# Efficient Underwater Sensor Network Data Collection Employing Unmanned Surface Vehicles

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**Abstract**

An efficient underwater sensor network data collection scheme is presented, where an unmanned surface vehicle is utilized as a mobile data collector. Considering the properties of underwater acoustic channels between the unmanned surface vehicle and Underwater Sensor Nodes (USNs), we study how to minimize the maximum energy consumption of all USNs by jointly optimizing the path of the unmanned surface vehicle, the USN wake-up scheduling policy and the USN transmission powers, under the constraint that the unmanned surface vehicle collects a required amount of data from each USN. This problem is formulated as a mixed-integer, non-convex optimization problem. Due to its non-convexity and large practical problem size (i.e., the number of USNs and the transmission time slots), this problem cannot be handled effectively by existing algorithms in the literature or off-the-shelve optimization tools. This paper develops an efficient block-coordinate descent algorithm with low complexity to obtain a sub-optimal solution. Numerical results show that our algorithm is more energy-efficient compared with a certain heuristic solution.

**Index Terms**

Underwater data collection, unmanned surface vehicle, path planning, scheduling policy, block-coordinate descent

## I. Introduction

As an essential part of the Internet of Underwater Things (IoUT), Underwater sensor networks have many promising applications, such as marine environment monitoring, resource exploration,

The introduction of this work was based on our previous extended abstract published in the conference WUWNET'19 [1], but the methodologies and numerical simulations are conducted *only* for this final project.

and disaster forecast [2]–[4]. However, collecting data from Underwater Sensor Nodes (USNs) is a challenging task, especially for those deployed far from the land and several hundred up to thousand meters under the sea surface, due to both the communication and energy limitations.

When USNs are close to the coast, e.g., within 1 kilometer, it is possible to use cable and underwater communication technologies to collect the data directly to the land [5]. When USNs are far from the coast, it is not feasible to deploy cable to connect sensors nodes with land facilities. In this scenario, one approach is to employ sea surface buoys and satellites [6], where USNs send their data to satellites with the relay of the buoys, and the satellites further forward the data to the data receiver, but this approach usually has a high cost for both buoy deployment and satellite communications. Another approach is to deploy a multi-hop network using both underwater relay nodes and sea surface buoys [7], which can help to relay the data of USNs to the data receiver. This approach reduces the cost of using satellites, but incurs higher network infrastructure deployment and maintenance costs.

Motivated by the growing interest in employing unmanned vehicles for data collection in Unmanned Aerial Vehicles (UAVs) enabled wireless sensor networks [8], [9], this paper considers utilizing an unmanned surface vehicle to collect data in underwater sensor networks. Specifically, an unmanned surface vehicle equipped with underwater acoustic modems travels to areas close to USNs to collect data via acoustic communication between the ship and USNs, and then goes to the destination. This data collection scheme does not need to deploy any extra network infrastructure for data collection, and can be useful for regularly collecting a large amount of marine data, e.g., ocean pollution monitoring data. A typical Internet of Underwater Things employing the unmanned surface vehicle is presented in Figure 1.

There are two crucial facts to consider in the design of this underwater data collection scheme. The first is that USNs are powered by batteries which are expensive to recharge. Therefore, the energy cost of the scheme should be minimized to extend the lifetime of the USNs. To reduce the energy cost, we can schedule USNs to transmit data only in the wake-up state and control their transmission powers. The second is the properties of underwater acoustic communication channels between the unmanned surface vehicle and USNs. In particular, with transmission distance increasing, the path loss of acoustic communication channels increases exponentially and the useful communication bandwidth decreases [10]. Therefore, the path of the unmanned surface vehicle should be appropriately planned to reduce the transmission distance between the unmanned surface vehicle and the USNs during their wake-up state.

