages.

On the other hand, in recent years an increasing number of alternative and relevant maritime applications (e.g., for safety and security of navigation, protection of marine environment etc.) have emerged. Such services operate independently to the AIS (i.e., they do not participate in the SOTDMA-based resource assignment) and naturally contend for the same spectrum. As a result, an overload of the AIS VDL is undergoing, with detrimental effects on the delivery of critical vessel position information.

In light of these trends, some effort is being devoted both in the research community and by standardization bodies [3] to allocate additional spectrum to new VDL services. However, considering the steadily increasing growth rate of maritime wireless applications, such attempts may not be able to accommodate all of them due to limited spectrum availability. Therefore, the definition of new paradigms to enable VDL traffic without disrupting legacy AIS services is of paramount importance.

From this perspective, in order to overcome spectrum scarcity and reduce communication cost, cognitive radio (CR) arises to be a promising solution by opportunistically using the frequency bands that are not heavily occupied by licensed users [4]. In this paper, a maritime Cognitive Radio AIS (CR-AIS) network scenario is proposed, where spectrum sensing is the key function to identify and exploit the available transmission opportunities.

Spectrum sensing is a well treated topic in the literature of cognitive radios [9], [10] and many of our prior work also exist on this topic [11]- [26]. In general, spectrum sensing can be classified into three major classes: energy based, cyclostationary feature based and matched filter based. In this work, as a preliminary step, we focus on the energy based spectrum sensing [27]. Furthermore, collaborative sensing techniques based on cooperative and distributed models [9], [10] also exist to improve the detection performance by means of sharing local sensing information with all the sensing nodes. Though spectrum sensing, and in particular the energy-based approach, is well studied in the literature, a clear characterization of the achievable performance for a maritime wireless channel has not been addressed yet.

In this paper we tackle for the first time this issue, drawing relevant insights on the feasibility and on the benefits that a CR approach may bring to AIS VDL services. In particular, we analyze the detection performance for the maritime environment considering (i) a costliness propagation channel and (ii) a deep sea propagation channel.

The main contribution of our work is thus the introduction of the idea of cognitive radio to AIS together with a first characterization of the achievable performance, and is meant to stimulate further discussions and interest on the topic.

The rest of the paper is organized as follows. In Section II we present the maritime cognitive AIS concept followed by the systems model in Section III. Section IV and Section V present the energy based sensing and the corresponding performance analysis respectively, and finally we present some concluding remarks in Section VI.

II. AIS AND MARITIME COGNITIVE RADIO AIS

In the maritime cognitive scenarios that we introduce in this paper, the AIS Class-A and Class-B services operating at two licensed maritime VHF channels centered at 161.975MHz and 162.025MHz are defined as licensed *Primary Users (PUs)*. Maritime services/applications other than AIS Class-A and Class-B are considered as *Secondary Users (SUs)*. Each ship as a CR user is capable of detecting the presence of PUs, identifying and accessing the available VHF spectrum to carry out SU services if PUs are absent, which increases maritime VDL spectrum efficiency.

From this viewpoint, it is relevant to point out that a vessel equipped with an AIS receiver gathers a precise knowledge of the surrounding activities thanks to the SOTDMA protocol it relies on (see Section I and [1] for further details). The collected set of information on unused slots in the AIS frames and frequency bands could then be directly fed to other VDL services and used to properly perform transmissions as SU. On the other hand, in many practical situations AIS data may in fact not be accessible to applications generating additional VDL traffic, making spectrum sensing paramount to take advantage of CR mechanisms. In this perspective, two relevant cases of interest can be identified:

- *non AIS-equipped vessels*: even though AIS units are present in many ships, they are not mandatory for all types of boats. Therefore, for vessels that are not provided with an AIS transceiver, the transmission pattern of the surrounding PUs cannot be determined by receiving and monitoring PU messages. In this case, in order to avoid the interference on the surrounding PUs, spectrum sensing can be used by ships to detect PU transmissions and find the available radio resources to perform SU services.
- *non-accessible AIS data*: even when operated by ships equipped with an AIS transceiver, alternative VDL services may in fact not have access to information that are internally processed by the AIS module (e.g., in terms of energy detected over one slot, or slots perceived as free). This case is particularly relevant if we think of the possibility to provide new VDL services as standalone, plug-and-play products that do not need any connection or interface with AIS transceivers.

