Stochastic Channel Access for Underwater Acoustic Networks with Spatial and Temporal Interference Uncertainty

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ABSTRACT

Designing medium access control protocols for underwater acoustic sensor networks (UW-ASNs) is a major challenge because of the spatial and temporal interference uncertainty caused by asynchronous transmissions and by the low propagation speed of sound, respectively. To deal with this uncertainty, this paper proposes a queue-aware distributed access scheme, in which each transmitter optimizes a transmission probability profile based on which it decides whether to transmit or to enqueue its packets over a series of time slots *based on a statistical characterization of interference* obtained through its past observations. To model the effect of unaligned interference, we propose a so-called L-measurement method, where interference is measured at multiple instants of time in each time slot to capture the effects of temporal uncertainty.

We present a mathematical formulation of the problem of dynamic transmission strategy optimization and propose an iterative distributed solution algorithm designed based on a best-response strategy. At each iteration, each node individually solves a nonconvex optimization problem of logarithmic complexity with the number of time slots jointly considered. The performance of the proposed distributed solution algorithm is evaluated by comparing it to two alternative distributed schemes and to the global optimum obtained through a newly-developed centralized globally optimal solution algorithm. Results indicate that considerable improvement in terms of sum-throughput can be achieved by the proposed distributed algorithm by jointly taking the queueing and multi-slot optimization into consideration.

Keywords

Distributed MAC, underwater acoustic sensor networks (UW-ASNs), spatial and temporal interference uncertainty.

1. INTRODUCTION

A major challenge in Underwater Acoustic Sensor Networks (UW-ASNs)[1] [1, 2] is to design medium access control (MAC) schemes, mainly because of the large propagation delay caused by the low speed of sound in the underwater environment [3]. In addition to the *temporal uncertainty* of interference caused by the asynchronous transmissions of different nodes and the time-varying wireless channels, in UW-ASNs the large (linearly dependent on distance) propagation delay of acoustic signals generates *spatial uncertainty*, i.e., it is hard to predict the current value of interference because acoustic signals simultaneously transmitted by different nodes located at different distances from an intended receiver do not necessarily reach the receiver at the same time. As a result, in presence of both *temporal* and *spatial uncertainties*, MAC protocols originally designed for radio-frequency (RF) in-air wireless communications cannot be applied in UW-ASNs directly. For example, it was shown that the benefits of synchronization of slotted ALOHA are completely lost in underwater environments due to the distance-dependent delay [4].

Second, the large propagation delay makes it hard for transmitters to adapt to the time-varying underwater channels because of the absence of instantaneous channel state information (CSI), which is usually obtained through feedback from the receiver. Therefore, the large propagation delay imposes great challenges on underwater communications at both the transmitter and receiver side.

Significant recent efforts have attempted to address these formidable challenges [4–8]. For example, it was shown in [4] that for slotted transmission the packet collision probability can be reduced by adding a guard band to each time slot to limit the negative effect of the spatial uncertainty of interference[2]. In [5, 6], different MAC schemes were proposed to achieve interference avoidance based on handshaking and acknowledge schemes, while the resulting hidden terminal problems were studied in [7]. Since these protocols mainly rely on guard bands or handshaking, which still suffer from

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[2]A user transmitting in a given time slot might interfere with others in two consecutive time slots.

the low-speed of sound in signaling exchanges, they might result in under-utilization of spectrum and time and therefore in low throughput.

While the above MAC protocols mostly attempt to mitigate the negative effect of the spatial uncertainty of interference, Chitre et al. pointed out in [8] that the large and distance-dependent propagation delay can be exploited through interference alignment (IA) in the time domain to achieve a throughput much higher than that without spatial uncertainty. Specifically, in [8] the coexisting nodes were scheduled in a centralized way such that interfering signals reach a given node only when the node is transmitting, i.e., interference is temporally aligned within the transmission duration. By doing so, each node is able to enjoy an interference-free communication environment, which results in higher throughput. However, the IA scheme in [8] largely relies on exact knowledge of global location information of all nodes and on centralized control, which is not easy to implement in practice due to high communication overhead required to collect exact location information and to broadcast schedules.

Moreover, none of the above discussed MAC protocols [4–8] has taken the temporal uncertainty of interference into consideration. First, they are basically designed based on the so-called unit-disk graph interference model, i.e., there is destructive interference between two nodes within transmission range of one another and a packet is lost whenever a collision occurs. While the model is helpful in simplifying protocol design, it cannot fully capture the statistical behavior of time-varying wireless channels. Moreover, previous work has not considered the asynchronous transmission behavior of each node; and does not account for the stochastic nature of random traffic arrivals.

This paper takes an initial step in this direction by studying an optimized distributed access scheme based on explicit stochastic modeling of the temporal and spatial uncertainty of interference. With spatial uncertainty caused by the low-speed of sound, interference observed at an intended receiver at a specific time slot may be caused by interfering transmissions originated in past time slots. This motivates us to develop an access scheme in which each transmitter dynamically optimizes a transmission probability profile based on which it decides whether to transmit or to enqueue its packets over a series of time slots *based on a statistical characterization of interference* obtained through its past observations. Moreover, the originated interfering signals might reach the receiver at different instants during a specific time slot. Therefore, it is insufficient to characterize interference using a single interference level for the whole time slot. In this paper, we propose an L-measurement method, which measures interference at multiple time points for each receiver in each time slot. At each measurement point, the effects of temporal uncertainty of interference, i.e., the asynchronous transmission times of different nodes or the time-varying channels, on the interference level at each measurement point are modeled using Gamma distribution functions.

Then, based *on this statistical characterization of interference*, each node is able to adapt its transmission strategy proactively to the time-varying interference to minimize the resulting packet loss rate. On one hand, it is desirable for a node to transmit with high probability only in time slots when the corresponding interference levels are expected to be low, while with lower (or even zero) probability in time slots with high interference. On the other hand, to reduce the probability that a packet waits too long in the queue and becomes useless when received at destination, a node should transmit with high (even one) probability in all time slots. Therefore, by regulating the transmission probability, each transmitter should find the optimal operating point along the tradeoff between transmission and queueing to minimize its packet loss rate (and therefore to maximize the expected throughput).

