Cognitive Spectrum Access for Underwater Acoustic Communications

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***Abstract*— While very successful in traditional radio communications, the usage of TDMA and CSMA schemes for underwater acoustic communications is severely limited in efficiency and scalability, primarily due to the very large propagation delays. FDMA seems a viable alternative in that the propagation delay does not impact significantly its efficiency. However, in underwater communications, the capacity achievable on a particular channel depends strongly both on its frequency and on the communication distance, unlike in traditional radio transmissions where FDMA channels usually have comparable performance. Therefore, fixed channel allocation schemes traditionally used for radio FDMA do not perform well in underwater communications.**

In this paper, we investigate the application of the principles of cognitive radio and dynamic spectrum access to underwater communications. In particular, we propose a channel allocation scheme which exploits user location knowledge in order to maximize the minimum channel capacity among those achieved by the users. This provides maximum fairness and makes a more efficient use of the available spectrum resources.

Performance evaluation carried out by means of simulation shows that our approach can achieve a great improvement in fairness among users, with respect to fixed allocation schemes, while at the same time scaling much better and thus allowing effective communications over larger distances.

I. Introduction and Related Work

Underwater communications are currently a hot research topic in the wireless communications field. The main difference with respect to terrestrial communications is found in the specific physical layer, which usually relies on acoustic waves. This is not the only option for underwater transmissions, yet it is seemingly the only one to provide sufficient coverage and data rate. In fact, radio waves are typically absorbed quickly by water, unless transmission is performed at very low frequency, which in turn severely limits the data rate. Optical signals are an option as well but, despite the higher data rate, they tend to have very limited coverage and to require good alignment of transmit and receive devices. Conversely, recent advances in acoustic communications have allowed to build reliable links over distances on the order of kilometers [1], [2], effectively paving the way for the creation of the first underwater wireless networks [3], [4].

Underwater acoustic communications present many differences with respect to radio communications. First of all, acoustic waves propagate in water at a very low speed $c = 1.5\,\mathrm{km/s}$, which is five orders of magnitude smaller than the propagation speed of radio waves in the air. Moreover, as we will discuss in Section II, the attenuation incurred by the signal and the receiver noise have a very strong dependence on distance and frequency [5]. As a consequence, when designing an underwater communication system, the transmission frequency and bandwidth should be carefully chosen depending on the expected communication distance. Furthermore, acoustic transducers are much more energy-consuming than radios, requiring transmission schemes that save as much energy as possible. These facts need to be taken into account in the design of any underwater network.

While the research on underwater communications networks is still in its infancy, some recent efforts have outlined the main performance differences of classic terrestrial radio access schemes as applied to acoustic communications. For example, [3] contains a first description of Time-Division and Frequency-Division Multiple Access (TDMA and FDMA) schemes, as well as a preliminary evaluation of clusters, which are also considered in [6], where different options for of intra-cluster and clusterhead-to-sink communication have been compared. Carrier Sense Multiple Access (CSMA) has also been evaluated [7] and compared to handshake-based schemes such as the IEEE 802.11 RTS/CTS-based access [8], that rely on the exchange of control messages prior to data transmission. The main conclusions drawn by these works can be summarized as follows. TDMA suffers from bad scalability: performance degrades rapidly as the number of nodes or the network deployment size increases. In fact, in order to protect the transmission occurring in a time slot from the interference caused by other transmissions in adjacent slots, a guard time must be inserted. This guard time must be at least as long as the maximum propagation delay in the network. Since the acoustic waves travel very slowly in water, the guard times can be long, requiring in turn to have long data transmission times in order to preserve efficiency. On the other hand, random access schemes such as CSMA and ALOHA [9] are very vulnerable to collisions due, again, to the long propagation times. Preliminary handshakes do not offer much help in this case, because the exchange of control messages would take a lot of time and decrease communication efficiency even further. Additionally, recall that transmissions are very energy-demanding, thus collisions should be avoided or limited in order not to waste energy. In trying to overcome the issues of TDMA and CSMA, other protocols designed explicitly for underwater networks are based on the balance between data transmissions, control messages, and sometimes awake-asleep schedules. For example, [10] tries to avoid collisions completely by carefully scheduling the length of the handshakes, whereas [11] can space transmissions more tightly, as it tries to prevent collisions through specific signaling messages. UWAN-MAC [12] is based on a sort of adaptive TDMA, where nodes try to synchronize their awake-sleep schedules. However, as for the basic TDMA case, the transmission epochs must be separated by guard times, which limits efficiency.