The performance of spectrum sensing in practice is often affected by multipath fading, shadowing and receiver uncertainty issues, so that channel properties play a very important role. Depending on node mobility and distribution as well as network properties, our maritime CR-AIS scenario is therefore categorized into (1)ship-to-ship, ship-to-shore networks close to shore, (2)ship-to-ship networks at deep sea networks, as illustrated in Fig. 1, which will be characterized and analyzed resorting to different and proper channel models in Section III.

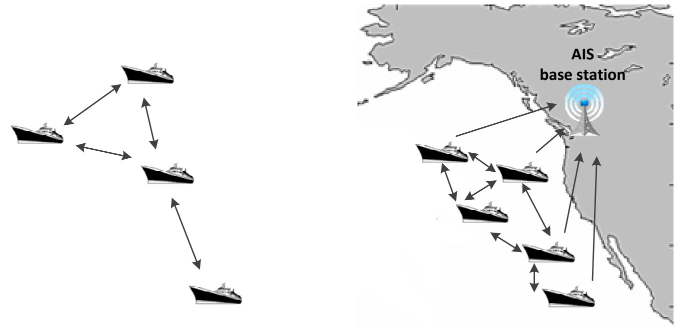

Fig. 1. Maritime cognitive radio AIS network

Based on the transmission pattern of AIS and maritime VDL channel properties, the energy detector sensing mechanism is used in our work for spectrum sensing and to analyze the detection performance in terms of the Receiver Operating Characteristic (ROC) curves. Given in Sec. V, the results will be compared with the standard Additive White Gaussian Noise (AWGN) based energy detection. Then we utilize the outcome of the energy detector to perform distributed sensing to improve the detection performance in detecting the primary users. The ROC curves for the distributed sensing then will be compare with energy detector based local sensing and the performance gain will be analyzed.

III. SYSTEM MODEL

In this section we present the AIS system model more in detail together with the maritime propagation channel models.

A. AIS Transmission System

AIS PU transceivers automatically broadcast information, such as their position, speed and navigational status, at regular intervals via two parallel maritime VHF frequency bands at 161.975MHz and 162.025MHz. Multiple AIS PU transceivers share these two VHF channels using SOTDMA technique to avoid signal collisions. Each channel is divided into 2250 time slots per minute [1]. At the power-on initialization phase, each AIS PU transceiver monitors the data link activities of these two VHF channels for one minute to determine its own transmission time slots without interfering other transceivers in a self-organized way, as shown in Fig. 2. AIS Class-A transmitters have two transmit power settings: low (1 watt) and high (12.5 W), while the transmit power for AIS Class-B is 2 W.

B. Maritime Wireless Channels

The wireless channel properties are highly affected by the propagation environment. Compared to land services, maritime communication environment has different properties and challenges due to sea surface movement. The movement of sea surface changes the antenna orientation and height of onboard AIS transceivers, which affects the antenna gain and received

