Rendezvous Planning for Multiple AUVs With Mobile Charging Stations in Dynamic Currents

Bingxi Li, Brian R. Page, John Hoffman, Barzin Moridian, and Nina Mahmoudian

***Abstract*—Operation of autonomous underwater vehicles (AUVs) in large spatiotemporal missions is currently challenged by onboard energy resources requiring manned support. With current methods, AUVs are programmed to return to a static charging station based on a threshold in their energy level. Although this approach has shown success in extending the operational life, it becomes impractical due to interruption of AUV operation and loss of energy needed to return to charging station. It is also not practical for large networks due to shortage of charging stations. We introduce mobile onsite power delivery, which will fundamentally change the range and duration of underwater operations. This letter presents a mission planning method to generate mobile charger trajectories, given pre-defined working AUV trajectories, considering environmental constraints such as currents and obstacles. The problem is formulated as a multiple generalized traveling salesman problem, which is then transformed into a traveling salesman problem. Energy cost in dynamic currents is integrated with a path planning algorithm using a grid-based environment model. A scheduling strategy extends the problem over multiple charging cycles. Simulation results show that the planning method significantly improves mission success and energy expenditure. Field experiments in Lake Superior using two types of AUVs, an unmanned surface vessel, and a manned support vessel validate the feasibility of the planned trajectories for long-term marine missions.**

***Index Terms*—Marine robotics, planning, scheduling and coordination, energy replenishment, mobile charging stations, autonomous underwater vehicles (AUVs).**

I. Introduction

AUTONOMOUS Underwater Vehicles (AUVs) have been adopted as both replacements for dangerous tasks and as solutions to once impossible ones, due to their clear cost and size advantage over traditional manned craft. For example, efforts in oceanographic surveying and meteorology as well as Naval mine sweeping have been aided by teams of independent robotic workers. The autonomous operation, high endurance, and small footprint of these vehicles have made them incredibly useful in recent times for operation in remote areas. However, the battery capacity and recharging needs have considerably hindered their persistent operation.

To overcome energy limitations, existing solutions aim to automate the recharging process and increase AUV network performance via multiple static wireless charging stations [1]–[3]. This type of autonomous energy replenishment is appropriate for missions that have restricted mission areas, such as surveillance and monitoring missions. However, the charging stations are still static in nature. This limits the total operational area of the vehicles by requiring them to expend energy on a return voyage to charge. Moreover, static charging stations are expensive to deploy and recover, limiting scalability for larger networks.

Although static charging systems improve the availability of energy to AUVs, there are still drawbacks associated with such a system. These drawbacks can be addressed by employing charging stations that autonomously reposition within the environment and connect to the working vehicle, fully recharge it, safely disconnect, and rendezvous with the next vehicle that needs recharging [4], [5]. Docking between a free floating dock and a REMUS 600 has been tested in [4]. It shows the possibility that a floating dock being towed by another vehicle can be adapted to an underwater mobile docking platform. Pyle et al. explored the potential of using a large AUV (Proteus) as a mobile docking/recharging station [5]. Proteus travels with working AUVs and is capable of charging two of them simultaneously. Their work combines an area coverage and an energy-depended control methodology to drive each AUV toward Proteus before the energy level becomes critical. Another effort on developing a system that facilitate autonomous docking and recharging is our other work on design of charging stations [6], [7]. This collapsible underwater docking system is light-weight and has a potential to be installed on Unmanned Surface Vehicles (USVs) (Fig. 1) or AUVs to convert these vehicles to mobile power delivery systems. Fig. 1 illustrates an area coverage scenario where two USVs are serving as mobile charging stations.

With the great promise for underwater charging, effectively allocating resources to achieve a mission becomes increasingly difficult. While there are no existing methods for underwater rendezvous planning with mobile docks, rendezvous planning for recharging has been extensively studied in other domains [8]–[10]. In air to ground recharging scenarios, ground vehicles are usually used as energy carrying agents to rendezvous with and charge aerial vehicles periodically for long-term operation.