We present a mathematical formulation of the problem of dynamic transmission strategy optimization and propose an iterative distributed solution algorithm designed based on a best-response strategy. At each iteration, each node individually solves a nonconvex optimization problem, in which the objective function can be transformed into a quasi-convex function so that the global optimum can be efficiently computed in time logarithmic with the number of time slots jointly considered. Then, the performance of the proposed distributed solution algorithm is evaluated by comparing it to the global optimum obtained by a newly-developed centralized solution algorithm.

The core novelty of the paper lies in the formulation and analysis of the distributed MAC scheme that jointly considering the temporal and spatial uncertainty of interference in UW-ASNs, including two contributions: i) propose the first interference model, L-measurement method, that handles the low-speed of sound and time-varying wireless underwater channels; ii) optimize the transmission strategy of each node based on the statistical characterization of interference while jointly considering the queueing behavior. It is worth pointing out that, since the proposed distributed MAC protocol handles the low-speed of sound in the time domain directly, its performance can be further enhanced by integrating it with MAC protocols designed based on code-division multiple access (CDMA) [9–11] and frequency-division multiple access (FDMA) [7] techniques, or by taking the routing into consideration in a cross-layer framework [12].

The rest of the paper is organized as follows. In Section 2 we present the system model. In Section 3 we describe the distributed solution algorithm and In Section 4 we present the globally optimal solution algorithm. In Section 5 we evaluate the proposed algorithm through simulation results, and finally we draw conclusions in Section 6.

Notation: $\mathrm{E}[\nu]$ and $\mathrm{D}[\nu]$ represent the expectation and variance of random variable ν, respectively. $\mathrm{P}[\mathrm{A}]$ represents the probability that event A occurs. $|\mathcal{N}|$ represents the cardinality of set $\mathcal{N}$. $\lfloor a \rfloor$ represents the maximum integer that is smaller than or equal to a.

2. SYSTEM MODEL

We consider a underwater acoustic sensor network consisting of a set $\mathcal{N}$ of transmitter-receiver pairs that share a given portion of the acoustic spectrum. As shown in Fig. 1, each pair $(\mathrm{T}_i, \mathrm{R}_i)$, $i \in \mathcal{N}$, consists of a transmitter i and its intended receiver, denoted as receiver i accordingly. The transmission time is divided into consecutive time slots, which are further grouped into consecutive frames each composed of a set $\mathcal{T}$ of time slots with $|\mathcal{T}| = T$. Each transmitter $i \in \mathcal{N}$ decides its transmission strategy for each time slot in a frame while using the same strategy for all frames. In the t-th time slot of a frame, transmitter i either transmits a packet with probability ω_i^t with $0 \leq \omega_i^t \leq 1$, $\forall i \in \mathcal{N}$, $\forall t \in \mathcal{T}$,

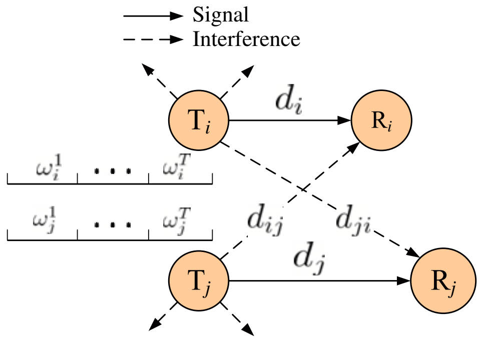


Figure 1: System model for underwater acoustic sensor networks.

or it stays silent with probability $1-\omega_i^t$ and enqueues its incoming packets in its buffer. We denote the transmission strategy vector as $\boldsymbol{\omega}_i = (\omega_i^t)_{t\in\mathcal{T}}$ for user $i \in \mathcal{N}$ and $\boldsymbol{\omega} = (\boldsymbol{\omega}_i)_{i\in\mathcal{N}}$ for all users.

A packet from user $i \in \mathcal{N}$ may be lost either because of a transmission error or because it exceeds the maximum playout deadline. If we denote the corresponding packet loss rates of user $i \in \mathcal{N}$ as $P_i^{err}(\boldsymbol{\omega})$ and $P_i^{dly}(\boldsymbol{\omega}_i)$, respectively, then the overall packet loss rate of user i denoted as $P_i^{los}(\boldsymbol{\omega})$ can be represented as

$$P_i^{los}(\boldsymbol{\omega}) = P_i^{err}(\boldsymbol{\omega}) + P_i^{dly}(\boldsymbol{\omega}_i) - P_i^{err}(\boldsymbol{\omega})P_i^{dly}(\boldsymbol{\omega}_i). \quad (1)$$

Next, we derive an explicit expression for $P_i^{los}(\boldsymbol{\omega})$ by describing the channel model, interference model and queueing model in sequence.

Channel model. Denote h_{ij} as the channel gain from transmitter i to receiver j, then h_{ij} can be represented as

$$h_{ij} = H_{ij}\rho^2, \quad (2)$$

where ρ^2 represents the fading coefficient, and H_{ij} represents the transmission loss that a narrow-band-acoustic signal experiences over a given spectrum and can be described using the Urick propagation model as [13],

$$H_{ij} = d_{ij}^2 \cdot 10^{(\alpha\cdot d_{ij}+A)/10}, \quad (3)$$

where α [dB/m] represents the medium absorption coefficient, A [dB] is the so-called transmission anomaly accounting for the degradation of the acoustic intensity caused by multiple path propagation, refraction, diffraction, and scattering of sound, and d_{ij} [m] represents the distance between transmitted i to receiver j.[3]

The channel model in (2) is applicable to both shallow and deep water environments. We focus on the former case, where the acoustic channel is usually heavily affected by multipath. We therefore assume that the number of rays goes to infinity and therefore consider a *worst-case scenario*; then, we have $A \in [5,\ 10]$ and the fading coefficient ρ can be modeled using a unit-mean Rayleigh distributed random variable with following cumulative distribution function

$$\mathrm{P}[\rho \le x] = 1 - \exp(-\pi x^2/4). \quad (4)$$

[3]In rest of this paper, we simplify h_{ij}, H_{ij} and d_{ij} as h_i, H_i and d_i if $i=j$.