To summarize, the major issues with MAC schemes which operate entirely in the time domain are limited efficiency and poor scalability due to the huge underwater propagation delay. For this reason, FDMA becomes very attractive, as its efficiency is not affected by long propagation delays. Actually, using FDMA imposes greater signal processing efforts, because the underwater channel tends to be highly time-variant and to create significant Doppler shifts. However, powerful and efficient algorithms for compensating channel effects are being actively researched in the community (*e.g.*, see [1], [2] and references therein), making FDMA an increasingly feasible option.

On the other hand, one of the main concerns with the use of FDMA in underwater communications is that the fixed channel allocation schemes traditionally employed in radio communications are expected to yield low efficiency and poor fairness, due to the strong interplay between communication performance and the particular frequency band being used. To address these issues, we propose a Cognitive Radio approach. In [13], Cognitive Radio is defined as an intelligent device with the aim of providing an efficient utilization of the spectrum by means of dynamic and opportunistic spectrum access.[1] In traditional radio communications, the use of the electromagnetic spectrum is very inefficient: some portions such as the unlicensed ISM bands are often overcrowded, while others such as the licensed TV bands are often underused. In recent years, it has been proposed to overcome this problem by allowing unlicensed access to licensed bands, whenever and wherever they are not in use by their licensee. As a consequence, in addition to the unlicensed bands, which can be very congested at some times and locations, a radio device might also be able to access some licensed portions of the spectrum, again depending on time and location. Cognitive Radio devices are expected to achieve a more efficient spectrum utilization by adapting to this availability of communication resources which varies greatly with location, time and frequency.

Underwater acoustic communications are somewhat similar to radio communications in this respect: as we will discuss in Section II, the performance of the communication has a strong dependence on both the portion of the spectrum in use and the location of the user; moreover, the underwater acoustic spectrum is very scarce, and thus the communication resources available to a single user strongly depend on the number of active users, which in turn depends on time and location. As a consequence, the dynamic spectrum access techniques which have been developed for radio communications are expected to be effective for underwater communications as well.

The procedure followed by a Cognitive Radio device to access the spectrum is described by the *cognition cycle*, which in [13] is defined by the following phases: 1) *radio-scene analysis*; 2) *channel identification*, which in particular includes the prediction of channel capacity; 3) *dynamic spectrum access*. In this paper, we propose a dynamic access technique for the underwater acoustic spectrum which conforms to this definition of the cognition cycle. First of all, the propagation scene is analyzed, determining the number of users and the possible spectrum allocations; then the capacity of each channel-user allocation is determined (note that capacity is directly dependent on distance, which in turn can be accurately estimated during a setup phase by means of round-trip time measurements); finally, the most fair allocation is selected. In the rest of this paper, after a brief introduction on the underwater acoustic channel, we will describe in detail our solution, and show how it can achieve a more fair acoustic spectrum usage with respect to traditional techniques such as FDMA with *a priori* fixed channel assignment.

[1]It is worth noting that the original definition of Cognitive Radio by Mitola [14] had a very broad scope and was not by any means limited to dynamic spectrum access. However, since the work by Haykin [13], dynamic spectrum access has become the most frequently investigated use case for Cognitive Radio, to the point that a Cognitive Radio today is most commonly referred to as an intelligent communication device performing dynamic spectrum access.

II. Channel Model

In this Section, we give a brief overview of the physics of acoustic propagation in water. The purpose of the following is to help the reader understand the tradeoffs found in spectrum allocation for underwater communications. A more in-depth description is beyond the scope of this paper, and can be found in [5], [15].