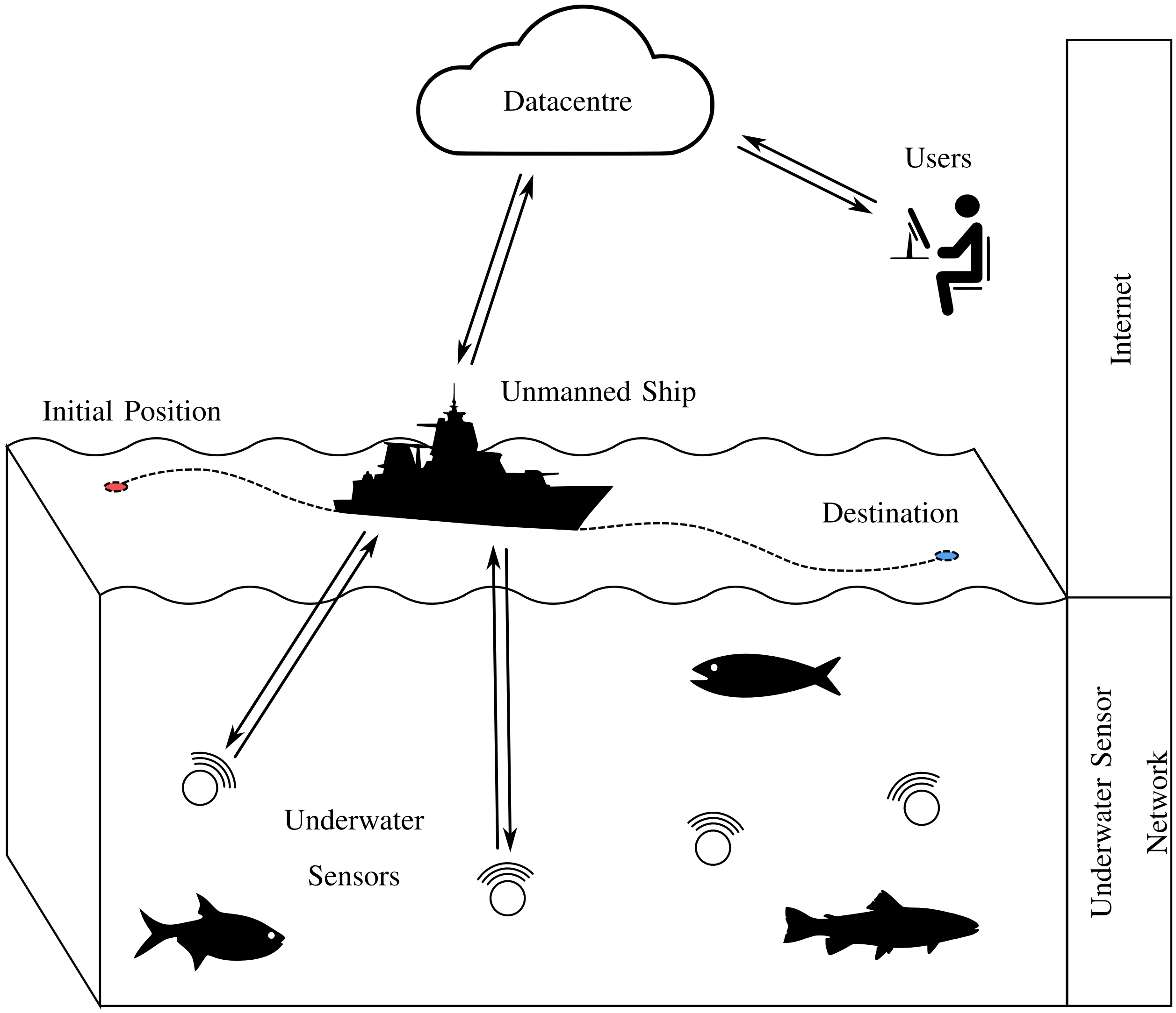



Fig. 1. Internet of Underwater Things

In this paper, the design of this underwater data collection scheme is formulated as an optimization problem that minimizes the maximum energy consumption of all USNs by the joint design of the unmanned surface vehicle path, the USN wake-up schedules, and the USN transmission powers. This formulated optimization problem is challenging due to its non-convexity and large problem sizes in terms of the number of USNs and the transmission time slots, so that it cannot be effectively solved by existing algorithms in the literature or off-the-shelve optimization tools. For example, due to the complicated underwater acoustic channel model considered in this paper, the optimization framework developed for the data collection in UAV enabled wireless sensor networks [8], [9] cannot solve our problem efficiently. We propose an efficient block-coordinate descent algorithm to obtain a sub-optimal solution of this problem with low complexity. Numerical results will show our algorithm also achieves better energy efficiency compared with certain heuristic solutions.

The remainder of this paper is organized as follows. The data collection problem and the corresponding optimization are discussed in Section II. The efficient block-coordinate descent algorithm is proposed in Section III. The numerical simulation results are presented in Section IV, and the paper is concluded in Section V.

## II. Problem Setup

We consider the data collection problem in an underwater sensor network, where an unmanned surface vehicle equipped with an underwater acoustic modem sequentially moves close to each of the Underwater Sensor Nodes (USNs) to collect data via acoustic communications. The goal is to save the energy consumption of USNs while ensuring the ship collects a required amount of data from each USN. In this section, we first review the underwater acoustic channel model between a USN and the unmanned surface vehicle, and then propose the system model together with the corresponding optimization problem for minimizing the maximum energy consumption among all USNs.