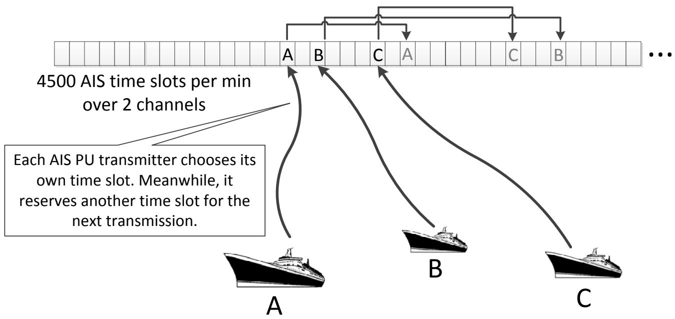

Fig. 2. Transmission of AIS PU services using SOTDMA

signal power. Different sea wave environments cause different signal reflections from sea surface. Sea movement is described by the sea state, typically categorized into 10 levels as per [7] by means of parameters such as sea wave height, average sea wave length and average sea wave period. Following this taxonomy, higher sea state is, higher wave height, longer wave length and period it is, which leads to more severe degradation for maritime radio signal.

In order to capture attenuation effects on the transmitted signal induced by the radio environment, we model the received power as:

$$P_{R_x} = P_{T_x} - PL \tag{1}$$

where PL is the total path loss caused by propagation channel in dB, and P_{T_x} and P_{R_x} are transmitted power and received power in the decibel scale respectively.

The two network categories introduced in the Sec. II are characterized by different properties of channel model, which results in different values of PL in (1). In the first case with narrow ship lanes and ports or harbors close to coastline, many signal reflections from surrounding environment can be expected. There is no dominant propagation along Line-of-Sight (LOS) path between the transmitter and receiver. Thus, the channel can be accurately modeled resorting to Rayleigh fading [5], such that:

$$PL = PL(d_o) + 20\log_{10}(d/d_o) + 10\log_{10}(R) \tag{2}$$

where R is an exponentially distributed random variable with unit mean.

In the second case with ship lanes in open deep sea, based on modified Pierson-Moskowitz spectral models a channel model derived by [6] can be used. With this channel model, the path loss PL caused by shadowing conditions in a deep-sea communication channel is a function of sea surface height and signal frequency, which can be represented as [6]:

$$\begin{aligned} &PL(h,f) = PL(d_o) + \\ &10 * [(0.498\log_{10}(f) + 0.793) * h + 2]\log_{10}(d/d_o) + X_f \end{aligned} \tag{3}$$

where f is the signal frequency in GHz, and sea surface height h is in meters, the distance in meters between transmitter and receiver is d. $PL(d_o)$ is the path loss measured at a reference location of distance $d_o = 1m$ from transmitter. Finally, X_f is a zero mean Gaussian random variable with standard deviation that is a function of the sea surface height h, given by [6]:

$$\sigma_f = [0.157f + 0.405] * h \tag{4}$$

IV. Spectrum Sensing and Detection of AIS Signals

Let us consider M secondary radios indexed by $i \in \{1, 2 \dots M\}$ present in the environment with a single primary user. We consider the energy based spectrum sensing for blind detection of AIS together with a distributed decision making process. As described in this section subsequently.

A. The Energy Detector

In this section we present the energy based spectrum sensing and detection scheme [27]. The energy of the RF stimuli is computed when the SU is scanning the spectrum and used as the test statistic to detect the presence of the PU. The base band equivalent sensed signal at the i^{th} SU can be represented considering the binary hypothesis H_0; *when a PU is not present*, and H_1; *when a PU is present*, as given below,

$$r(i;t) = \begin{cases} \nu(i;t) & ;\text{for } H_0 \\ x(t) + \nu(i;t) & ;\text{for } H_1 \end{cases} \tag{5}$$

where, $x(t)$ is the complex signal received from the PU with any channel fading, and $\nu(i;t)$ is the complex AWGN noise with zero mean and variance ς_i^2. The energy based test statistic $\epsilon(i)$ at the i^{th} SU is then given by,

$$\epsilon(i) = \int_{t_1}^{t_2} r(i;t)\tilde{r}(i;t)dt \tag{6}$$

where, $\tilde{r}(i;t)$ is the complex conjugate of $r(i;t)$, and $t_1, t_2 \in \mathbb{R}$. For the fading signal $x(t)$ defined over the period of $t_a \le t \le t_b$ we define the received signal to noise ratio (SNR) as,