First of all, recall that acoustic waves propagate in salted water at a slow speed $c \approx 1500\,\mathrm{m/s}$. The actual propagation speed is affected by depth, temperature, and salinity, but we will consider it fixed for simplicity. However, perhaps the most important feature of the underwater acoustic channel is the dependence of the optimal transmission frequency and bandwidth on the distance between the communicating nodes [5]. To explain this, consider Urick's model for the attenuation of a tone transmitted at frequency f [15]:

$$A(d, f) = d^k a(f)^d . \tag{1}$$

where d is the distance between transmitter and receiver, and k is the counterpart of the path loss coefficient in terrestrial radio, and is used to model the geometry of propagation. A practical value $k = 1.5$ is usually adopted. The factor $a(f)$ in (1) is called the absorption loss, and models the conversion of acoustic pressure into heat. This factor can be approximated by Thorp's formula [16]:

$$\mathcal{A}(f) = \frac{0.11 f^2}{1 + f^2} + \frac{44 f^2}{4100 + f^2} + 2.75 \cdot 10^{-4} f^2 + 0.003\,, \tag{2}$$

where $\mathcal{A}(f) = 10 \log_{10} a(f)$. Equation (2) returns $a(f)$ in $\mathrm{dB/km}$ for f in kHz. It should be noted from the formulas above that the attenuation increases with frequency and that the presence of the exponential term $a(f)^d$ in (1) strengthens the dependence of attenuation on distance.

The noise power spectral density (psd) is also frequency-dependent, and is usually expressed as $N(f) = N_t(f) + N_s(f) + N_w(f) + N_{th}(f)$, where the right hand side denotes the superposition of four contributions: turbulence (subscript t), shipping and other human activities (s), wind and waves (w), and thermal noise in the receiver circuitry (th). These components can be modeled as follows [5]:

$$\begin{aligned}
\mathcal{N}_t(f) &= 17 - 30 \log_{10}(f) \\
\mathcal{N}_s(f) &= 40 + 20(s - 0.5) + 26 \log_{10}(f) - 60 \log_{10}(f + 0.03) \\
\mathcal{N}_w(f) &= 50 + 7.5\sqrt{w} + 20 \log_{10}(f) - 40 \log_{10}(f + 0.4) \\
\mathcal{N}_{th}(f) &= -15 + 20 \log_{10}(f)\,,
\end{aligned} \tag{3}$$

where $\mathcal{N}_x(f)$ stands for $10 \log_{10} N_x(f)$, $x \in \{t, s, w, th\}$. Moreover, s in $\mathcal{N}_s(f)$ is the *shipping factor*, representing the intensity of shipping activities on the surface of the water, and has values ranging between 0 and 1. The factor w in $\mathcal{N}_w(f)$ is the wind speed in $\mathrm{m/s}$. The different components impact the noise psd at different frequencies. For example, in the high portion of the acoustic spectrum, typically used for transmissions over short distances (tens of meters), the turbulence and shipping components have very little effect, whereas the other two can become dominant.

We are now ready to define the average SNR of a tone transmitted at frequency f and traveling a distance d as [5]

$$SNR(d, f) = \frac{P_T}{A(d, f)N(f)\Delta f}\,, \tag{4}$$

where P_T is the transmit power and $N(f)$ is the noise power spectral density (assumed constant in a narrow band Δf around f). In (4), the factor $[A(d, f)N(f)]^{-1}$ is the frequency-dependent term. It should be noted that $A(d, f)$ increases with frequency while $N(f)$ decreases (at least to a certain point). Hence, the inverse of the product of the two factors has a maximum for some frequency f_0. This maximum represents the best frequency to use to transmit the tone.