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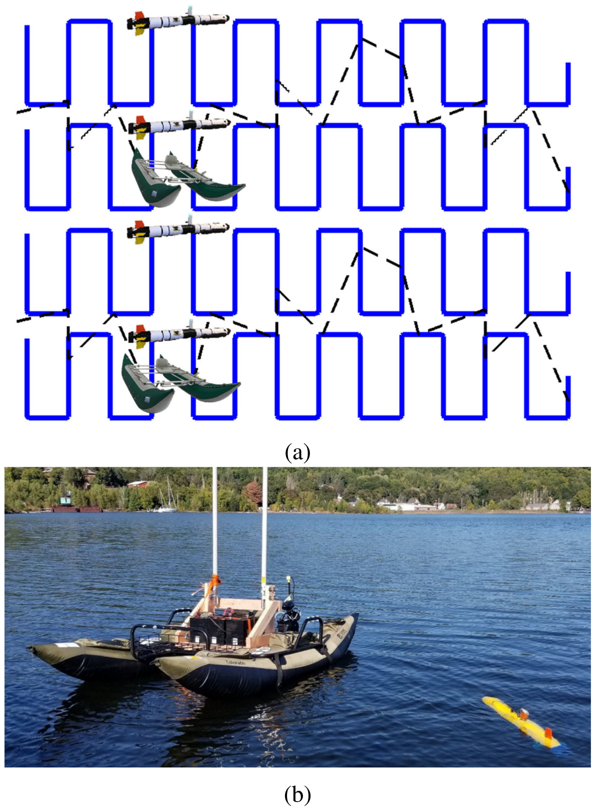


Fig. 1. (a) Illustration of an area coverage mission where four AUVs are following lawnmower trajectories in blue and two USVs are used as mobile charging stations following dashed lines trajectories and meeting rendezvous locations. (b) The AUV and USV used in one of the field experiments.

Paths of aerial and ground vehicles are found with heuristic [9] and optimal [10] methods. Multiple ground robots rendezvous planning for recharging with pre-defined UAV trajectories are also solved with both heuristic and optimal methods [8]. However, none of these methods are applicable to underwater scenarios where environmental constraints (such as currents and obstacles) impact missions and need to be accounted for.

Planning and scheduling of underwater vehicles requires a precise understanding of the environment. The main forces to consider in the underwater domain are local currents which can affect a vehicle's heading or cause drift. The performance and path planning of AUVs under complex current conditions are studied extensively [11]–[13]. These methods fail to take energy limitations into account, and therefore the practical problem of energy depletion remains. Path planning for AUV rendezvous has also been developed while considering energy limitations and being aware of the dynamic currents and obstacles [14], [15]. However, neither methods are scalable for missions that have a large operational area or require quick completion because they only consider a single rendezvous.

This letter addresses the need for an energy-aware underwater planning architecture for collaborative AUV missions. Mission planning in the marine environment is challenged by environmental conditions as well as the extended time necessary for rendezvous and charging compared to aerial or ground operations.

These rendezvous and charging periods propagate in time and add to the complexity of planning for recharging attempts further in the future. This letter extends the prior work on scheduling and planning persistent missions [8] to underwater scenarios by including real-world constraints with non-instantaneous rendezvous and recharging.

This letter contributes a scheduling and planning method for mobile charging stations to rendezvous and recharge AUVs that are moving along pre-defined trajectories. The focus is on overcoming the energy limitations of AUVs through a scalable and robust distributed network of mobile on-site power delivery vehicles considering environmental constraints. A graph transformation method is applied to formulate the problem into an Multiple Generalized Traveling Salesman Problem (MGTSP) and then into a Traveling Salesman Problem (TSP). The energy cost for multiple mobile charging stations under the effect of dynamic currents and obstacles are considered by a grid-based path planning method. To integrate the current effect into path planning, travel time of mobile charging stations is calculated within a discretized model of the environment containing obstacle and current information. The transformed problem is then solved using a LinKernighan Heuristic (LKH) method. A strategy to extend MGTSP to include multiple charging cycles is developed. The rendezvous points and trajectories for mobile power delivery vehicles are provided through the proposed method, which allows the system to better scale with the number of tasks, the number of AUVs, and the available recharging resources. The proposed method is simulated and evaluated using the realistic mission scenarios. The method is verified through simulation of realistic mission scenarios including non-instantaneous charging period and multi-cycle recharging of multiple AUVs. Simulation results demonstrated higher reliability and energy efficiency of our method with real-world considerations. Field experiments with two types of AUVs featuring multiple rendezvous with mobile power delivery system also validated the implementation of the proposed method for underwater applications.