$$\rho_i \triangleq \frac{1}{\varsigma_i^2[t_b - t_a]} \int_{t_a}^{t_b} x(t)\tilde{x}(t)dt \tag{7}$$

where we assume ρ_i to be a constant for the sake of analysis. In the discrete domain, the energy based test statistic equivalent of (6) is given by,

$$\epsilon(i) \approx \sum_{n=0}^{N_s-1} r[i;n]\tilde{r}[i;n] \tag{8}$$

where, N_s is the total number of samples, which is also known as the time-bandwidth product [27]. We adopt the discrete model for the energy detector in our work and we refer to the same in the rest of the paper.

The hypothetical decisions on the presence or absence of the PU is then performed by using $\epsilon(i)$ at the i^{th} SU as follows,

$$\hat{d}(i) = \begin{cases} 0 \ ; \ H_0 & \text{for } \epsilon(i) < \mu_i \\ 1 \ ; \ H_1 & \text{for } \epsilon(i) \ge \mu_i \end{cases} \tag{9}$$

where, μ_i is the decision threshold used at the i^{th} SU.

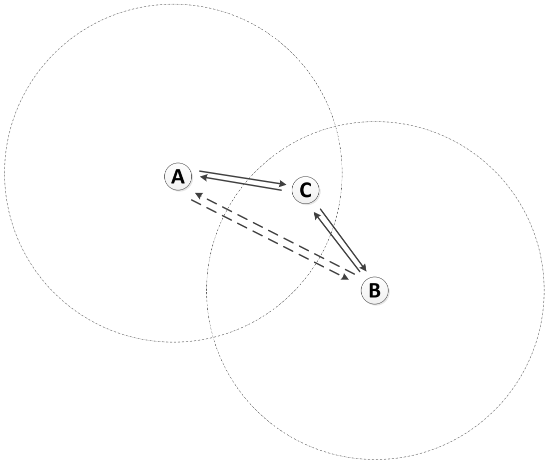

Fig. 3. Hidden node issue of local spectrum sensing

B. Distributed Detection of AIS

If each ship performs local spectrum sensing, the hidden node issue might occur. For instance, as shown in Fig. 3. because ship A and B are far from each other, when the local spectrum sensing is performed on ship A and B, ship A cannot detect the transmission of PU on ship B and vice versa. Thus, if SU on ship B tries to use the spectrum of PU on ship A, there will lend to a signal collision on ship C.

In order to address this hidden node problem and to better detect the PUs in the environment, collaborative sensing is performed by every SU node sharing its local decisions with every other SU in the vicinity by fusing the data. The fusion of the data depends on whether hard or soft local decisions were shared amongst the SU modes [9], [10]. In our work we consider hard decision based sharing (i.e. every SU node shares $\hat{d}(i)$ with each other). The fusion strategy that we adopt to fuse the gathered data at a SU node is the N-out-of-M strategy [10] where a PU is decided to be present when N out of the M received local decisions $\hat{b(i)}$ are true. Furthermore, the N-out-of-M rule becomes the logical 'OR' rule when $N = 1$, in other words the SU decides the the PU is present if at least one SU has reported that it is true.

V. PERFORMANCE ANALYSIS

The performance of the spectrum sensing techniques are characterized by the two probabilities of interest, detection and false alarm probabilities. The receiver operating characteristic curves (ROC) gives the false alarm and the miss detection probabilities in x-axis and y-axis respectively which we use to analyze the detection performance of the energy detector in this paper. Note that the miss detection probability is given by one minus the detection probability.