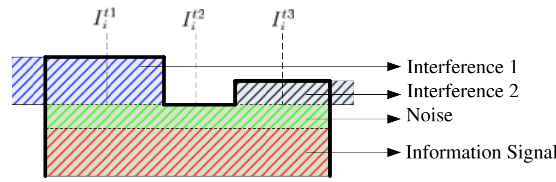


Figure 2: The received signal is sampled at three points during a time slot. The signal at each sampling point consists of information signal, noise and interfering signal. Information signal and noise keep the same for different sampling points.

The proposed distributed channel access scheme can also be extended to the deep water case, where the acoustic channel is not severely affected by multipath, and A and ρ^2 can be set to $A \in [0,\ 5]$ and $\rho^2 = 1$.

Interference model. Due to the distance-dependent propagation delay caused by the low-speed sound, acoustic signals transmitted simultaneously by different devices do not in general arrive at an intended receiver at the same time. As a result, the interference received at a receiver is nontrivially coupled with the transmission strategy $\boldsymbol{\omega}$, which makes interference modeling rather challenging. To the best of our knowledge, in the existing literatures there is no interference model that can characterize the statistical behavior of interference in multiuser underwater networks.

To address this challenge, we propose an L-measurement interference model, in which each receiver $i \in \mathcal{N}$ measures the received signal at a set $\mathcal{L}_i^t$ of time points during the t-th time slot[4]. Then, the measured interference forms a vector, denoted as $\mathcal{I}_i^t = (I_i^{tl})_{l\in\mathcal{L}_i^t}$, where I_i^{tl} represents the l-th interference measurement. Figure 2 shows an example of the L-measurement method with $L=3$. Denote g_{ij}^{tl}, with $l \in \mathcal{L}_i^t$, as the time slot in which user $j \in \mathcal{N}/i$ causes interference to user i at the l-th measurement point of the t-th time slot. Then, the measured interference power can be expressed as

$$I_i^{tl} = \sum_{j\in\mathcal{N}/i} P_j h_{ij}\alpha(g_{ij}^{tl}), \quad (5)$$

where P_j [watt] represents the transmission power of user j, and the indicator function $\alpha(g_{ij}^{tl}) = 1$ if user j transmits a packet at the g_{ij}^{tl}-th time slot while $\alpha(g_{ij}^{tl}) = 0$ otherwise.

With the channel model given in (2), (3) and (4), the probability density function of I_i^{tl} can be modeled through a Gamma distribution function denoted as $\gamma_i^{tl}(x)$,

$$\mathrm{P}[I_i^{tl} = x] = \gamma_i^{tl}(x) = \frac{x^{k_i^{tl}(\boldsymbol{\omega})}e^{-x/\theta_i^{tl}(\boldsymbol{\omega})}}{\Gamma(k_i^{tl}(\boldsymbol{\omega}))[\theta_i^{tl}(\boldsymbol{\omega})]^{k_i^{tl}(\boldsymbol{\omega})}}, \quad (6)$$

where $k_i^{tl}(\boldsymbol{\omega})$ and $\theta_i^{tl}(\boldsymbol{\omega})$ are the shaping parameters which can be estimated online as explained later in this paper. Instead, $\Gamma(k_i^{tl}(\boldsymbol{\omega}))$ can be represented as

$$\Gamma(k_i^{tl}(\boldsymbol{\omega})) = \int_0^\infty x^{k_i^{tl}(\boldsymbol{\omega})-1}e^{-x}dx. \quad (7)$$

[4]The optimal number of measurements of interference in a time slot needs to be determined through off-line measurement for a given network or online learning. In this paper, we assume that the number of measurements is known.

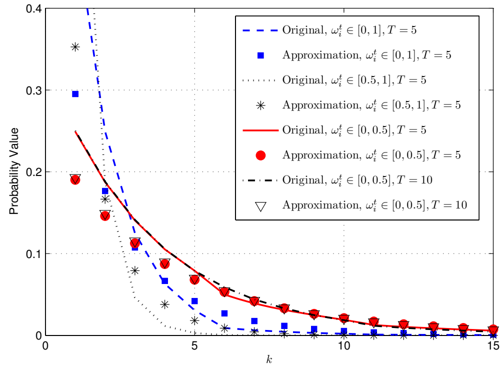


Figure 3: Illustration of approximating the original probability density function $\mathrm{P}[\nu_i = k]$ using exponential distribution function $\widetilde{\mathrm{P}}[\nu_i = k]$.

Then, the cumulative distribution function of I_i^{tl}, denoted as $\vartheta_i^{tl}(x, \boldsymbol{\omega})$, can be represented as

$$\mathrm{P}[I_i^{tl} \le x] = \vartheta_i^{tl}(x, \boldsymbol{\omega}) = \frac{\varphi\left(k_i^{tl}(\boldsymbol{\omega}), \frac{x}{\theta_i^{tl}(\boldsymbol{\omega})}\right)}{\Gamma(k_i^{tl}(\boldsymbol{\omega}))}, \tag{8}$$

where $\varphi\left(k_i^{tl}(\boldsymbol{\omega}), \frac{x}{\theta_i^{tl}(\boldsymbol{\omega})}\right)$ is the incomplete gamma function

$$\varphi\left(k_i^{tl}(\boldsymbol{\omega}), \frac{x}{\theta_i^{tl}(\boldsymbol{\omega})}\right) = \int_0^{\frac{x}{\theta_i^{tl}(\boldsymbol{\omega})}} s^{k_i^{tl}(\boldsymbol{\omega})-1} e^{-s} ds, \tag{9}$$

while $\Gamma(k_i^{tl}(\boldsymbol{\omega}))$ is defined in (7).

