Energy-efficient Sensor Management in Multi-static Active Sonar Networks

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***Abstract*—In this paper, we formulate the sensor scheduling problem for multi-static active sonar sensor networks. We also present algorithms that schedule both sources and receivers to achieve desired duty cycles, while optimizing both the temporal and spatial sensing coverage. Finally, we present simulation results, based on a simplified propagation model, that demonstrate the performance of the presented sensor management algorithms.**

I. Introduction

This paper investigates the sensor management problem in multi-static active sonar networks and presents resource allocation algorithms that ensure coverage for target detection while conserving energy.

Sonar sensor networks, including passive and active sonar, have been deployed with some limited scope for providing persistent underwater surveillance. The basic operating concept of a multi-static sonar network is to proactively "ping" from an acoustic source and correlate the echo returns across multiple receivers in the field to detect, localize, and track targets of interest. In order to provide necessary coverage for the surveillance area and sufficient spatial diversity for target localization, multiple receivers and acoustic sources are deployed and distributed throughout the field. This redundancy can also improve the reliability and extend the lifetime of the sensor network.

When energy management is necessary to achieve the required network lifetime, sensor management in multi-static sonar networks presents a number of unique challenges that have received little attention by the research community. First, the activities of the network's active sources need to be properly scheduled to avoid potential inter-ping interference while providing sufficient coverage. The coverage of an active sonar source is determined by the multi-static geometry and is characterized by a collection of Cassini ovals depending on the locations of both the source and potential receivers. Furthermore, the group of receivers which collaborate to detect the target's location is dictated by the pinging source and its members are typically not within communication range of each other. Hence, existing sensor coordination techniques that exploit the proximity among passive sensors that all detect the target do not apply in this scenario [2], [4]. Finally, the coupling between the control of actives sources and the relevant collaboration among multiple receivers result in an energy management problem that is significantly more complex than the problem in passive sensor networks.

We present an algorithm that both schedules the network's active sources and controls the receivers' duty cycles. We prove that the proposed algorithm extends the network's lifetime while at the same time provides sufficient coverage for detection. The presented technique can be applied to sensor management in other active sensor networks such as ultra-wide band radar sensor networks [3].

II. Sensor Management Problem

A. Basic assumptions

We assume that the network comprises N sources, $\mathcal{S} = \{S_1, \ldots, S_N\}$, and M receivers, $\mathcal{R} = \{R_1, \ldots, R_M\}$. Furthermore, we assume that the objective of the network is to provide surveillance for an area denoted by $F \subset \mathbb{R}^2$. Without loss of generality, we assume the sensor management decisions are made at discrete points of time denoted by $t_1, \ldots, t_k, t_{k+1}, \ldots$.[1] A sensor management decision at time k, denoted by $d(k)$, is defined by

$$d(k) = (s(k), r(k)),$$

where $s(k) \in \mathcal{S}$ is the source selection[2] at time k, and $r(k) \subset \mathcal{R}$ is the set of active receivers at time k.

We define a sensor schedule as a sequence of decisions over time,

$$\Pi = \{d^\Pi(1), d^\Pi(2), \ldots, d^\Pi(k), \ldots\}.$$

The sensor management problem is to compute a sensor schedule to meet the surveillance performance requirement while taking into account energy efficiency. Note that a sensor schedule defines the duty cycles for both the sources and receivers, in that sources and receivers not scheduled at time k can go to sleep or operate at a low-energy consumption state. The decision at time k also determines the set of receivers in which relevant information is available for collaborative signal processing.

[1] We will use time k to mean time t_k throughout the paper.

[2] We assume in this paper that at most one source is engaged at any time to avoid potential interference among sources.

B. Geometric coverage models for multi-static sonar

We assume that all sonar sensors are at the same depth and consider the coverage geometry in two dimensions as a simplifying approximation.