The defined problem with proposed approach is introduced in Sec. II. The simulation results and discussion are detailed in Sec. III. Field experiments showing the implementation of the work are reported in Sec. IV. Sec. V summarizes the conclusion and future works.

II. Multi-AUV Rendezvous and Recharging Planning Problem

In this section, we define the problem of finding the energy efficient paths and recharge scheduling for a team of mobile chargers to rendezvous with and charge a team of primary working AUVs. A graph transformation taking the effect of dynamic currents and obstacle areas into account is proposed to solve the problem. We make the following assumptions:

- The location of obstacles and a model of the dynamic currents in the environment is pre-known.
- The number of AUVs and mobile chargers is chosen by the user.
- The AUVs follow pre-defined trajectories during the mission and have the same configurations.

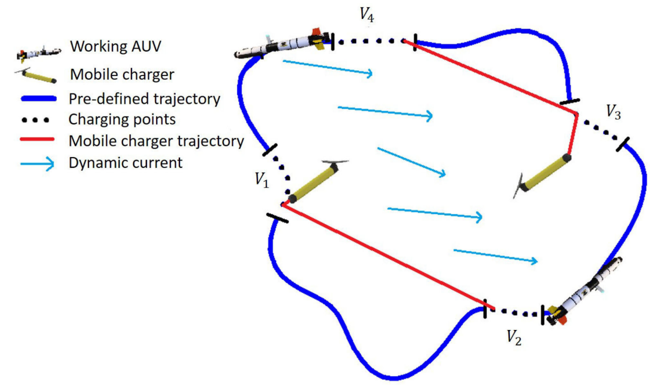


Fig. 2. Problem illustration of finding paths and scheduling rendezvous for two underwater mobile charging stations to meet two AUVs twice, which follow the pre-defined trajectories of a surveillance mission under the effect of dynamic currents.

- All mobile chargers are homogeneous (same maximum speed and charge rate) with unlimited energy.
- The recharging process takes a fixed period of time for each rendezvous and is only allowed after the the battery level of an AUV drops below a threshold level.

Given a two-dimensional mission area where a team of W AUVs are deployed, C mobile chargers need to rendezvous with and recharge the AUVs within the charging window. The charging window is defined as the part of trajectories that the vehicles traverse with battery levels below the threshold value.

The charging windows are then discretized into charging points $p_i(t), i \in \{1, \ldots, W\}, t \in \mathbb{R}^+$. The mission area including obstacles and currents is also discretized into uniform cells, based on the fidelity of currents model. Mobile chargers need to rendezvous with AUVs and charge them by visiting one point in each charging window for a Δt period of time.

A directed graph $\mathbb{G}(V, A, \mathfrak{R}(x, y, t), \mathfrak{B}(x, y))$ is constructed, where V is the set of vertices, A is the set of edges, $\mathfrak{R}(x, y, t)$ is the model of currents, and $\mathfrak{B}(x, y)$ represents the obstacle area, where $x, y \in \mathbb{R}$ are the coordinate of the cell and $t \in \mathbb{R}^+$ is the time. Vertices set V contains disjoint subsets $V_1, \ldots, V_l, l \in \mathbb{R}^+$. Each subset contains charging points in each charging window. Edges between two vertices are established with a direction from the first vertex to the second one. Edge costs associated with the edges are the energy costs of mobile chargers traveling from one vertex to the other, based on obstacle $\mathfrak{B}(x, y))$ and currents $\mathfrak{R}(x, y, t)$ model.