If we use $SINR_i^{tl}$ to represent the signal-to-noise-plus-interference ratio (SINR) at receiver $i \in \mathcal{N}$ at the l-th measurement point in the t-th time slot, then $SINR_i^{tl}$ can be represented as

$$SINR_i^{tl} = P_i h_i / (I_i^{tl} + N_i), \tag{10}$$

where N_i represents the noise power at receiver $i \in \mathcal{N}$. Let $SINR_{th}$ denote the lowest SINR required by a receiver to successfully decode a received packet and $\beta_i^{tl}(\boldsymbol{\omega})$ represent the packet decoding failure probability that occurs when $SINR_i^{tl} < SINR_{th}$, then $\beta_i^{tl}(\boldsymbol{\omega})$ can be represented as

$$\begin{aligned} &\mathrm{P}[SINR_i^{tl} < SINR_{th}] = \beta_i^{tl}(\boldsymbol{\omega}) \\ =&1 - \int_0^\infty \frac{\pi x^3}{2} e^{-\frac{\pi x^2}{4}} \vartheta_i^{tl}\left(\frac{P_i H_i x^2}{SINR_{th}} - N_i, \boldsymbol{\omega}\right) dx. \end{aligned} \tag{11}$$

Let $P_{i,t}^{err}(\boldsymbol{\omega})$ represent the packet error rate of user $i \in \mathcal{N}$ in time slot $t \in \mathcal{T}$ and assume that a packet can be decoded correctly only if the SINR levels at all the measurement points are equal to or higher than the threshold $SINR_{th}$. Then, $P_{i,t}^{err}(\boldsymbol{\omega})$ can be represented as

$$P_{i,t}^{err}(\boldsymbol{\omega}) = 1 - \prod_{l \in \mathcal{L}_i^t} (1 - \beta_i^{tl}(\boldsymbol{\omega})), \tag{12}$$

and the overall packet error rate of user i caused by transmission error, denoted as $P_i^{err}(\boldsymbol{\omega})$, can be represented as

$$P_i^{err}(\boldsymbol{\omega}) = \frac{1}{\sum\limits_{t \in \mathcal{T}} \omega_i^t} \sum_{t \in \mathcal{T}} \omega_i^t P_{i,t}^{err}(\boldsymbol{\omega}). \tag{13}$$

Queueing model. We let random variable ν_i represent the number of consecutive time slots it takes for user i to transmit a packet. Then, the probability density function (PDF) of ν_i can be expressed as

$$\mathrm{P}[\nu_i = k] = \begin{cases} \frac{1}{T} \sum\limits_{t \in \mathcal{T}} \omega_i^t, & k = 1, \\ \frac{1}{T} \sum\limits_{t \in \mathcal{T}} \prod\limits_{g \in \mathcal{T}_t} (1 - \omega_i^g) \omega_i^t, & k \le T, \\ \left(\prod\limits_{t \in \mathcal{T}} (1 - \omega_i^t)\right)^{\hat{k}} \mathrm{P}[\nu_i = \tilde{k}], & k > T, \end{cases} \tag{14}$$

where $\hat{k} = \lfloor \frac{k}{T} \rfloor$, $\tilde{k} = k - T \cdot \hat{k}$, ω_i^g represents the transmission probability of the g-th time slot in a frame with $\mathcal{T}_t$ representing the set of indices of the $k-1$ consecutive time slots before the t-th time slot, e.g., if $k = 3$ and each frame consists of at least three time slots, i.e., $T \ge 3$, then for $t = T$ we have $\mathcal{T}_t = \{T-1,\ T-2\}$, and for $t = 1$ we have $\mathcal{T}_t = \{T,\ T-1\}$.

From (14) we observe that the expression of $\mathrm{P}[\nu_i = k]$ is rather involved, which complicates theoretical analysis and the development of practical, computationally feasible optimization schemes. To keep our analysis tractable, we approximate $\mathrm{P}[\nu_i = k]$ in (14) through an exponential distribution function

$$\widetilde{\mathrm{P}}[\nu_i = k] = \phi(\boldsymbol{\omega}_i) e^{-\phi(\boldsymbol{\omega}_i) k},\ \forall i \in \mathcal{N}, \tag{15}$$

where the service rate parameter $\phi(\boldsymbol{\omega}_i)$, which depends on $\boldsymbol{\omega}_i$, is set to the average service rate in a time slot according to (14), i.e., $\phi(\boldsymbol{\omega}_i) = \frac{1}{T} \sum\limits_{t \in \mathcal{T}} \omega_i^t$.

In Fig. 3, we present a comparison between $\mathrm{P}[\nu_i = k]$ and $\widetilde{\mathrm{P}}[\nu_i = k]$, where the number of time slots in a frame is set to five and ten, respectively, i.e., $T = 5,\ 10$. In the legend, $\omega_i^t \in [a,\ b]$ represents the case when the value of ω_i^t is generated randomly between a and b. We can see that the exponential-function-based PDF provides a good approximation of the original. Similar results can be observed for different values of T.

We assume that the incoming packets generated at each user $i \in \mathcal{N}$ follow a Poisson arrival process with average packet arrival rate λ_i [packets/second]. Then, based on the above discussion, the queue of each user $i \in \mathcal{N}$ can be modeled using a $M/M/1$ model [14], and the packet loss rate of user i caused by exceeding the maximum queueing delay, denoted as T_i^{th} [second], can be represented as

$$P_i^{dly}(\boldsymbol{\omega}_i) = e^{-(\frac{\phi(\boldsymbol{\omega}_i)}{T_{slt}} - \lambda_i) T_i^{th}}, \tag{16}$$

where T_{slt} represents the time duration of a time slot in second. Considering that $P_i^{dly}(\boldsymbol{\omega}_i) \le 1$, we have $\sum\limits_{t \in \mathcal{T}} \omega_i^t \ge \lambda_i T_{slt}$.

Expected throughput. Based on above formulations and according to (1), the expected packet throughput of user $i \in \mathcal{N}$, denoted as $R_i(\boldsymbol{\omega})$, can be expressed as

$$R_i(\boldsymbol{\omega}) = \lambda_i \big[1 - P_i^{dly}(\boldsymbol{\omega}_i) - P_i^{err}(\boldsymbol{\omega}) + P_i^{dly}(\boldsymbol{\omega}_i) P_i^{err}(\boldsymbol{\omega})\big], \tag{17}$$

and can be rewritten approximately by neglecting the second-order item $P_i^{dly}(\boldsymbol{\omega}_i) P_i^{err}(\boldsymbol{\omega})$ as

$$R_i(\boldsymbol{\omega}) = \lambda_i \big[1 - P_i^{dly}(\boldsymbol{\omega}_i) - P_i^{err}(\boldsymbol{\omega})\big]. \tag{18}$$

Then, the ideal objective of our problem would be to maximize the sum throughput of all users in $\mathcal{N}$ by adjusting the transmission strategy $\boldsymbol{\omega}_i$ of each user $i \in \mathcal{N}$. However, this objective is clearly not achievable with distributed control. Furthermore, the centralized optimization problem is not convex, which means that, in general, only suboptimal solutions can be computed in polynomial time even with centralized algorithms. With this understanding, we first propose a low-complexity distributed solution algorithm, and then present a centralized algorithm to compute the globally optimal solution to provide a benchmark for the performance of the proposed distributed algorithm.