To describe the coverage geometry of the multi-static sonar systems, we first consider a bi-static case where only one source-receiver pair is present. Let $X_s = (x_s, y_s)$ and $X_r = (x_r, y_r)$ be the locations of the source and receiver, respectively. If we assume that r detects a potential target when the received signal energy is above a certain threshold, then the coverage of the $s - r$ pair is characterized by the interior of the so-called, *equi-power* surface. This equi-power surface is the set of all target locations that lead to echoes whose power at the receiver is above the desired threshold.

As in the case for bi-static radar systems [3], the equi-power surface can be approximated by a Cassini oval with X_s and X_r as the foci, assuming no energy loss at the target. A Cassini oval is characterized by two parameters: the distance between the two foci $2a$ and the constant product of distances from the foci to any point on the Cassini curve, b^2:

$$\left[(x - x_s)^2 + (y - y_s)^2\right] \cdot \left[(x - x_r)^2 + (y - y_r)^2\right] = b^4 \quad (1)$$

where the parameter b can be derived based on a path-loss model and a specific detection threshold.

Given this description, the approximate coverage area for a source-receiver pair is the interior of the Cassini oval defined above, minus a masking area within which the ambiguity between the line-of-sight (LOS) signal and the echo from the target cannot be resolved. This masking area can be approximated by the interior of a *equi-time-of-arrival* surface, which is an ellipse with X_s and X_r as its foci.

Extending to the multi-static case, the geometric coverage of a source and a set of receivers can be approximated by the union of bi-static coverages of all distinct source-receiver pairs. For example, Figure 1 illustrates the coverage of a source and its three nearby receivers, as the union of the three source-receiver Cassini ovals.

We introduce the following notation for geometric coverage:

- Coverage of a source-receiver pair: $C(S, R) \subset \mathbb{R}^2$;
- The coverage of a source S and a set of receivers $\mathcal{R}'$ is denoted by $C(S, \mathcal{R}')$ and defined as

$$C(S, \mathcal{R}') = \bigcup_{R \in \mathcal{R}'} C(S, R).$$

- The *full coverage* of a source $C(S)$ is the overall coverage provided by the source S when all the receivers in $\mathcal{R}$ are active. In other words, $C(S) = C(S, \mathcal{R})$;
- The coverage of a decision $d(k) = (s(k), r(k))$, $C(d(k))$ is defined by the selected source $s(k)$ and the set of receivers $r(k)$, that is, $C(d(k)) = C(s(k), r(k))$.

C. Optimization problems

The coverage metrics need to capture both the temporal and spatial aspects of the coverage problem, as we do not expect that any single source can provide complete coverage of the field. Intuitively, we would like to avoid having any substantial area not covered over a long period of time.

Given a compact regular area (e.g, a unit square) $\delta A \subset F$ and a sensor schedule Π, we define a discrete-time binary coverage process for δA, $x^{\Pi}_{\delta A}(k)$, $k = 1, 2, \ldots$, by

$$x^{\Pi}_{\delta A}(k) = \begin{cases} 1 & \text{if } \delta A \subset C(d(k)); \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

In other words, δA is covered at time k, if it lies within $C(d(k))$ and is uncovered otherwise. The size of the area δA is a design parameter that depends on the target's velocity, the localization uncertainty, and the desired accuracy for tracking.

Based on $x^{\Pi}_{\delta A}(k)$, we also define a *temporal hole* process, $h^{\Pi}_{\delta A}(k)$, which characterizes the lack of coverage:

$$h^{\Pi}_{\delta A}(1) = 0,$$

and for $k > 1$,

$$h^{\Pi}_{\delta A}(k) = \begin{cases} h_{\delta A}(k-1) + 1 & \text{if } x^{\Pi}_{\delta A}(k-1) = 0, \\ 0 & \text{otherwise.} \end{cases} \quad (3)$$

Note that $h^{\Pi}_{\delta A}(k)$ is equal to the time elapsed from the last decision that covered δA, following the schedule Π. In the sequel, we will drop the superscript Π for the two processes defined above if their dependency on the schedule is clear from the context.