### A. Underwater Acoustic Channel Model

As a first step, we consider a simple model as the approximation of the general underwater acoustic channel, by adding the following assumptions. Assume that the acoustic modems equipped on the unmanned surface vehicle and all USNs work in the same channel with frequency $f$ and bandwidth $W$. The attenuation factor $A(d, f)$ of the channel for distance $d$ can be empirically modeled as [11]:

$$A(d, f) = (d/d_{\text{ref}})^k \alpha(f)^d \tag{1}$$

where $d_{\text{ref}}$ is the reference distance, $k$ is the spreading factor that defines the geometry of propagation (i.e., $k = 1$ is for cylindrical spreading, and $k = 1.5$ is for practical spreading), and $\alpha(f)$ is the absorption coefficient. The absorption coefficient can be expressed by using Thorp's formula (also empirically derived) [12]:

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

where $\alpha(f)$ is given in dB/km and $f$ is in kHz.

The underwater ambient noise power spectral density is [13]:

$$N(f) = N_t(f) + N_s(f) + N_w(f) + N_{th}(f) \tag{3}$$

where

$$\begin{aligned} 10\log N_t(f) =& 17 - 30\log f \\ 10\log N_s(f) =& 40 + 20(s-0.5) + 26\log f - 60\log(f+0.03) \\ 10\log N_w(f) =& 50 + 7.5w^{1/2} + 20\log f - 40\log(f+0.4) \\ 10\log N_{th}(f) =& -15 + 20\log f \end{aligned} \tag{4}$$

are the turbulence noise, the shipping noise with ship factor $s$, the waves noise with wave factor $w$, and the thermal noise, respectively.

We denote $S_k(f)$ as the power spectral density of the transmitted signal of the $k$-th underwater node, and we assume that all the nodes share the same transmission bandwidth $B$ with different powers $p_k$, i.e.,

$$p_k = B \cdot S_k(f) \tag{5}$$

Assume that the underwater ambient noise is Gaussian, and the channel is time-invariant for a time interval of communication. The underwater data transmission rate for the $k$-th node over distance $d$ can be approximated as [14]:

$$C(d,k) = \sum_i \log_2\left[1 + \frac{p_k/B}{N(f_i)A(d,f_i)}\right]\Delta f \tag{6}$$

where the channel is separated into a number of such channels each with sub-bandwidth $\Delta f$ and frequency $f_i$.

To simplify the model, the outage probabilities of underwater acoustic communication systems and some more complicated communication schemes will not be considered here. Moreover, we assume that $C(d,k)$ is the exact communication rate for the $k$-th node with distance $d$ in bits per second.

### *B. System Model*

Suppose that an unmanned surface vehicle is employed to collect data from $K$ USNs, where the location of the $k$-th USN is $\boldsymbol{l_k} = (l_{xk}, l_{yk}, l_{zk})$, where $l_{xk}$, $l_{yk}$ are the locations on horizontal coordinates, and $l_{zk}$ is the depth beneath the sea surface. Define the sea surface has zero depth, and the unmanned surface vehicle floats on the sea surface.

For ease of the path planning of the unmanned surface vehicle, the total time horizon $t_f$ is discretized into $M$ time slots equally, i.e., $t_f = M\delta$, with $\delta$ be the slot size. Denote the location of the unmanned surface vehicle at time slot $m$ as $\boldsymbol{q}[m]$, for $0 \leq m \leq M$. Suppose that the path sequence satisfies the initial and final location constraints:

$$\boldsymbol{q}[0] = \boldsymbol{q}_0, \quad \boldsymbol{q}[M] = \boldsymbol{q}_f. \tag{7}$$

Moreover, the speed of the unmanned surface vehicle is upper bounded by $V_{\max}$, which is equivalent to constraining the maximum distances of the unmanned surface vehicle can move in one time slot:

$$\|\boldsymbol{q}[m] - \boldsymbol{q}[m-1]\| \leq V_{\max}. \tag{8}$$

A wake-up mechanism [8] of USNs is employed, where at most one USN is waked up to connect with the unmanned surface vehicle during each time slot. Define the wake-up schedule of the $k$-th USN as $x_k[m]$, where $x_k[m] = 1$ when the $k$-th USN is waked up in the $m$-th slot, and $x_k[m] = 0$ otherwise. Therefore, the wake-up scheduling constraint can be represented as

$$\begin{cases} \sum_{k=1}^{K} x_k[m] \leq 1, & \forall m \\ x_k[m] \in \{0, 1\}, & \forall m, \forall k. \end{cases} \tag{9}$$