We define the multiple AUV rendezvous planning problem as finding a set of paths $\{P_1, \ldots, P_C\}$ of mobile chargers on graph $\mathbb{G}(V, A, \mathfrak{R}(x, y, t), \mathfrak{B}(x, y))$ collectively visiting all vertex subsets $V_1, \ldots, V_l$ (charging windows) once with minimum energy cost. The example of using two mobile chargers to support two AUVs is illustrated in Fig. 2. It should be noted that the charging windows on a trajectory of an AUV are not pre-defined for the duration of the mission, but depends on the last rendezvous time and relies on the planned schedule.

To solve the proposed multiple AUV rendezvous planning problem with environmental constraints, which can be formulated as a Multiple Generalized Traveling Salesman Problem

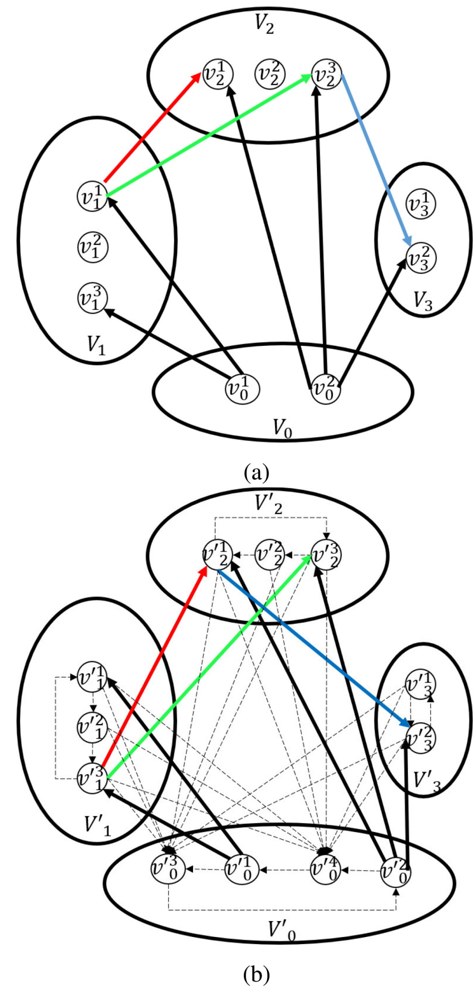


Fig. 3. Modified Noon-Bean Transformation illustration using a scenario with three AUVs and two mobile chargers. (a) Proposed MGTSP problem. (b) Transformed problem from (a) using modified Noon-Bean Transformation. Dashed lines indicate created zero-cost edges. Moved edges are indicated by the same color. For clarity of the presentation, not all edges are shown in the figures.

(MGTSP), we use a modified Noon-Bean transformation to convert MGTSP into a standard TSP. This method is described in detail in [8].

The MGTSP on graph $\mathbb{G}(V, A, \mathfrak{R}(x, y, t), \mathfrak{B}(x, y)$ is shown in Fig. 3a. V_0 is the vertex subset with initial positions of two mobile chargers v_0^1 and v_0^2. The goal is to find a set of paths starting from V_0 collectively visiting V_1, V_2, and V_3 exactly once with the lowest cost. A new graph $\mathbb{G}'(V', A', \mathfrak{R}(x, y, t), \mathfrak{B}(x, y)$ is used to represent the transformed TSP (Fig. 3b). V' has the same vertices as V in addition to vertices ${v'}_0^3$ and ${v'}_0^4$ indicating the finish vertices. Zero-cost edges from vertices in V'_1, V'_2, and V'_3 ending at ${v'}_0^3$ and ${v'}_0^4$ are added to the graph (dashed lines between subsets). The addition of ${v'}_0^3$ and ${v'}_0^4$ and their zero-cost edges allow constructing a large TSP path from multiple smaller paths that are concatenated together. In this example, two separate paths construct the total TSP path, one ending at ${v'}_0^3$ and the other at ${v'}_0^4$. The zero-cost edges are added within V'_0 to construct a directed cycle with vertices ordered alternating between start and end vertices (e.g., $\{{v'}_0^1, {v'}_0^3, {v'}_0^2, {v'}_0^4\}$). Vertices in V'_1, V'_2, and V'_3 are connected together using zero-cost

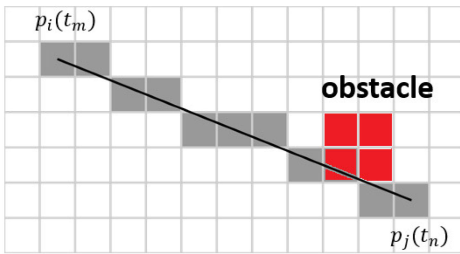


Fig. 4. Illustration of calculating the edge cost of an edge between two vertices (charging points) and detecting obstacles.