3. DISTRIBUTED PROBLEM FORMULATION

Based on the system model developed in the previous section, we now present a distributed problem formulation and a low-complexity distributed algorithm. Then, we discuss several issues related to the implementation of the algorithm. The distributed solution algorithm is designed based on a best-response strategy, i.e., each node iteratively, independently and asynchronously solves the problem of dynamic queueing and transmission in UW-ASNs. At each iteration, each user individually maximizes its own expected throughput based on the statistical characterization of the interference obtained through past observations and based on its queue information.

Distributed problem statement. We let $\boldsymbol{\omega}_{-i} = (\boldsymbol{\omega}_j)_{j \in \mathcal{N}/i}$ represent the transmission probability vector of all users in $\mathcal{N}$ except i. Then, the expected throughput $R_i(\boldsymbol{\omega})$ in (18) can be equivalently expressed as $R_i(\boldsymbol{\omega}_i, \boldsymbol{\omega}_{-i})$, i.e.,

$$R_i(\boldsymbol{\omega}_i, \boldsymbol{\omega}_{-i}) = \lambda_i \big[1 - P_i^{dly}(\boldsymbol{\omega}_i) - P_i^{err}(\boldsymbol{\omega}_i, \boldsymbol{\omega}_{-i})\big], \quad (19)$$

where $P_i^{err}(\boldsymbol{\omega}_i, \boldsymbol{\omega}_{-i})$ is the corresponding equivalent representation of $P_i^{err}(\boldsymbol{\omega})$ given in (13). Then, at each iteration, each user $i \in \mathcal{N}$ optimally chooses its transmission probability vector $\boldsymbol{\omega}_i$ by solving the following optimization problem,

$$\begin{aligned}
\textit{Given}: \quad & P_i,\ d_i,\ N_i,\ k_i^{tl}(\boldsymbol{\omega}_{-i}), \\
& \theta_i^{tl}(\boldsymbol{\omega}_{-i}),\ \forall t \in \mathcal{T},\ \forall l \in \mathcal{L}_i^t \quad (20)\\
\textit{Find}: \quad & \boldsymbol{\omega}_i \\
\textit{Maximize}: \quad & R_i(\boldsymbol{\omega}_i,\ \boldsymbol{\omega}_{-i}) \quad (21)\\
\textit{Subject to}: \quad & 0 \le \omega_i^t \le 1,\ \forall t \in \mathcal{T} \quad (22)\\
& \sum_{t \in \mathcal{T}} \omega_i^t \ge \lambda_i T_{slt} \quad (23)
\end{aligned}$$

where the objective function $R_i(\boldsymbol{\omega}_i, \boldsymbol{\omega}_{-i})$ in (21) is defined through (13) and (16), $k_i^{tl}(\boldsymbol{\omega}_{-i})$ and $\theta_i^{tl}(\boldsymbol{\omega}_{-i})$ in (20) are the shaping parameters in (6) depending on the transmission strategies of all other users in $\mathcal{N}$ except i, i.e., $\boldsymbol{\omega}_{-i}$.

Individual optimization. It is nontrivial for each user $i \in \mathcal{N}$ to determine its own optimal transmission strategy $\boldsymbol{\omega}_i$, because the above optimization problem is in general nonlinear and non-convex due to non-convexity of the expression in (13) (hence, it is difficult to solve to obtain the optimal solution). In the following, we propose an efficient algorithm to search for the globally optimal solution by taking advantage of the special structure of the objective function $R_i(\boldsymbol{\omega}_i,\ \boldsymbol{\omega}_{-i})$.

To maximize $R_i(\boldsymbol{\omega}_i,\ \boldsymbol{\omega}_{-i})$ in (21), each user $i \in \mathcal{N}$ only needs to minimize its overall packet loss rate

$$P_i^{los}(\boldsymbol{\omega}) = P_i^{dly}(\boldsymbol{\omega}_i) + P_i^{err}(\boldsymbol{\omega}) \quad (24)$$

Algorithm 1 Distributed Solution Algorithm

Input: $P_i,\ d_i,\ N_i$, for all $i \in \mathcal{N}$, $n_{\max}$, $\kappa = 0.01$
Initialize: Set iteration counter $n = 0$, $\boldsymbol{\omega}_i(n) = \boldsymbol{\omega}_i^0,\ \forall i \in \mathcal{N}$

repeat
(S.1) Each user $n \in \mathcal{N}$ finds $\boldsymbol{\omega}_i^*$ to maximize $R_i(\boldsymbol{\omega}_i, \boldsymbol{\omega}_{-i})$ by searching for the optimal y_i through solving the optimization problem in (27)-(30).
(S.2) Set $\boldsymbol{\omega}_i(n) = \boldsymbol{\omega}_i^*$ for all $i \in \mathcal{N}$.
(S.3) Set $n \leftarrow n + 1$.
until $||\boldsymbol{\omega}_i(n) - \boldsymbol{\omega}_i(n-1)|| \le \kappa,\ \forall i \in \mathcal{N}$ or $n = n_{\max}$.

where $P_i^{dly}(\boldsymbol{\omega}_i)$ and $P_i^{err}(\boldsymbol{\omega})$ are defined in (16) and (13), respectively. To this end, we introduce a new variable $y_i = \sum_{t \in \mathcal{T}} \omega_i^t$. Then, by substituting y_i into (16) and (13), $P_i^{dly}(\boldsymbol{\omega}_i)$ and $P_i^{err}(\boldsymbol{\omega})$ can be respectively rewritten as

$$P_i^{dly}(y_i) = e^{-(\frac{y_i}{T \cdot T_{slt}} - \lambda_i) T_i^{th}}, \quad (25)$$

$$P_i^{err}(y_i, \boldsymbol{\omega}) = \frac{1}{y_i} \sum_{t \in \mathcal{T}} \omega_i^t P_{i,t}^{err}(\boldsymbol{\omega}_{-i}). \quad (26)$$