Suppose that the $k$-th node has $r_k$ bits of data to be collected. Let

$$R(p_k, \boldsymbol{q}[m]) = C(\|\boldsymbol{q}[m] - \boldsymbol{l}_k\|, k). \tag{10}$$

In order to collect the required amount of data from each USN,

$$\sum_{m=1}^{M} x_k[m] R(p_k, \boldsymbol{q}[m]) \geq b_k \triangleq \frac{r_k}{\delta W}, \quad k = 1, \ldots, K, \tag{11}$$

where $W$ denotes the channel bandwidth in Hz.

### C. Problem Formulation

Denote $\boldsymbol{p} = \{p_k, \forall k\}$, $\boldsymbol{q} = \{\boldsymbol{q}[m], \forall m\}$, $\boldsymbol{X} = \{x_k[m], \forall k, m\}$. Our goal is to minimize the maximum energy consumption among all USNs:

$$
\begin{aligned}
\min_{\boldsymbol{p},\boldsymbol{q},\boldsymbol{x}} \quad & \max_k \sum_{m=1}^{M} x_k[m] p_k \delta && \text{(12a)}\\
\text{s.t.} \quad & \|\boldsymbol{q}[m] - \boldsymbol{q}[m-1]\| \le V_{\max},\ \forall m && \text{(12b)}\\
& \boldsymbol{q}[0] = \boldsymbol{q}_0, \boldsymbol{q}[M] = \boldsymbol{q}_f && \text{(12c)}\\
& \sum_{k=1}^{K} x_k[m] \le 1, \quad \forall m && \text{(12d)}\\
& \sum_{m=1}^{M} x_k[m] R(p_k, \boldsymbol{q}[m]) \ge b_k, \quad \forall k && \text{(12e)}\\
& x_k[m] \in \{0, 1\}, \quad \forall k, \forall m. && \text{(12f)}
\end{aligned}
$$

Problem (12) is a mixed-integer problem with nonlinear and nonconvex constraints (e.g., the constraint (12e)). Similar problem setups have been systematically studied in [8], [9] in Unmanned Aerial Vehicles (UAVs) enabled wireless sensor networks. However, our problem in the underwater scenario is more challenging because of the complex underwater acoustic channel so that the approach in [8], [9] cannot handle constraint (12e).

To resolve the non-smoothness of the objective function of (12), we introduce an upper bound variable $\theta$ and split the objective into multiple smooth constraints as follows:

$$
\begin{aligned}
\min_{\boldsymbol{p},\boldsymbol{q},\boldsymbol{x},\theta} \quad & \theta && \text{(13a)}\\
\text{s.t.} \quad & \sum_{m=1}^{M} x_k[m] p_k \delta \le \theta, \quad \forall k = 1, \dots, K && \text{(13b)}\\
& (12b), (12c), (12d), (12e), (12f).
\end{aligned}
$$

To facilitate the efficient solution of (12) for practical large size, we propose a *block-coordinate descent* algorithm to get a sub-optimal solution.

## III. Block-Coordinate Descent Algorithm

We apply a block coordinate descent algorithm to optimize $\boldsymbol{x}, \boldsymbol{q}$, and $\boldsymbol{p}$ alternatively, i.e., we fix two out of $\boldsymbol{x}, \boldsymbol{q}$, and $\boldsymbol{p}$ and optimize the other one in each iteration.

### A. Wake-up Schedule Optimization

Firstly, for any given path planning $\boldsymbol{q}$ and the transmission power policy $\boldsymbol{p}$, the wake-up schedule solution can be obtained by solving the integer programming problem:

$$\begin{aligned} \min_{\boldsymbol{x},\theta} \quad & \theta \\ \text{s.t.} \quad & (12d), (12e), (12f), (13b) \end{aligned} \tag{14}$$

which is a mixed-integer disciplined convex problem, and can be solved efficiently by off-the-shelf software, e.g., CVX.