Given a sensor schedule Π defined over $k \in [1, T]$, $T \in \mathbb{N}$, its coverage (or more exactly lack-of-coverage) for δA can be characterized by the maximum duration over which the area δA is not covered. If we assume that the field F is discretized into $N_F(\delta A)$ of unit areas $\delta A \subset F$, then we can measure the coverage across the field based on the average temporal hole over any area δA.

Specifically, we define the average temporal hole across the field F at time k by

$$h^{\Pi}_F(k) = \frac{1}{N_F(\delta A)} \sum_{\delta A \subset F} h^{\Pi}_{\delta A}(k) \quad (4)$$

Then, the coverage metric we will consider can be written as

$$H(\Pi, [1, T]) = \max_{k=1,\ldots,T} \left\{ h^{\Pi}_F(k) \right\}. \quad (5)$$

If the schedule Π is periodic, then the performance is measured based on $H(\Pi, [1, T])$ over one period and we will drop the dependency on $[1, T]$.

One potential deficiency of the metric defined by (5) is that it does not directly penalize large contiguous "spatial holes" (versus a collection of smaller areas) if the unit area δA is too small. One possible approach to address this issue is to work with a larger unit area δA. However, doing so would also require revising the definition of the coverage process (2) to address the loss of resolution. For example, one should consider an area covered, if the sensor decision covers some percentage of δA.

The optimization problem we will solve is the following: Given a time horizon $[1, T]$, $T \in \mathbb{N}$ and a definition of the unit area δA,

$$\min_{\Pi=\{d(1),\ldots,d(T)\}} H(\Pi, [1, T]). \quad (6)$$

To ensure that the optimization problem defined in (6) is non-trivial and well-posed, we make the following additional assumptions:

A.1 No single source-receiver pair can provide full coverage of the field. That is, for any $S \in \mathcal{S}$ and any $R \in \mathcal{R}$,

$$F/C(S, R) \neq \emptyset.$$

A.2 The collection of the sources and receivers can provide complete coverage of the field over time. That is,

$$F \subset \bigcup_{S\in\mathcal{S}} C(S).$$

III. Sensor Scheduling Algorithms

We consider only deterministic schedules in this paper. If we assume that all the sources and receivers are always available, then it suffices to consider periodic sensor schedules. Our goal is to develop algorithms that compute sensor schedules which optimize the coverage metric defined in (5), while achieving the desired sensor duty cycles (for both sources and receivers). Simultaneous optimization of source and receiver schedules will lead to a challenging combinatorial optimization problem when the size of the network is large. For this reason, we first consider the problem of source scheduling assuming full duty cycles for the receivers. This scenario is relevant since sources are expected to consume more energy than receivers. To achieve a desired duty cycles for receivers, we present a simple randomized algorithm to achieve desired duty cycle taking into account the source schedule.

A. Source scheduling with duty cycle constraints

We assume that an upper bound on the duty cycles is specified. Let us first restrict our attention to the periodic schedules that engage each source exactly once over each period. Hence the problem is to identify an ordering among the sources such that the coverage provided by the schedule following the ordering is optimized. Such a periodic schedule leads to a $1/N$ duty cycle for each source. A greedy algorithm can be described as following:

- Find the source $s(1) \in \mathcal{S}$ with maximum full coverage. That is,

$$s(1) = argmax_{S\in\mathcal{S}}|C(S)|_A,$$

  where $|X|_A$ is the area of a compact set $X \subset \mathbb{R}^2$.
- For $k = 2, \ldots, N$, find $s(k) \in \mathcal{S}/\{s(1), \ldots, s(k-1)\}$ to minimize

$$N_F(\delta A)h_F(k+1) = \sum_{\delta A\subset F} h_{\delta A}(k). \quad (7)$$

Instead of the greedy approach taken in (7) where the direct average is used for the sequential search, one might consider a weighted average that places emphases on areas with larger temporal holes. For example,

$$\sum_{\delta A\in F} w(h_{\delta A}(k+1))h_{\delta A}(k+1), \quad (8)$$

where $w(\cdot)$ is a non-negative increasing function.