The detection and false alarm probabilities for the Rayleigh fading channel is known to the literature [28], and is provided below for reference,

$$P_D(i) = \exp\left(\frac{-\mu}{2\varsigma^2}\right)\sum_{n=0}^{N_s-2}\frac{1}{n!}\left(\frac{\mu}{2\varsigma^2}\right)^n + \left(\frac{\varsigma^2+2N_s\rho}{2N_s\rho}\right)^{N_s-1}\times \left[\exp\left(\frac{-\mu}{2\varsigma^2+4N_s\rho}\right) - \exp\left(\frac{-\mu}{2\varsigma^2}\right)\sum_{n=0}^{N_s-2}\frac{\left(\frac{\mu N_s\rho}{\varsigma^2(\varsigma^2+2N_s\rho)}\right)^n}{n!}\right] \tag{10}$$

where, $\Gamma(a,b) = \int_b^\infty u^{a-1}\exp(-u)du$ is the upper incomplete Gamma function and $\Gamma(\cdot)$ is the standard Gamma function. On the other hand the theoretical expression for the detection probability under the deep-sea fading channel is not known and therefore we conduct simulations to study the detection performance for the same. Monte-Carlo based simulations are performed to analyse the spectrum sensing and detection performance for detecting AIS in maritime channels. We initially verify our simulation results by simulating the Rayleigh fading channel and comparing them with the theoretical performance curves, and thereafter we present the detection performance of the energy based sensing technique under the deep-sea fading channel. We also present simulation results for analysing the detection performance of distributed sensing under the deep-sea fading channel.

A. Sensing Performance in Maritime Fading Channels

The energy based spectrum sensing technique was simulated to sense AIS Class-A transmitters with an EIRP of $1W$ at a carrier frequency of $f_c = 161.975$MHz. The noise power at all the receivers was set at $\varsigma = -90$dBW for all the simulations. As discussed before two maritime wireless channels are considered for the detection performance analysis. Initially simulations were conducted for the Rayleigh fading channel for different signal to noise ratio levels as well as for different values of N_s. The results are depicted in Fig-4. In the figure both the simulation results and the theoretical expression for the miss detection and false alarm probabilities are presented, a close matching of the two are observed which validates our simulation analysis. Moreover, the figure shows the improvement in the detection performance for increasing values of the signal to noise ratio and the number of samples, as expected.

Next we analyze the detection performance of the energy based detector in the deep sea fading channel for different channel conditions as well as for different values of d. The channel conditions are varied by considering different sea levels h. Fig-5 depicts the ROC curves for the deep sea channel for different values d giving rise to different signal to noise ratio levels due to the increase mean path loss when d is increased, a sea level of $h = 0.9$m was considered in this case. From the figure we observe that the detection performance degrade with increasing distances, as expected. Moreover, we observe that the AIS Class A signal can be detected at a distance of 150km with a detection probability of 0.99 and a false alarm probability of 0.01.

Fig-6 shows the detection performance of the energy detector for the deep sea fading channel with varying sea levels h at a distance of $d = 150$km. The ROC curves show the degradation in the detection performance with slight