### B. Path Planning Optimization

For any given wake-up schedule $\boldsymbol{x}$ and transmission power policy $\boldsymbol{p}$, the objective function is fixed. Similar as in [8], we find a feasible path planning that satisfies certain data rate contraints:

$$\max_{\boldsymbol{q},\eta} \quad \eta \tag{15a}$$

$$\text{s.t.} \quad (12b), (12c)$$

$$\frac{1}{b_k}\sum_{m=1}^{M} x_k[m] R(p_k, \boldsymbol{q}[m]) \geq \eta, \ \forall k = 1, \ldots, K. \tag{15b}$$

Problem (15) is a non-convex optimization problem due to the non-convex constraints (15b). We solve its penalty form instead by adding the inequality constraints violations of (15b) into the objective:

$$\max_{\boldsymbol{q},\eta} \quad \eta - \lambda \sum_{k=1}^{K} \left( \eta - \frac{1}{b_k} \sum_{m=1}^{M} x_k[m] R(p_k, \boldsymbol{q}[m]) \right)^{+} \tag{16a}$$

$$\text{s.t.} \quad (12b), (12c)$$

where $\lambda > 0$ is a penalty parameter to be chosen. We develop a customized algorithm to solve this problem based on the successive convex optimization (SCA) technique [15]. The overall algorithm is proposed in Algorithm 1.

The SCA-based algorithm includes two steps in each iteration. The details of these two steps are as follows:

*a) Step 1: Convex Approximation of (16):* In each iteration $\ell$, we first obtain a convex approximation of (16). Let $\boldsymbol{q}^{(\ell)} = \{\boldsymbol{q}^{(\ell)}[m], \forall m\}$ denote the given path in the $\ell$-th iteration. Since evaluating derivatives for the penalty term in (16a) is difficult, it is not feasible to approxiamte (16a) with a concave function by Taylor expansion. Instead, a *partical method* [16] is employed to obtain an affine appoximation of the penalty term in (16a). Given the path $\boldsymbol{q}^{(\ell)}$ together with the trust region $\mathcal{T}^{(\ell)} \triangleq \{\boldsymbol{q} \mid \|\boldsymbol{q} - \boldsymbol{q}^{(\ell)}\|_\infty \le \rho^{(\ell)}\}$ with $\rho^{(\ell)}$ adaptively updated, sample points $\tilde{\boldsymbol{q}}^{1,(\ell)}, \tilde{\boldsymbol{q}}^{2,(\ell)}, \dots, \tilde{\boldsymbol{q}}^{S,(\ell)}$ uniformly over the trust region $\mathcal{T}^{(\ell)}$. Fix $k$ and $m$, we approximate $R(p_k, \boldsymbol{q}[m])$ defined in (10) with an affine function $f_{k,m}^{(\ell)}(\boldsymbol{q}[m])$ such that

$$f_{k,m}^{(\ell)}(\boldsymbol{q}^{(\ell)}[m]) = R(p_k, \boldsymbol{q}^{(\ell)}[m]) \tag{17a}$$

and the quadratic error presented below is minimized:

$$\min_{f_{k,m}^{(\ell)}} \quad \sum_{s=1}^{S} \left( f_{k,m}^{(\ell)}(\tilde{\boldsymbol{q}}^{s,(\ell)}[m]) - R(p_k, \tilde{\boldsymbol{q}}^{s,(\ell)}[m]) \right)^2 \tag{17b}$$

Such a function can be found by solving the KKT system [17].

For each $k$ and $m$, substituting $R(p_k, \boldsymbol{q}[m])$ with $f_{k,m}^{(\ell)}(\boldsymbol{q}[m])$ in (16a), we obtain an affine approximation of the objective function, which makes this problem convex. As the approximation is only validated in the trust region $\mathcal{T}^{(\ell)}$, an extra norm constraint is added:

$$\begin{aligned} \max_{\boldsymbol{q},\eta} \quad & \eta - \lambda \sum_{k=1}^{K} \left( \eta - \frac{1}{b_k} \sum_{m=1}^{M} x_k[m] f_{k,m}^{(\ell)}(\boldsymbol{q}[m]) \right)^+ && (18a) \\ \text{s.t.} \quad & (12b), (12c) \\ & \boldsymbol{q} \in \mathcal{T}^{(\ell)} && (18b) \end{aligned}$$