The complexity of the problem increases for more general duty cycle requirements. Given a periodic schedule with period T, $\{(s(1), r(1)), \ldots, (s(T), r(T))\}$, the duty cycle of a source $S \in \mathcal{S}$, denoted as $\mu(S)$, is defined by

$$\mu(S) = \frac{|\{s(k) = S, k = 1, \ldots, T\}|}{T},$$

where $|\cdot|$ denotes the set cardinality. Optimization of coverage with explicit requirement on $\mu(S)$ is challenging. We propose an alternative representation of duty cycle requirements that will lead to a more tractable optimization problem for source scheduling. We assume: (1) a desired upper-bound U is specified on the number of times a source is selected over each cycle of a periodic schedule; and (2) every source has to be scheduled at least once. Note that under these requirements the duty cycle of sources satisfies the following inequalities:

$$\frac{1}{N} \leq \mu(S) \leq \frac{U}{N+U-1}, \quad (9)$$

for any $S \in \mathcal{S}$. One can also generalize the formulation to place different upper bounds for different sources if motivated by the application. Under this alternative duty cycle requirement, the algorithm presented above can be extended to compute the source schedule by

- Keeping track of the number of times each source has been selected to ensure no source is selected more than U times; and
- Avoiding a source if it leads to a degradation in performance as measured by (7) after it has been selected once.

We note an interesting property of the algorithm described above: no source will be scheduled back to back because this will always increase the size of the temporal holes.

B. Probabilistic receiver scheduling with receiver duty cycle constraint

If no explicit effort is made to control the receiver duty cycles, they are then dictated by the source schedule and the coverage geometry. Given a specific source $S \in \mathcal{S}$, it is expected that only a subset of receivers provide useful information for detection, denoted as $\mathcal{R}(S) \subset \mathcal{R}$. Hence a source schedule would result in varying duty cycles for the different receivers. However, this "passive" control of receiver duty cycles might not meet the desired energy efficiency one wishes to achieve. Next, we present a simple randomized scheme to further control the receiver duty cycles.

Given a source schedule, $\Pi_S = \{s(1), \ldots, s(T)\}$, we define the uncontrolled duty cycle for each receiver $R \in \mathcal{R}$ as

$$\mu^{\Pi_S}(R) = \frac{|\{R \in \mathcal{R}(s(k)), k = 1, \ldots, T\}|}{T}. \quad (10)$$

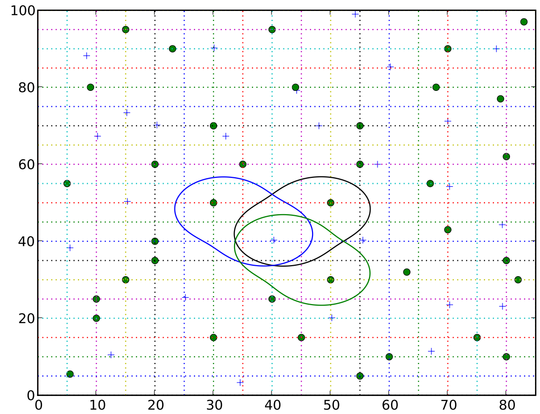

Fig. 1. Random Topology: 26 sources (blue crosses) and 37 receivers (green circles) are randomly distributed across the field, F, of size 85 m $\times$ 100 m. The size of δA is 5 m $\times$ 5 m.

In general, $\mu^{\Pi_S}(R)$ varies for different receivers. Assume that a desired maximum average receive duty cycle is given as $\bar{\mu}_R > 0$. Then given a source schedule $\Pi_S = \{s(1), \ldots, s(T)\}$, a simple randomized receiver scheduling algorithm is described as follows: At time k,

- For $R \in \mathcal{R}(s(k))$, schedule R with probability

$$\frac{\bar{\mu}_R}{\max\{\bar{\mu}_R, \mu^{\Pi_S}(R)\}}.$$

Since coverage is not taken into account in the receiver scheduling algorithm described above, we shall a degradation in coverage if a low receiver duty cycle is desired.