Since the main objective of this paper is to devise efficient and fair channel allocation schemes, it is important to understand the impact of frequency-dependent channel effects on allocation policies. To this end, we show in Figure 1 the frequency-dependent factor in (4), $[A(d, f)N(f)]^{-1}$, for a number of values of d. Each gray line corresponds to a different distance; some relevant distance values are labeled for illustration. This figure shows that there is in fact an optimal frequency f_0 where a transmitted tone incurs the most favorable propagation/noise conditions, depending on distance. A channel allocation example is also shown in Figure 1. A simple case is considered, where two users share a common bandwidth to transmit to a sink. User 1 is $1\,\mathrm{km}$ away, whereas user 2 is located farther, at a distance of $5\,\mathrm{km}$ from the sink. The system bandwidth spans from $10\,\mathrm{kHz}$ to $40\,\mathrm{kHz}$, and is divided into two equally wide channels of $15\,\mathrm{kHz}$ each. Only two different allocations are possible in this case: i) user 1 on channel 1 and user 2 on channel 2, or ii) vice-versa. According to the chosen allocation, each user will experience a different channel response. This is highlighted in Figure 1 by a bold solid line and a bold dash-dot line that correspond to the channel responses undergone by the users in case i) and ii), respectively. Assume that both users transmit with the same power: therefore user 2 experiences the minimum throughput, because of the larger distance and worse channel effects. Also, assume that we want to maximize the minimum throughput experienced by the users. In this light, the throughput of user 2 must be maximized, and allocation 1 (solid line) is not optimal, because combined attenuation and noise effects are very large, and severely limit throughput. On the contrary, allocation 2 (dash-dot line) is optimal. A further observation is in order here: better allocations assign lower-frequency channels to far users, as this usually corresponds to more favorable propagation effects. This fact uniquely depends on the propagation characteristics of the underwater acoustic channel, whereas in terrestrial radio all users would experience

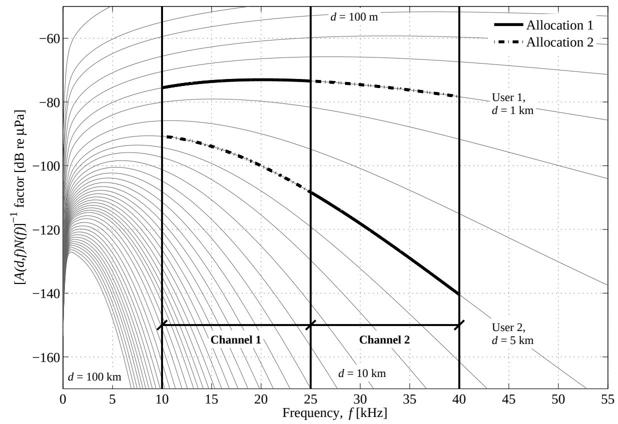

Fig. 1. Frequency-dependent part of the SNR for an acoustic tone transmitted underwater, and example of band allocation to two users, one at $1\,\mathrm{km}$, the other at $5\,\mathrm{km}$. Grey lines represent the $[A(d, f)N(f)]^{-1}$ factor for different distances. The bold solid and dot-dashed black lines represent the non-optimal and optimal allocation, respectively.

the same long-term channel effects in all subbands, hence making any frequency allocation equally good (as long as each user gets a channel).

Given the above characterization, it is useful to recall how the channel capacity is computed for a specific scenario. To this end, assume that f_ℓ and f_r are the upper and lower frequencies of a specific channel used for communication. Assume also that the signal to be transmitted has a spectrum $S(f)$. According to the Shannon-Hartley theorem, the channel capacity is then given by

$$\int_{f_\ell}^{f_r} \log_2 \left(1 + \frac{S(f)}{N(f)}\right) \mathrm{d}f\,. \tag{5}$$

Note that this definition can be applied to any signal or noise spectrum. In the following, we will assume that the throughput of a user on a certain channel is equal to the channel capacity, calculated according to (5).

III. The Channel Allocation Problem

In the following, we study channel allocation policies and their effects on medium access and network performance. To better focus on these aspects, we consider a single-hop network, and leave the extension of this evaluation to multi-hop settings as future work. We consider a scenario where the available acoustic spectrum is partitioned into channels of equal bandwidth. Each user is to be assigned to a single channel, and each channel to a single user; we consider that, in principle, all user-channel associations are feasible. Users are expected to be located at different positions, and will thus be at different distances from their destinations. As discussed in the previous section, since attenuations and noise vary with both frequency and distance, each user will get a different communication capacity for each channel it could be assigned.