Then, with given y_i and $P_{i,t}^{err}(\boldsymbol{\omega}_{-i})$ (which can be calculated according to (5)-(12) for fixed $\boldsymbol{\omega}_{-i}$; As explained later in this section, the value of $\boldsymbol{\omega}_{-i}$ is actually unavailable to transmitter i while the effects of $\boldsymbol{\omega}_{-i}$ on $P_{i,t}^{err}(\boldsymbol{\omega}_{-i})$ can only be estimated online by measuring the statistical behavior of interference caused by all interfering transmitters), $P_i^{los}(\boldsymbol{\omega})$ in (24) can be minimized by solving a simple linear optimization problem. Denote the corresponding minimum as $\min_{\boldsymbol{\omega}_i} P_i^{los}(y_i, \boldsymbol{\omega}_{-i}, \boldsymbol{\omega}_i)$, then the optimization problem formulated in (20)-(23) can be equivalently expressed as

$$\begin{aligned}
\textit{Given}: \quad & P_i,\ d_i,\ N_i,\ k_i^{tl}(\boldsymbol{\omega}_{-i}), \\
& \theta_i^{tl}(\boldsymbol{\omega}_{-i}),\ \forall t \in \mathcal{T},\ \forall l \in \mathcal{L}_i^t \quad (27)\\
\textit{Find}: \quad & y_i \\
\textit{Minimize}: \quad & \min_{\boldsymbol{\omega}_i} P_i^{los}(y_i, \boldsymbol{\omega}_{-i}, \boldsymbol{\omega}_i) \quad (28)\\
\textit{Subject to}: \quad & y_i \le T \quad (29)\\
& y_i \ge \lambda_i T_{slt}. \quad (30)
\end{aligned}$$

It can be proven experimentally that the objective function in (28), i.e., $\min_{\boldsymbol{\omega}_i} P_i^{los}(y_i, \boldsymbol{\omega}_{-i}, \boldsymbol{\omega}_i)$, is a quasi-convex function of y_i [15] for a wide set of network settings. This implies that the globally optimal solution of y_i can be iteratively calculated in logarithmic time (which is less than polynomial hence very efficient) by using the bisection method. At each iteration, the optimal transmission probability vector $\boldsymbol{\omega}_i$ with given y_i can be obtained by simply solving a linear optimization problem.

Implementation issues. The proposed distributed solution algorithm is summarized in Algorithm 1. In the proposed distributed access schemes, each node $i \in \mathcal{N}$ individually maximizes its own throughput with given $\boldsymbol{\omega}_{-i}$. However, in a complete distributed algorithm, the transmission strategy of interfering users are in general unavailable to user i. For practical implementation, each user i only needs to estimate the two shaping parameters $k_i^{tl}(\boldsymbol{\omega}_{-i})$ and $\theta_i^{tl}(\boldsymbol{\omega}_{-i})$ based on the past measurements of the interference at the receiver side.

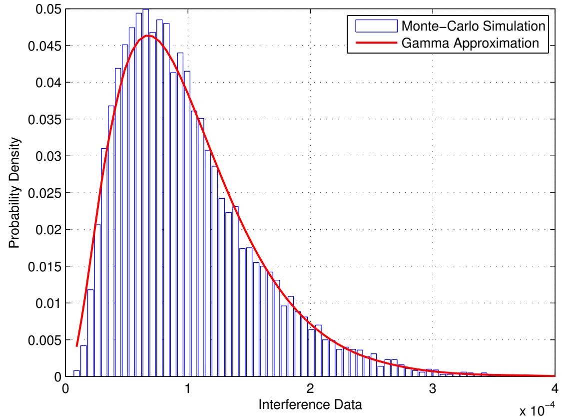


Figure 4: Approximation of interference using a Gamma distribution function in shallow water environment.

To this end, we let $\mathrm{E}[I_i^{tl}]$ and $\mathrm{D}[I_i^{tl}]$ represent mean and variance of I_i^{tl}, respectively, then they can be derived as follows,

$$\mathrm{E}[I_i^{tl}] = \mathrm{E}\left[\sum_{j\in\mathcal{N}/i} P_j h_{ij}\alpha(g_{ij}^{tl})\right] = \sum_{j\in\mathcal{N}/i} P_j \omega_j^{g_{ij}^{tl}} H_{ij}\mathrm{E}[\rho^2], \tag{31}$$

$$\mathrm{D}[I_i^{tl}] = \mathrm{D}\left[\sum_{j\in\mathcal{N}/i} P h_{ij}\alpha(g_{ij}^{tl})\right] = \sum_{j\in\mathcal{N}/i} P_j^2 \omega_j^{g_{ij}^{tl}} (H_{ij})^2\mathrm{D}[\rho^2] \tag{32}$$

where we have $\mathrm{E}[\rho^2] = \frac{4}{\pi}$ and $\mathrm{D}[\rho^2] = \frac{16}{\pi^2}$ according to (4).

According to the probability density function of the interference I_i^{tl} in (6), $\mathrm{E}[I_i^{tl}]$ and $\mathrm{D}[I_i^{tl}]$ can also be represented as

$$\mathrm{E}[I_{it}^{fl}] = k_i^{tl}(\boldsymbol{\omega})\theta_i^{tl}(\boldsymbol{\omega}), \tag{33}$$

$$\mathrm{D}[I_{it}^{fl}] = k_i^{tl}(\boldsymbol{\omega})[\theta_i^{tl}(\boldsymbol{\omega})]^2, \tag{34}$$

where $k_i^{tl}(\boldsymbol{\omega})$ and $\theta_i^{tl}(\boldsymbol{\omega})$ are the two shaping parameters in (6). Then, from (31)-(34), we have

$$\theta_i^{tl}(\boldsymbol{\omega}) = \mathrm{D}[I_i^{tl}]/\mathrm{E}[I_i^{tl}], \tag{35}$$

$$k_i^{tl}(\boldsymbol{\omega}) = (\mathrm{E}[I_i^{tl}])^2/\mathrm{D}[I_i^{tl}], \tag{36}$$

where $\mathrm{E}[I_i^{tl}]$ and $\mathrm{D}[I_i^{tl}]$ are given in (31), (32), respectively.