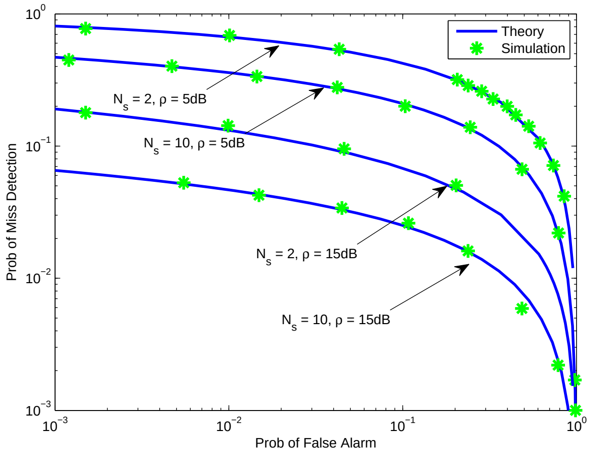

Fig. 4. ROC curves for the Rayleigh fading channel

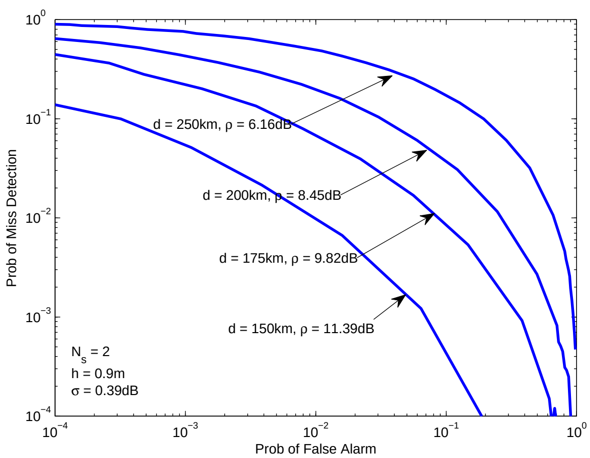

Fig. 5. ROC curves for the deep-sea fading channel w.r.t d

increments in the sea level. It should be noted that minor variations in the sea level h will have significant impact on the mean path loss as well as on the standard deviation σ. This therefore gives rise to the significant degradation in the detection performance over minor variations in the seal levels as observed in the figure. In practice the sea level varies randomly and therefore one would need a statistical model for h in order to better study the detection performance of the energy detector with respect to the sea level h.

Finally. we compare the detection performance of the two channel models, Rayleigh and deep-sea with respect to the no fading scenario (i.e. additive white Gaussian noise (AWGN) only case). Fig-7 shows the comparison for a signal to noise ratio of 9.82dB. From the figure we observe that the Rayleigh channel shows poor performance overall and on the other hand the performance of deep sea channel shows not much difference to the AWGN case for a sea level of $h = 0.9$m. Fig-8 compares the deep sea channel with AWGN for sea levels of $h = 2$m and $h = 4$m. From the figure we observe that the increase in h gives rise to the increase in σ and hence a degradation in the detection performance is observed for the

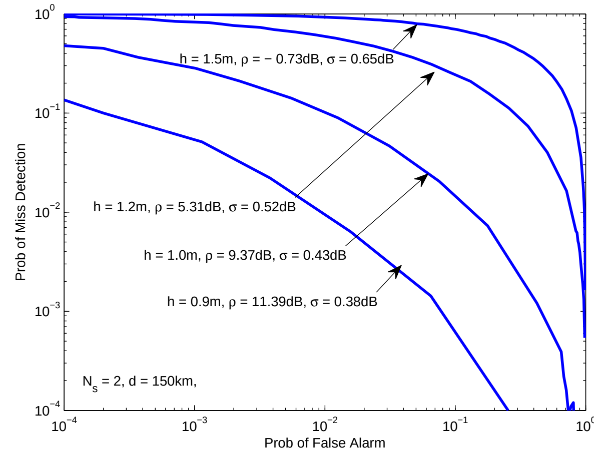

Fig. 6. ROC curves for the deep-sea fading channel w.r.t h

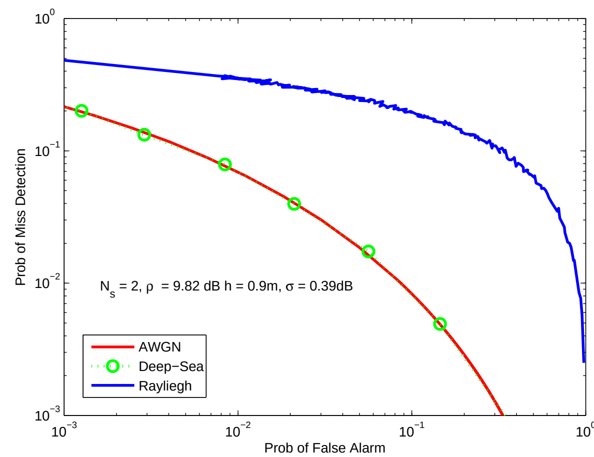

Fig. 7. Comparison of the ROC curves for the AWGN only, Rayleigh and deep-sea fading maritime channels

deep sea channel compared to the AWGN. Note that in fig 7 the value of σ was not that significant and hence the performance of the deep sea channel did not show any variations compared to the AWGN case.