IV. Performance Evaluation

A. Methodology

We developed a Python simulator to evaluate the efficiency of the proposed scheduling algorithm. For simplicity, we represent the surveillance area as an N m $\times$ M m grid, with a unit square (δA) of size $k \times k$ m ($k = 5$). In order to calculate the coverage $C(S, R)$ of a source-receiver pair, we consider that if any part of the unit square is covered by the pair's Cassini oval, then that whole unit square is covered. We use the same approach to calculate the full coverage of source $C(S)$.

We determine the size of the Cassini oval using a simple path loss model and a corresponding detection threshold. Specifically, we first define a threshold value for the received signal strength. If the received signal strength is below this threshold the receiver will not detect the target. We then use the log-distance path loss model, with exponent $\gamma = 2$, to calculate the signal strength at distance d from the source and from that the parameter b^2 of the Cassini oval that ensures detection at the receiver given the detection threshold.

Alternative strategies. We compare the proposed scheduling algorithm against two other strategies: *random with replacement* (RwR) and *random without replacement* (RnoR). The RwR strategy selects source $s(k)$ randomly from $\mathcal{S}$, while the RnoR strategy selects a random source among those that have not been selected during the current cycle. As a result, the last strategy will achieve a $1/N$ duty cycles for all the sources in $\mathcal{S}$. Finally, we use a linear weight factor for the proposed greedy algorithm (cf. (8)) and therefore refer to it as the *linear greedy* algorithm.

	Greedy $\mu(\sigma)$	RnoR $\mu(\sigma)$	RwR $\mu(\sigma)$
Uniform Topology	4.94(0.22)	6.20(0.85)	9.01(1.52)
Random Topology	5.44(0.48)	7.06(0.91)	9.91(1.76)

TABLE I
Mean and standard deviation on average temporal hole size in the uniform and random topology

Performance metrics. We use two metrics to compare the three alternative strategies described above: average temporal hole size and duty cycle. The first metric captures the fitness of every decision $d(k)$ in reducing coverage holes, while the duty cycle reflects how well the algorithm minimizes the utilization level of the different sources and receivers.

B. Effect of topology

We start with a topology in which 20 sources and 25 receivers are uniformly distributed across a 100 m $\times$ 85 m grid. We also use a random topology that better reflects real deployment scenarios. Figure 1 shows one such topology in which 26 sources and 37 receivers are randomly placed over the same grid. In both cases we set $U = 3$.

As Table I indicates, the greedy algorithm provides better performance in terms of average temporal hole size across both topologies. This is because it chooses the source that minimizes the temporal holes at every decision step $d(k)$, as long as the U bound is observed. While Table I presents the overall performance of the three algorithms, Figure 2 shows the average temporal hole size as a function of time for the random topology. It is evident from this figure that a few holes are not covered for long time periods. The reason is that, contrary to uniform topology, there are some parts of the grid that are covered only by a few (or even one) sources. In this case, the temporal hole keeps increasing until that source is rescheduled (see Figure 3).

The results so far show that the greedy algorithm reduces the duration of coverage holes in the area that the sensor network covers. Next, we look at the source utilization across the three different algorithms. As Table II shows, the greedy algorithm also achieves the lowest average source duty cycle for both topologies. Moreover the standard deviation is small, suggesting that the different sources are equally utilized. However, the standard deviation increases for the random topology. This increase is due to the fact that, unlike the uniform topology where different sources have approximately the same coverage, some of the sources in the random topology have significantly larger coverage. Moreover, some areas can