In Fig. 4, we present an example to show validity of the Gamma-function-based approximation of the aggregate interference. We can see that he model can provide a very good approximation the statistical characteristic of aggregate interference. Note that in the case of network changes, e.g., due to arriving or leaving of any nodes, both $k_i^{tl}(\boldsymbol{\omega})$ and $\theta_i^{tl}(\boldsymbol{\omega})$ need to be re-estimated, which might result in another round of transmission probability adaption through Algorithm 1.

4. GLOBALLY OPTIMAL SOLUTION ALGORITHM

As discussed in Section 2, an ideal objective would be to maximize the sum throughput of all users in the network. The objective can not be achieved trivially due to lack of centralized control and non-concavity of the utility function $R_i(\boldsymbol{\omega}_i, \boldsymbol{\omega}_{-i})$ in (18). In this section, we propose a centralized but globally optimal solution algorithm based on the branch and bound framework to solve the overall optimization problem expressed as follows.

$$\mathit{Given:} \quad P,\ d_{ij},\ N_i,\ \forall i,j\in\mathcal{N} \tag{37}$$

$$\mathit{Find:} \quad \boldsymbol{\omega} \tag{38}$$

$$\mathit{Maximize:} \quad R(\boldsymbol{\omega}) = \sum_{i\in\mathcal{N}} R_i(\boldsymbol{\omega}) \tag{39}$$

$$\mathit{Subject\ to:} \quad 0 \le \omega_i^t \le 1,\ \forall t\in\mathcal{T},\ \forall i\in\mathcal{N} \tag{40}$$

$$\sum_{t\in\mathcal{T}} \omega_i^t \ge \lambda_i T_{slt},\ \forall i\in\mathcal{N} \tag{41}$$

Overview of the solution algorithm. The proposed algorithm searches for a globally optimal solution with predefined precision of optimality. If we denote the globally optimal sum-throughput objective function as R^*, $0 < \varepsilon \le 1$ as the optimality precision, then the algorithm searches for an ε-optimal solution R, which satisfies $R \ge \varepsilon R^*$,with ε being arbitrarily close to 1.

Denote $\boldsymbol{\Omega}_0 = \{\boldsymbol{\omega}\}$ as the original search space, including all possible combinations of $\boldsymbol{\omega} = (\boldsymbol{\omega}_i)_{i\in\mathcal{N}}$. The proposed algorithm maintains a set of sub-domains $\boldsymbol{\Omega} = \{\boldsymbol{\Omega}_n \subset \boldsymbol{\Omega}_0,\ n = 1, 2, \cdots\}$, where n represents the iteration step of the algorithm. For any $\boldsymbol{\Omega}_n$, consider $\mathrm{UP}(\cdot)$ and $\mathrm{LR}(\cdot)$ as the upper and lower bounds on sum-throughput over $\boldsymbol{\Omega}_n$. We refer to $\mathrm{UP}(\boldsymbol{\Omega}_n)$ and $\mathrm{LR}(\boldsymbol{\Omega}_n)$ as the local upper bound and local lower bound, respectively.

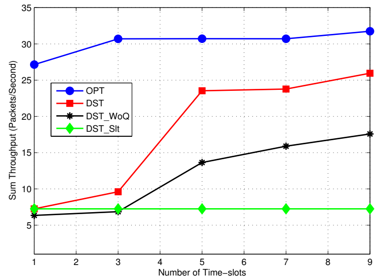
The branch and bound framework requires that, for given $\boldsymbol{\Omega}_n$, the $\mathrm{UP}(\boldsymbol{\Omega}_n)$ and $\mathrm{LR}(\boldsymbol{\Omega}_n)$ should be easy to calculate. To determine $\mathrm{UP}(\cdot)$, we rely on relaxation, i.e., we relax the original nonlinear non-convex problem into a convex problem that is easy to solve to obtain the globally optimal solution. For $\mathrm{LR}(\cdot)$, we locally search for a *feasible solution* starting from the relaxed solution (which is also a feasible solution) and set the corresponding sum-throughput as the local lower bound.

The proposed algorithm searches for the optimal solution iteratively. At each iteration, the algorithm maintains a global upper bound $\mathrm{UP_{glb}}$ and a global lower bound $\mathrm{LR_{glb}}$ on the sum-throughput such that

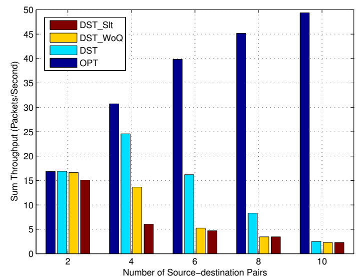
$$\mathrm{LR_{glb}} \le R^* \le \mathrm{UP_{glb}}. \tag{42}$$

We use $\mathrm{UP_{glb}}$ to drive the branch and bound technique and use $\mathrm{LR_{glb}}$ to check how close the obtained solution is to R^* and decide when to terminate the algorithm. If $\mathrm{LR_{glb}} \ge \varepsilon\cdot\mathrm{UP_{glb}}$, the algorithm terminates and sets the optimal sum-throughput to $R = \mathrm{LR_{glb}}$. Otherwise, the algorithm chooses one sub-domain (which is obtained through partitioning the original problem), and further partitions it into two sub-domains and calculates $\mathrm{UP}(\cdot)$ and $\mathrm{LR}(\cdot)$ for them each, and finally updates the $\mathrm{UP_{glb}}$ and $\mathrm{LR_{glb}}$. As the problem-partition progresses, the gap between $\mathrm{UP_{glb}}$ and $\mathrm{LR_{glb}}$ converges to 0. Furthermore, from (42), $\mathrm{UP_{glb}}$ and $\mathrm{LR_{glb}}$ converge to the globally maximal sum-throughput R^*.

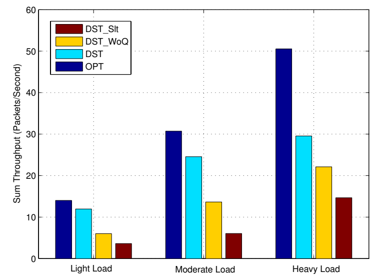
In the next section, the globally optimal solution will be calculated using the developed centralized algorithm to provide a benchmark for performance evaluation of the distributed solution proposed in the previous section.