The channel which is optimal for a given user, *i.e.*, the channel which has the highest capacity for that user, is not necessarily optimal from another user's perspective: a high frequency channel will be more suitable to nearby users, whereas far users will be better off using a low frequency channel. Unfortunately, due to the particular shape of the attenuation-noise function, it is not possible in general that each user be assigned its optimal channel: therefore, some tradeoff must be achieved. We note that, in practical scenarios where the transmission power is limited, a near user will achieve a fairly high capacity even when using a sub-optimal channel, whereas a far user may experience very low capacity unless it is assigned a sufficiently low-frequency channel. In this respect, a good channel allocation scheme will be able to enhance the capacity of far users without sacrificing too much the capacity of nearer users.

In this study, we discuss the implementation and the performance of a max-min fair channel allocation scheme; for this purpose, it is convenient to recall the notion of max-min fairness here. For any feasible channel allocation x, let $C = (c_{x,1}, c_{x,2}, \ldots, c_{x,N})$ be its capacity vector, where each entry indicates the capacity experienced on a particular channel for a certain feasible allocation x. For any x, let C be sorted such that $c_{x,1} \le c_{x,2} \le \cdots \le c_{x,N}$. A feasible channel allocation y is said to be a max-min fair allocation if, for any other feasible allocation x, $c_{x,i} \le c_{y,i}\ \forall i$.

IV. Channel Allocation Algorithm

Let N be the number of users, which in the scenario we consider is also equal to the number of channels to be assigned. The channel allocation problem is conveniently modeled as a matching problem on a bipartite graph. Let the vertices $i = 1, 2, \ldots, N$ represent the users, and let the vertices $j = N+1, N+2, \ldots, 2N$ represent the channels. A solution to the assignment is a set A of edges (i, j) such that

- $|A| = N$
- A is a *matching, i.e.*, if $(i_1, j_1) \in A$ and $(i_2, j_2) \in A$, then $i_1 \ne i_2$ and $j_1 \ne j_2$

First of all, we note that an exhaustive search algorithm is not practical to find the max-min capacity allocation, since the number of feasible allocations is $N!$. Let P be the set of all edges which can belong to a solution, *i.e.*, $P = \{(i, j) | i = 1, 2, \ldots N, \quad j = N+1, N+2, \ldots, 2N\}$. Our algorithm works by successively removing from P the edge which has lowest capacity, until a feasible solution is no longer present. Let $(\bar{i}, \bar{j})$ be the edge whose removal inhibits the solution of the problem. The capacity of $(\bar{i}, \bar{j})$ is the maximum, over all feasible allocations, of the minima of the channel capacities in each allocation; thus, the value of the capacity of $(\bar{i}, \bar{j})$ will appear in the capacity vector of the max-min fair channel allocation. In order to find a complete max-min fair solution (i.e., all channel-user allocations), the algorithm is repeated by removing all the edges incident in either $\bar{i}$ or $\bar{j}$ (because user $\bar{i}$ and channel $\bar{j}$ have already been assigned), and solving the same problem for the allocation of $N-1$ users onto $N-1$ channels. The algorithm terminates when all users and channels have been allocated.

One of the key points of the algorithm is how to determine whether a feasible solution exists. To this aim, we note that finding a solution is the same as finding a matching over P with cardinality equal to the number of users (and channels) which have to be assigned. In order to do so, it suffices to find a highest-cardinality matching (HCM) over P, which represents an assignment that satisfies the maximum number of users.

```
P_0 := P;    Q_0 := ∅;    k := 0;
while |Q_k| < N do
  increment k
  (i, j) := MinCapacityEdge (P_{k-1})
  P_k := P_{k-1} \ {(i, j)}
  M_k := HighestCardinalityMatching (P_k)
  if |M_k| + |Q_{k-1}| < N then
    Q_k := Q_{k-1} ∪ (i, j)
    for all m such that (i, m) ∈ P_k do
      P_k := P_k \ {(i, m)}
    end for
    for all n such that (n, j) ∈ P_k do
      P_k := P_k \ {(n, j)}
    end for
  else
    Q_k := Q_{k-1}
  end if
end while
return Q_k
```

Fig. 2. Algorithm for max-min fair channel allocation

If the cardinality of the HCM is less than the number of users (and channels) to be allocated, then the assignment is not complete. This indicates that the last removed arc leads to infeasible solutions, and therefore must not be removed.