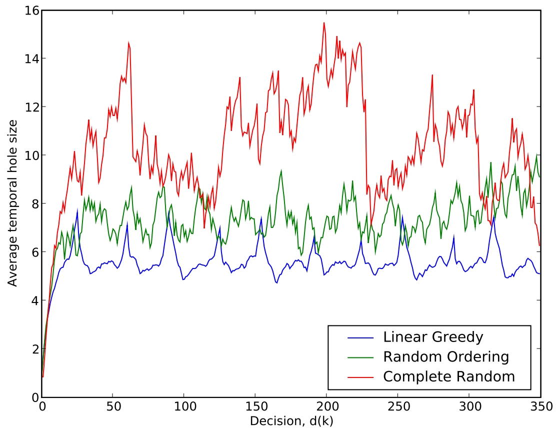

Fig. 2. Average temporal hole size for random topology with 26 sources and 37 receivers. The source selection upper bound $U = 3$.

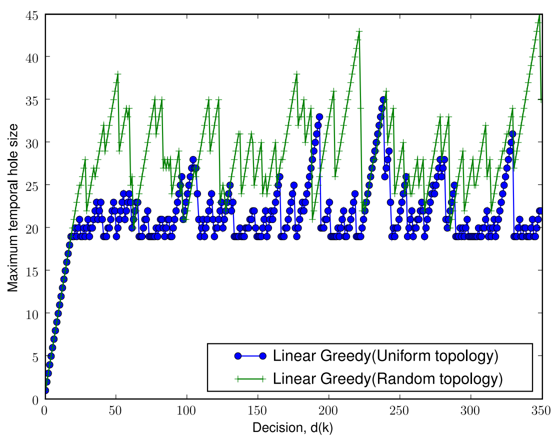

Fig. 3. Maximum hole size for the uniform and random topologies. Large values suggest that a unit square remained uncovered for a long time period.

only be covered by certain sources. Due to these facts, the greedy algorithm will utilize some sources multiple (up to U) times, leading to longer cycles and larger imbalances.

C. Effect of U

Intuitively, varying U should affect the average temporal hole size and duty cycle. Specifically, as U increases, the average temporal hole size will decrease, as the greedy algorithm can repeatedly utilize the appropriate sources within the same cycle. Doing so however will also increase the disparity in source utilization, as we argued above. Indeed, Table III, which shows how average temporal hole size and duty cycle change as a function of U, validates this intuition.

D. Probabilistic receiver scheduling

Invoking the same sources multiple times also increases the duty cycle of the receivers associated with those sources. Figure 4, which plots the receiver activation PDF for the random

	Greedy $\bar{\mu}_{(}S)$	RnoR $\bar{\mu}_{(}S)$	RwR $\bar{\mu}_{(}S)$
Uniform Topology	0.049(0.004)	0.05(0.00)	0.049(0.003)
Random Topology	0.038(0.008)	0.038(0.00)	0.039(0.009)

TABLE II
MEAN AND STANDARD DEVIATION OF SOURCE DUTY CYCLES FOR THE UNIFORM AND RANDOM TOPOLOGIES.

U	1	2	3
Temporal hole size $(\mu(\sigma))$	5.66(0.61)	5.60(0.50)	5.60(0.49)
Duty Cycle $(\mu(\sigma))$	0.038(0.0)	0.038(0.01)	0.038(0.01)

TABLE III
EFFECT OF U ON AVERAGE TEMPORAL HOLE SIZE AND SOURCE DUTY CYCLE.

topology, quantifies the extent of this effect. It is apparent that in this case some receivers are used much more frequently than others (up to three times), leading to radically different receiver lifetimes. Thereby, one is interested in bounding the number of times that receivers will be utilized in a cycle, to ensure a minimum lifetime for all the network's receivers. However, setting a hard bound on the number of times a receiver can be used during a cycle can lead to inefficiencies. This is because the coverage of sources scheduled at the end of the cycle might be diminished due to the reduced number of feasible receivers. Instead, the probabilistic method described in Section III-B introduces a "soft" bound on receiver utilization.