(a)



(b)



(c)

Figure 5: (a) Sum throughput achieved in the case of different number of time slots in each frame. (b)Sum throughput achieved in the case of different users. (c) Sum throughput achieved in the case of different traffic loads.

5. SIMULATION RESULTS

In this section, we evaluate the performance of the proposed distributed solution algorithm through simulations. We consider an UW-ASN of ocean-bottom sensor nodes deployed over an area of 1500×1500 m^2. The number of source-destination pairs is set to $N = 2, 4, 6, 8, 10$, with distance for each communicating pair randomly chosen between $[300, 500]$ m. The number of time slots in each frame is set to vary from $T = 1$ to 9 with step of 2. For example, in the case of $T = 5$, based on the proposed distributed algorithm, each node optimizes its transmission probability jointly for the next consecutive 5 time slots, while optimizes separately for each individual time slot with $T = 1$. The number of measurement points in each time slot is set to $L = 5$ for the L-measurement-based interference modeling method. Three different schemes are used for performance evaluation of the proposed distributed algorithm, called DST for short, i.e., i) DST_WoQ, which corresponds to the DST algorithm without taking the packet loss rate due to exceeding the maximum delay threshold into consideration in transmission probability vector optimization, ii) DST_Slt, which dynamically adjusts the transmission strategy for each single time slot, and iii) DST_SM, which uses only one single measurement point to represent the interference level for a whole time slot. All results presented in this section are obtained by averaging over 50 independent simulations.

The performance of the four algorithms is shown in Fig. 5 (a) for the case of four source-destination pairs and different number of time slots in each frame. We can see that, significant improvement in sum throughput can be achieved by jointly optimizing the transmission strategy for a group of time slots. For example, in the case of $T = 5, 7, 9$, i.e., when the number of time slots jointly considered is larger than that of the concurrent users (4 in this simulation), a sum-throughput around 14 can be achieved by DST_WoQ, which is two times higher than the sum-throughput achieved by DST_Slt, which considers only a single time slot for transmission strategy optimization. Further improvement can be achieved by taking queueing into consideration, e.g., a value of 25 sum-throughput can be achieved by DST, which is three times higher that of DST_Slt and more than 80% of the global optimum.

In Fig. 5 (b), performance of the proposed distributed algorithm is evaluated with user number N varying from 2 to 10 while the time slot number is set to 5. We can see that, the proposed DST solution algorithm consistently outperforms the other two distributed algorithm. For example, in the case of 4 users, a sum throughput of 25 can be achieved by DST while only less than 15 and around 7 can be achieved by DST_WoQ and DST_Slt, while in the case of 6 users, a sum throughput of 17 can be achieved by DST which is about three times higher than that achieved by DST_WoQ and DST_Slt. It is worth pointing out that, unsurprisingly, as the number of users increases, the price of anarchy caused by the lack of a centralized controller can be very large, e.g., in the case of 10 users, only less than 10% of the global optimum can be achieved through distributed, uncoordinated algorithms with no message exchange. A possible solution method is to introduce partial cooperation among interfering node, e.g., design distributed solution algorithms based on pricing strategies [16]; this will be the subject of our future work.

The performance of the proposed DST algorithm is evaluated in Fig. 5 (c) with 4 users, 5 time slots in a frame and varying average incoming packet rates corresponding to light, moderate and heavy traffic loads. We observe that a sum-throughput close to the global optimum can be achieved by the proposed DST algorithm in the former two cases, while only 60% of the global optimum can be achieved in the third case. Performance degradation of DST is due to the fact that, with heavier traffic, each user prefers to transmit more often to avoid high packet loss rates due to violating the delay constraint, which results in higher level of interference in the UW-ASNs. Again, in this case, partial cooperation among interfering users might be helpful for efficient MAC protocol design.

Advantages of the L-measurement-based interference modeling method are illustrated in Fig. 6 through performance comparison between DST and DST_SM in the case of four source-destination pairs, i.e., $N = 4$. Much higher throughput can be achieved by the proposed DSM than DST_SM with the number of time slots larger than N. For example, with $T = 5$, a sum throughput close to 25 can be achieved by DST, which is over three times as high as the sum-throughput of DST_SM. By representing the interference level in each time slot based on multiple measurement points, the statistical behavior of interference with both spatial and temporal uncertainty can be modeled more precisely, and hence each transmitter has more flexibility in optimally adapting its own probabilistic transmission strategy

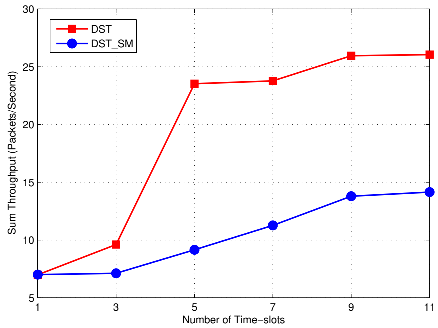


Figure 6: Comparison between the L-measurement method and traditional single-measurement method.

profile to avoid interference from other transmitters.

6. CONCLUSIONS

We studied a stochastic, distributed and asynchronous channel access scheme for underwater acoustic networks in which each transmitter optimizes a transmission probability profile based on which it decides whether to transmit or to enqueue its packets over a series of time slots *based on a statistical characterization of interference* obtained through its past observations. To capture the effects of temporal uncertainty of interference, we proposed an L-measurement method to model the effect of unaligned interference at a receiver.

We have presented a mathematical formulation of the problem of dynamic transmission strategy optimization and proposed an iterative distributed solution algorithm based on a best-response strategy. The performance of the proposed distributed access scheme was also evaluated through simulations by comparing it to two alternative distributed schemes. Results indicated that considerable improvement in sum-throughput can be achieved by jointly taking the queueing and multi-slot optimization into consideration.

By comparing the proposed distributed access scheme to the global optimum, we found that while our scheme performs very well in case of low or moderate interference, in the case of high interference, e.g., with many concurrent transmitting nodes or with high traffic loads, the price of anarchy caused by the absence of centralized control can be very large. We will explore partial cooperation strategies among competing users to fill this performance gap. Moreover, it worth pointing out that, in this paper we have not considered the effects of any advanced transmission technologies, e.g., channel coding, modulation and retransmission schemes, on the throughput performance and this will be explored in our future research.

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