B. Distributed Sensing Performance

If the local detection and false alarm probabilities at the i^{th} SU node are given by $P_D(i)$ and $P_F(i)$ respectively then the overall detection and the false alarm probabilities for the 'OR' based distributed detection scheme are given by [10],

$$\overline{P}_F = 1 - \prod_{i=1}^{M}(1 - P_F(i)) \tag{11}$$

$$\overline{P}_D = 1 - \prod_{i=1}^{M}(1 - P_D(i)).$$

The distributed sensing scenario was simulated for the deep sea channel for $M = 1, 2, 3$ and 4 and the corresponding ROC corves are depicted in fig-9. From the figure we observe that the detection performance improves for increasing values of M

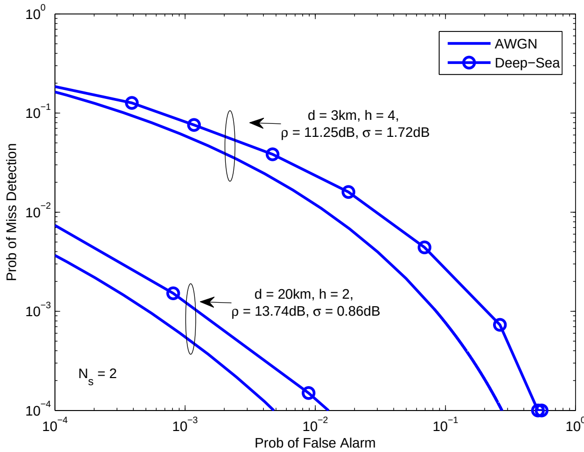

Fig. 8. Comparison of the ROC curves for the AWGN only and deep-sea fading maritime channels

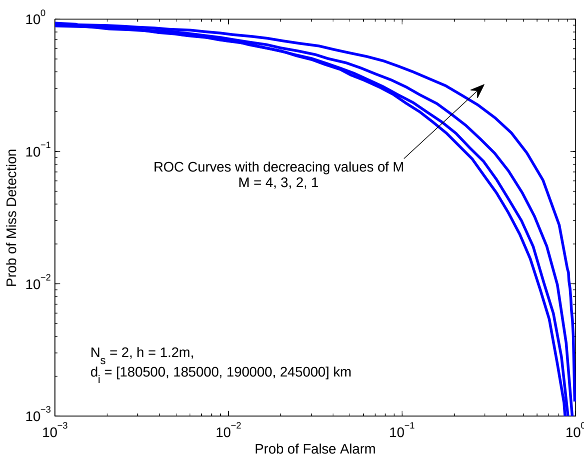

Fig. 9. ROC curves for the distributed detection using for various values of M

as expected, however the performance gain for higher values of M does not seem that significant. On the other hand, the triggered gain is rather contained and does not scale significantly with M. Such a result is particularly interesting in view of the overhead (in terms of channel load and complexity) that would be required to trigger a distributed sensing procedure, as it proves that even a simpler and non-shared CR approach would be capable or reaping a good fraction of the possible benefits in a maritime environment.

VI. Conclusions

This paper proposes a maritime CR-AIS VHF network scenario, in which maritime VDL services other than AIS Class-A and Class-B perform spectrum sensing to detect and exploit the available AIS VHF spectra; white spaces without interfering AIS services. The performance analysis shows that within the maritime VDL channel properties, CR spectrum sensing can be considered as a very appealing alternative to static spectrum allocation schemes for new emerging maritime VDL services to solve the spectrum overloading issue on AIS VHF network.

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