Figure 5 compares this probabilistic method to a strict upper bound on receiver utilization. In both cases, we set the receiver upper bound to 5. The average temporal hole size for the probabilistic method is $\mu = 5.94$, compared to $\mu = 6.28$ for the strict method and $\mu = 5.66$ when no bounds are set. Finally, Figure 6 plots the duty cycle for all the receivers in

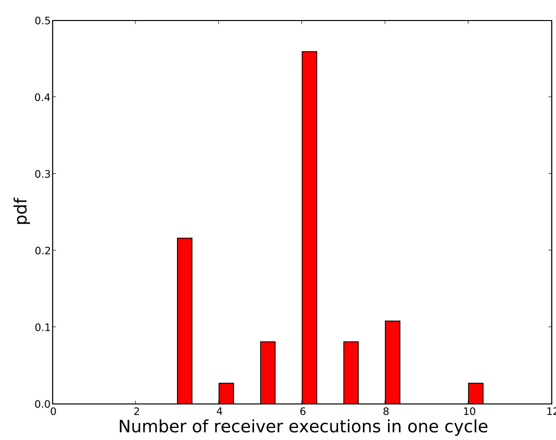

Fig. 4. PDF of the number of times a receiver is activated during a source activation cycle in the random topology.

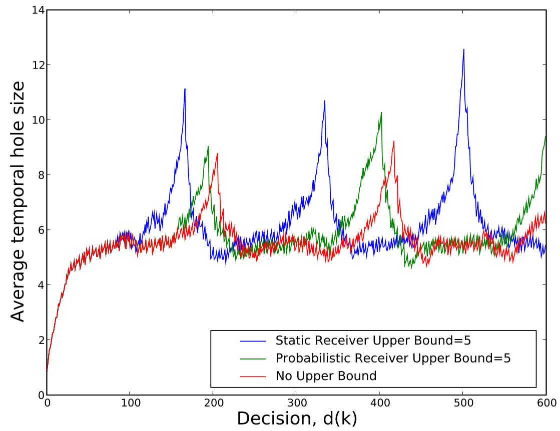

Fig. 5. Average receiver duty cycle for the probabilistic method in the random topology. Also shown is the receiver duty cycle when a strict bound is applied and when no bound is used. In all cases, $U = 3$ and the receiver bound is set to 5.

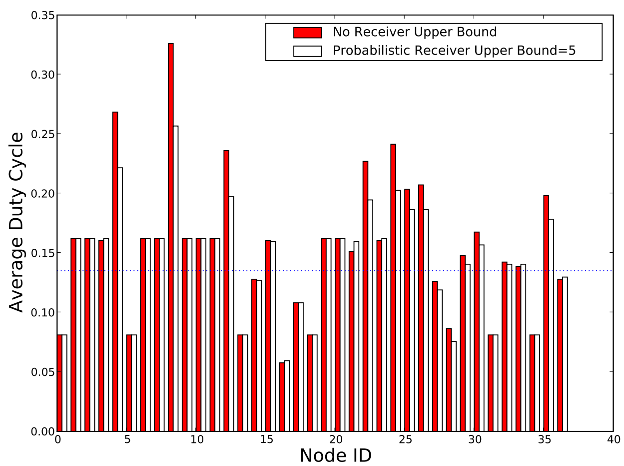

Fig. 6. Achieved receiver duty cycle for the probabilistic method in the random topology. Also shown is the ideal maximum duty cycle $\bar{\mu}_R = 0.135$, when the receiver bound is set to 5.

the random topology. It is evident that the probabilistic method reduces the duty cycle of the most heavily used receivers.

V. Summary

We formulate the problem of sensor scheduling in multi-static active sonar sensor networks and present algorithms that schedule both sources and receivers. The proposed algorithms achieve the desired duty cycles, while optimizing both the temporal and spatial coverage necessary for target detection. Even tough the simulation results shown above use a geometric coverage model derived from a simplified propagation model, the proposed approach is inherently geometry independent and can be applied to the scheduling of active sensors using more general (and possibly irregular) coverage models.

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