*b) Step 2: Solving for the Convex Approximation:* For fixed iteration $\ell$, since the objective is a linear function with respect to $\boldsymbol{q}[m]$ and $\eta$, the problem (18) is a convex quadratically constrained quadratic program (QCQP), which can be solved efficiently by existing solvers such as MOSEK [18]. Denote the optimal solution of (18) as $\tilde{\boldsymbol{q}}$, and the corresponding objective value for (16) and (18) as $\phi^{(\ell)}$ and $\hat{\phi}^{(\ell)}$. The trust region radius for $\mathcal{T}^{(\ell+1)}$ is updated in the same way of the traditional trust region method technique [19, section 2.5]:

$$\rho^{(\ell+1)} = \begin{cases} \beta^{\text{succ}} \rho^{(\ell)}, & \text{if } \delta^{(\ell)} \ge \alpha \cdot \hat{\delta}^{(\ell)} \\ \beta^{\text{fail}} \rho^{(\ell)}, & \text{if } \delta^{(\ell)} < \alpha \cdot \hat{\delta}^{(\ell)} \end{cases} \tag{19}$$

where $\delta^{(\ell)} = \phi^{(\ell)} - \phi^{(\ell-1)}$, $\hat{\delta}^{(\ell)} = \hat{\phi}^{(\ell)} - \phi^{(\ell-1)}$, and we set $\alpha = 0.1, \beta^{\text{succ}} = 1.1, \beta^{\text{fail}} = 0.5$. Moreover, we update the trajectory policy $\boldsymbol{q}^{(\ell+1)} = \tilde{\boldsymbol{q}}$ if $\delta^{(\ell)} \geq \alpha \cdot \hat{\delta}^{(\ell)}$, and $\boldsymbol{q}^{(\ell+1)} = \boldsymbol{q}^{(\ell)}$ if otherwise.

In summary, the non-convex problem (15) can be approximately solved by optimizing its penalty form (16). Based on the SCA technique, (16) is solved by iteratively solving the convex approximation (18), and updating the trust region center $\boldsymbol{q}^{(\ell)}$ and radius $\rho^{(\ell+1)}$. The overall algorithm description is summarized in Algorithm 1.

**Algorithm 1** SCA for solving problem (15)

**Require:** Wake-up schedule $\boldsymbol{x}$ and transmission power policy $\boldsymbol{p}$;

Initialize the path as $\boldsymbol{q}^0$, and trust region radius $\rho^{(0)}$;
Set $\ell \leftarrow 0$ and tolerance tol $> 0$;
**repeat**
    For fixed $k, m$, approximate $R(p_k, \boldsymbol{q}[m])$ with the affine approximation $f_{k,m}^{(\ell)}$ by considering (17a) and (17b).
    Solve for the QCQP subproblem (18) for given $\boldsymbol{q}^{(\ell)}$.
    Update $(\boldsymbol{q}^{(\ell+1)}, \rho^{(\ell+1)})$ by the trust region rule.
    $\ell \leftarrow \ell + 1$.
**until** predefined stopping condition is satisfied.

**Ensure:** The optimized path planning $\boldsymbol{q}$.

**Algorithm 2** Iterative Algorithm for Problem (13)

Initialize the path as $\boldsymbol{q}^0$, and the transmission powers policy as $\boldsymbol{p}^0$;
Set $t \leftarrow 0$ and tolerance tol $> 0$;
**repeat**
    Solve the subproblem (14) for given $\boldsymbol{q}^t$ and $\boldsymbol{p}^t$, and denote the optimal solution as $\boldsymbol{x}^{t+1}$;
    Solve the subproblem (16) for given $\boldsymbol{x}^{t+1}$, and denote the optimal solution as $\boldsymbol{q}^{t+1}$;
    Solve the subproblem (18) for given $\boldsymbol{q}^{t+1}$ and $\boldsymbol{x}^{t+1}$, and denote the optimal solution as $\boldsymbol{p}^{t+1}$;
    $t \leftarrow t + 1$
**until** the fractional decrease of the objective value of (14) is below tol.

### C. Transmission Powers Optimization

Finally, given the wake-up schedule $\boldsymbol{x}$ and path $\boldsymbol{q}$, the transmission policy $\boldsymbol{p}$ is obtained by solving the subproblem

$$\begin{aligned} \min_{\boldsymbol{p},\theta} \quad & \theta \\ \text{s.t.} \quad & (13b), (12e). \end{aligned} \tag{20}$$