A precise formulation of the algorithm is provided in Figure 2. The $\mathrm{MinCapacityEdge}()$ operation simply returns the edge which has minimum capacity in the given set; this operation on P_k can be implemented with constant complexity if the edges in P_0 have been sorted initially, which can be done with complexity $\mathcal{O}(N^2 \log N)$. The $\mathrm{HighestCardinalityMatching}()$ operation can be solved efficiently using well-known graph theory techniques such as the augmenting path algorithm and the Hopcroft-Karp algorithm [17], with complexity $\mathcal{O}(|P_k|\sqrt{N})$ in the latter case. The number of steps performed by the max-min capacity channel allocation algorithm is bounded by the number of edges, which is N^2. Therefore, the overall complexity of our algorithm is $\mathcal{O}(N^4\sqrt{N})$, and the cost of initially sorting P_0 is negligible.

V. Performance Evaluation

We compare the performance of our cognitive channel allocation scheme with a traditional fixed allocation approach. The comparison is carried out by means of simulation, using the NS-Miracle framework [18] together with a module we developed specifically for this study, and which implements the channel model discussed in Section II [19]. We considered a scenario where the network nodes must transmit data to a common sink. The sink is placed in the middle of a square area of given size; a varying number of users is randomly placed in this area. All users transmit using a channel allocated in the $10\,\mathrm{kHz}$–$40\,\mathrm{kHz}$ band. For this purpose, the band has been subdivided into as many equal-bandwidth channels as the number of users. All users transmit a signal with a power spectral density of $97\,\mathrm{dB\ re\ }\mu\mathrm{Pa\ per\ Hz}$ in the allocated band, and zero outside the band.[2] We implemented our cognitive channel allocation scheme in a centralized controller which is

[2]In other words, we assume an ideal spectral mask. This is of course not what would happen in reality; however, we note that accounting for a realistic transmission mask is possible and would not change qualitatively our results.

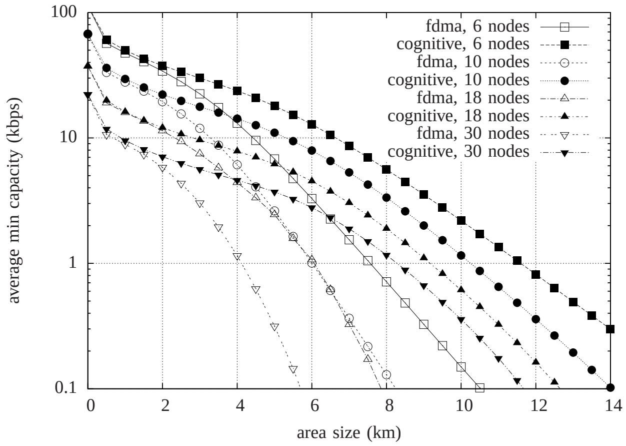

Fig. 3. Observed performance for the considered channel allocation schemes.

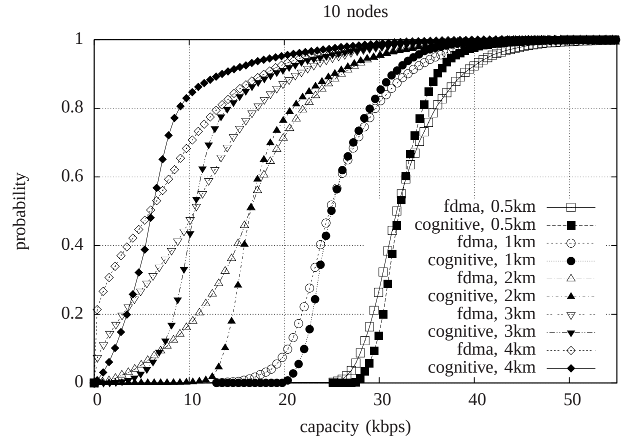

Fig. 4. Cumulative Distribution Function of the capacity for 10 nodes.

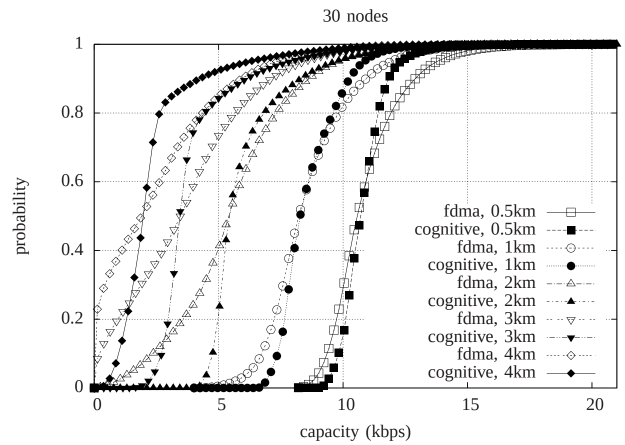

Fig. 5. Cumulative Distribution Function of the capacity for 30 nodes.

assumed to have knowledge of the capacity of each potential channel-user association.[3] To evaluate the performance of our cognitive channel allocation algorithm, we compare it to a traditional FDMA solution in which the user-channel association is fixed (*i.e.*, channel 1 is always assigned to user 1, channel 2 always to user 2, and so forth), regardless of their position and hence of the capacity that could be actually achieved over each channel. Simulations have been run for different values of the number of users and of the size of the square area. For each specific pair of these values, the obtained performance was averaged over 1000 independent random user placements.

In Figure 3, we report the average minimum capacity achieved by the two schemes as a function of the area size. As expected, the cognitive allocation scheme achieves significant performance improvements over the fixed allocation approach. These improvements are up to more than one order of magnitude at sufficiently large area size (*e.g.*, $0.3\,\mathrm{kbps}$ against $3\,\mathrm{kbps}$ for 6 nodes and area size $9\,\mathrm{km}$). It should be noted that all curves related to the cognitive approach have smaller slope, with respect to the fixed allocation (dubbed "fdma") curves. Therefore, the performance improvement achieved by the cognitive method increases for increasing area size. In fact, in this case the distances of the users from the sink tend to be sufficiently different from one another, yielding a higher variability in the channel response experienced by each user on each channel. Therefore, the cognitive scheme can successfully exploit more degrees of freedom, and has a better opportunity to find an allocation that substantially improves the minimum throughput. On the other hand, when the area is small, the distance of different users to the sink is similar and relatively short, and all users tend to get similar performance from all channels; consequently, there is no significant room for optimization, and the fixed allocation scheme performs similarly to the cognitive scheme. Note that this is a direct consequence of the effects of underwater propagation. For illustration, refer to Figure 1: if the distances of all users are on the order of $1\,\mathrm{km}$, the channel response has limited variability with respect to both distance and frequency. Conversely, if the distances vary from hundreds of meters to $10\,\mathrm{km}$ or more, the channel response would differ by several tens of dBs, and in addition it would be much more variable with frequency, making it more effective to assign low-frequency channels to farther users. Therefore, the cognitive algorithm can achieve a more significant improvement over the fixed allocation approach.

The performance difference between the cognitive and the fixed scheme strongly depends on the number of network nodes as well. As expected, the min throughput decreases for increasing number of nodes, regardless of the scheme, because the size of the channels is smaller, and hence the channel capacity is also smaller. However, a greater number of users translates into more degrees of freedom available for the cognitive algorithm, which therefore achieves a better performance for the same reasons described before. In fact, the average min throughput curves of the fixed allocation scheme show a steeper slope for greater numbers of nodes, whereas for the cognitive algorithm all curves have roughly the same slope. Hence we can conclude that the cognitive approach scales well with respect to both the number of users and the area size.