The closed-form solution of (20) is given by:

$$\theta^* = \max_{k=1,\dots,K} p_k^* \cdot \left( \sum_{m=1}^{M} x_k[m] \cdot \delta \right), \tag{21a}$$

where $\{p_k^*, \forall k\}$ are the solutions to the nonlinear system

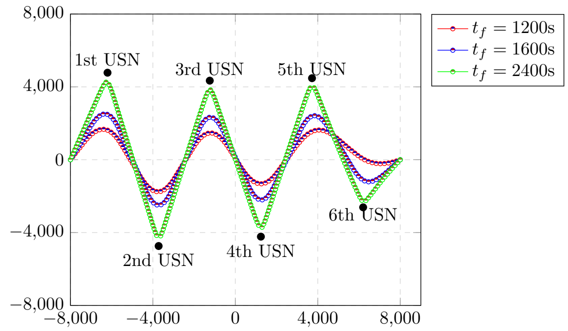
$$\sum_{m=1}^{M} x_k[m] \cdot R(p_k, \boldsymbol{q}[m]) = b_k, \ \forall k. \tag{21b}$$

The overall algorithm for solving the relaxed mixed-integer problem (13) is by alternatively minimizing the wake-up scheduling $\boldsymbol{x}$, the unmanned surface vehicle's path $\boldsymbol{q}$, and the transmission policy $\boldsymbol{p}$ via solving the subproblems (14),(16), and (18) respectively, in an iterative manner, which is summarized in Algorithm 2.

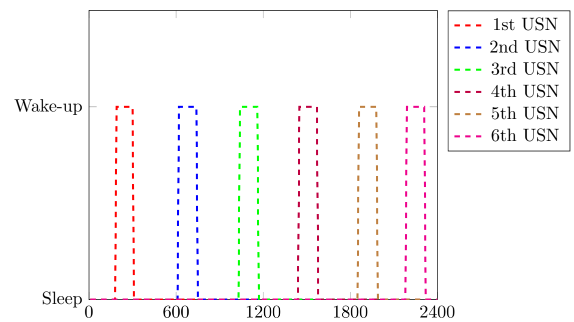
### D. Overall Algorithm and Convergence

It is worth noting that for classical block coordinate descent method, the subproblem in each iteration is required to be solved exactly with optimality in order to guarantee the convergence [20]. However, in our case, for the trajectory optimization subproblem (16), we only solve the approximated problem (18) for several iterations. therefore, the convergence analysis for the classic block coordinate descent method cannot be applied.

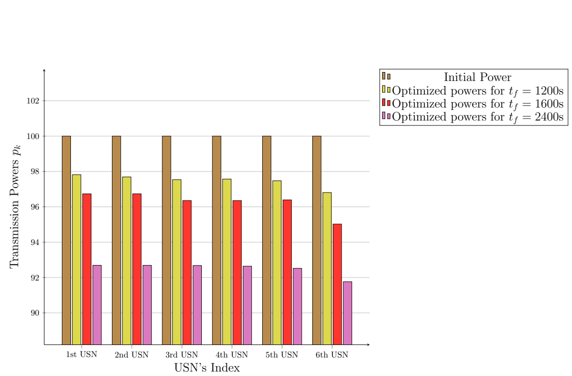
Now we discuss the convergence results of the purposed Algorithms as follows. It can be verified from (17a) that the optimal solution obtained in the $\ell$-th iteration is feasible for in $(\ell+1)$-th iteration for solving subproblem (18), which implies that the optimal value for (16) is non-decreasing with iteration index $\ell$. Therefore, the purposed Algorithm 1 is guaranteed to converge. Moreover, the optimal solution obtained in the $t$-th iteration is feasible in $(t+1)$-th iteration for the iterative algorithm for solving problem (13), which implies that the optimal value for (16) is non-decreasing with iteration index $t$. Since a monotone increasing and bounded above sequence will converge to its supremum, the purposed Algorithm 2 are also guaranteed to converge.



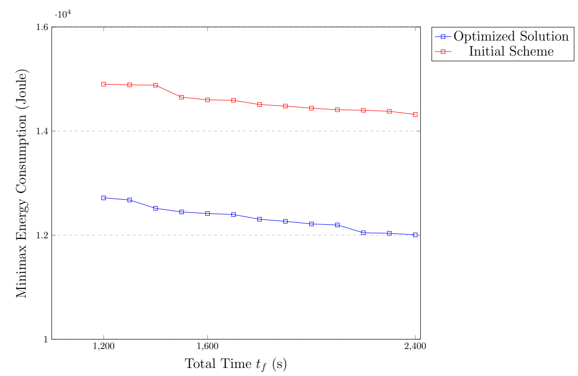

(a) The unmanned ship's path;




(b) Wake-up schedule of USNs with total time $t_f = 2400$s;




(c) Transmission powers of USNs;




(d) $\theta$ versus travel time $t_f$.

Fig. 2. Simulation results for optimized solutions compared with certain heuristic solutions.