In Figures 4 and 5, we report the cumulative distribution function of the capacity achieved by all users, *i.e.*, the prob-

[3]This could be achieved in practice through feedback information provided by the users. Alternatively, some location information could be exploited together with a channel model such as the one described in Section II.

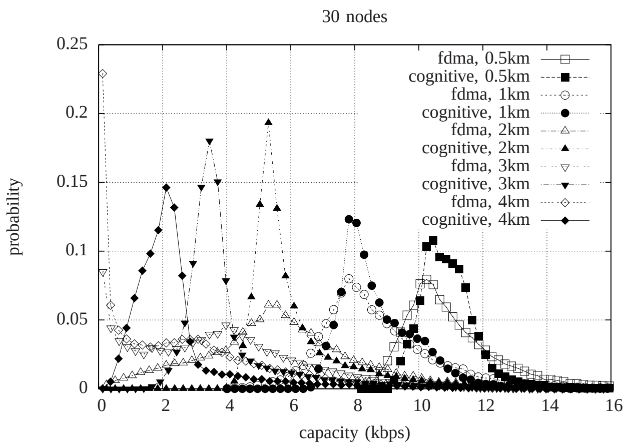

Fig. 6. Probability Density Function of the capacity for 30 nodes.

ability that the capacity achieved by a user placed randomly in an area of given size is less than or equal to the value of the abscissa. We consider two different cases, with 10 and 30 nodes (in Figures 4 and 5, respectively), and four different values for the area size. We observe that, for low values of the distance (the right-most curves) the capacity distribution obtained with the two schemes is similar. Conversely, as the area size increases, the fixed FDMA scheme has a higher low-capacity tail, revealing that the suboptimal allocations force more often some of the users to operate in very low capacity channels. The cognitive scheme exhibits a steeper distribution which again confirms that capacity is distributed more fairly to all users. This behavior is more visible for denser networks (Figure 5): with more nodes, the fixed allocation scheme assigns low-capacity channels with even higher probability, whereas the cognitive approach can exploit the greater number of degrees of freedom coming from the different channel responses experienced by different users.

In order to understand the importance of the tails of the capacity distributions, Figure 6 shows the probability density function (pdf) of the capacity for the case $N = 30$ users, and Table I reports the average value and relevant statistical dispersion values (the standard deviation and the 10$^{\text{th}}$ and 90$^{\text{th}}$ percentiles, P_{10} and P_{90}) for area size equal to $0.5\,\text{km}$ or $4\,\text{km}$. We observe that the capacity distributions achieved by the cognitive scheme are more concentrated around their average value. The fixed allocation, while achieving similar results for small area sizes, leads to more dispersed capacity values and hence to worse fairness for larger areas.

From these results, we can conclude that the proposed cognitive allocation scheme can effectively support larger networks and wider deployment areas, and provide greater fairness for all nodes and an overall better use of network resources in the highly constrained underwater scenario.

VI. Conclusions

In this paper, we have proposed and evaluated a cognitive channel allocation technique for underwater acoustic networks. Being based on FDMA, this scheme does not suffer from the detrimental effects of huge propagation times, which would limit the use of TDMA and CSMA schemes in practical underwater scenarios. Moreover, a cognitive channel selection scheme, which accounts for the particular features of the underwater channel, allows a more fair and efficient spectrum use, greatly outperforming traditional fixed-allocation FDMA. Finally, the proposed scheme is general and can be applied in practice to different definitions of channel capacity and actual modulation/coding schemes. Future work on this topic includes a comparison with other dynamic channel allocation techniques and the design and evaluation of practical cognitive schemes that enable distributed acoustic spectrum access.

TABLE I

Statistical dispersion indices for Figure 6 (capacities in kbps)

Size	Method	Mean	σ	P_{10}	P_{90}
$0.5\,\text{km}$	Cognitive	10.7	0.883	9.59	11.6
	FDMA	10.7	1.46	9.14	12.6
$4\,\text{km}$	Cognitive	2.44	1.77	0.954	4.14
	FDMA	2.51	2.44	0.053	5.79

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