## *E. Trajectory Initialization*

In this subsection, we propose a low-complexity trajectory initialization scheme for Algorithm 2 based on the simple piecewise linear trajectory. Specifically, the initial USV trajectory is set to be piecewise linear with $K+1$ segments and $K$ break points $\{\boldsymbol{m}_1, \boldsymbol{m}_2, \ldots, \boldsymbol{m}_K\}$, with the USV speed taking a constant value $V$, where $0 < V \leq V_{\max}$. To balance the tradeoff between the time limit and data collection task, we determine the break points to make it as close to targeted USNs under the maximum traveling distance constraint. In other words, these break points can be obtained by solving the linear programming problem:

$$\begin{aligned}
\min_{\{\boldsymbol{m}_1, \boldsymbol{m}_2, \ldots, \boldsymbol{m}_K\}} \quad & \sum_{k=1}^{K} \|\boldsymbol{m}_k - \boldsymbol{l}_k\|_1 \\
\text{s.t.} \quad & \sum_{k=0}^{K} \|\boldsymbol{m}_{k+1} - \boldsymbol{m}_k\| \leq d_{\max} \triangleq \frac{t_f}{V_{\max}} \\
& \boldsymbol{m}_0 = \boldsymbol{q}_0, \quad \boldsymbol{m}_{K+1} = \boldsymbol{q}_f.
\end{aligned}$$

## IV. Numerical Results

Numerical results[1] are provided to demonstrate the effectiveness of our prosed algorithm. We consider a system with $K = 6$ USNs, which are randomly located within an area of size $16 \times 16 \times 0.2\text{km}^2$. The unmanned ship's initial and final locations are set as $\boldsymbol{q}_0 = [-8000, 0, 0]^{\mathrm{T}}$ and $\boldsymbol{q}_f = [8000, 0, 0]^{\mathrm{T}}$ in meter. Furthermore, we set $\delta = 10\text{s}, V_{\max} = 20$m/s, $r_k = 10$ Mbits for all $k$, and $d_{\text{ref}} = 10$m. For the purposed SCA algorithm 1, the penalty parameter $\lambda = 30$. The iteration of algorithm 1 is terminated if the iteration number is larger than 30 or the fractional increase of the objective value of (16) is below tol $:= 10^{-8}$. The USNs' initial transmission power policy is set to be $\{P_k = 100\text{W},\ \forall k\}$, and the initial trajectory is set as in Section III, part E. This initialization is also used as the benchmark to compare with our optimized design of the underwater data collection scheme.

Fig. 1 shows the results of our proposed algorithm based on one instance of the sensor's locations. Specifically, Fig. 1(a) shows the optimal trajectory planning of the USV under total traveling time $t_f = 1200\text{s}, 1600\text{s}, 2400\text{s}$, in which the coordinates denote the horiztonal locations of the ship. It's observed that as the total traveling time $t_f$ increases, the USV moves closer to sensors. Fig. 1(b) shows the wake-up scheduling of USNs under the case $t_f = 2400\text{s}$, which reveals that USNs remain sleep for most of the time unless the ship moves sufficiently close to them. Fig. 1(c) shows the optimized transmission powers of USNs under total traveling time $t_f = 1200\text{s}, 1600\text{s}, 2400\text{s}$, which are smaller compared with the initial scheme. Therefore, the USNs can finish the data transmission task with less transmission time and lower transmission power, which saves their energy consumptions. Fig. 1(d) shows the minimax energy consumption of USNs for our proposed algorithm compared with the initialization, under different traveling time constraints. It's observed that our design of data collection of the unmanned ship can significantly decrease energy consumption.

## V. Conclusion

In this paper, we introduced a data collection scheme for USNs employing an unmanned ship. The joint design of the path planning of the unmanned ship, the wake-up scheduling policy and the transmission power policy of USNs is proposed to minimize the maximum energy consumption of USNs. An efficient block-coordinate descent algorithm has been developed to

[1]The MATLAB code for the numerical results is available on the website https://walterbabyrudin.github.io/

solve this design problem, which is non-convex and has a large number of optimization variables. The numerical results show that our design can outperform a certain heuristic solution. This paper also motivates several research directions in the future:

- Firstly, since the ocean disturbance cannot be ignored, it is necessary to design an efficient algorithm for the online trajectory planning of USVs;
- Secondly, it is important to extend this work to scenarios with multiple unmanned ships;
- Thirdly, it is interesting to consider the scheme where some USNs may act as relay nodes to help others transmit their data to the unmanned ship, which may further outperform the current schemes.

We wish to address these open problems in future work.

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