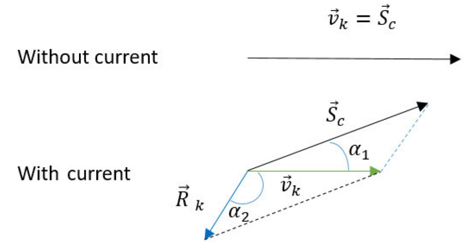


Fig. 5. The current changes direction of the travel of a mobile charger. α_1 is the angle between the desired travel direction and the mobile charger's heading, and α_2 is the angle between the desired travel direction and the current.

edges to form a directed single cycle. In V'_1, V'_2, and V'_3, the inter-set edges for each vertex are moved to the previous one in those cycles. For example, moved edges in Fig. 3a and Fig. 3b are indicated by the same color. Finally, except for edges ending at v'^3_0 and v'^4_0, penalty is added to all the edges between each subsets' vertices (bold edges in the figure) to encourage the path to go through the subset cycles before moving to another subset.

A LinKernighan Heuristic (LKH) solver is implemented to find a heuristic solution to the converted TSP problem on graph $\mathbb{G}'(V', A', \mathfrak{R}(x,y,t), \mathfrak{B}(x,y)$. LKH is a well-known heuristic solver for TSP [16]. A feasible path can be found by a nearest-neighbor algorithm at the beginning. Then, LKH exchanges sub-paths by iterations. In each iteration, a sub-path visiting a chosen number of points will be replaced by a new sub-path with the same number of points visited. To improve the efficiency, the new sub-path needs to meet some criterion such as feasible and sequential check. LKH keeps finding shorter total paths until no improvement is made by exchanging sub-paths. When the LKH solver stops, the output of the TSP solver is then translated to the solution of the proposed problem.

To realize underwater long-term autonomy, we provide our method to calculate the edge costs for A' considering environmental constraints. In the following subsections, we use a grid-based energy cost evaluation to account for the effect of dynamic currents and obstacles (Sec. II-A). A method to solve the multi-cycle recharging problem is also developed (Sec. II-B).

A. Dynamic Currents Integration

For every edge in A', we find N cells along the edge to estimate the time required to travel through them. If none of the cells are obstacle cells ($\mathfrak{B}(x,y)$), the time for traveling through each cell is added up, otherwise a large value is assigned to the edge as a penalty. We find the estimated travel energy $E_{m,n}$ for a mobile charger traveling between two charging points $p_i(t_m)$ and $p_j(t_n)$ (where $i, j \in \{1, \ldots, W\}$ and $m, n \in \mathbb{R}^+$) as shown in the Fig. 4, where t_m and t_n are the time that AUVs i and j arrive at those charging points.

For cell $k \in \{1, \ldots, N\}$, we apply the current model at the time of a mobile charger's visit to this cell based on the mobile charger's speed. We calculate the global speed $\vec{v_k}$ of a mobile charger under the currents by calculating the water referenced velocity vector $\vec{S_c}$ and the current vector $\vec{v_k} = \vec{S_c} + \vec{R_k}$, where $\vec{R_k} = \mathfrak{R}(x, y, t_k)$, and t_k is the time spent visiting cell k. The velocity of a mobile charger under the current effect ($\|\vec{v_k}\|$) at time t_k can be calculated as

$$\|\vec{v_k}\| = \cos\alpha_1 \|\vec{S_c}\| + \cos\alpha_2 \|\vec{R_k}\|, \tag{1}$$

$$\alpha_1 = \arcsin(\sin\alpha_2 \|\vec{R_k}\| / \|\vec{S_c}\|), \tag{2}$$

where α_1 is the angle between the desired travel direction $\vec{v_k}$ and the mobile charger's heading, and α_2 is the angle between the desired travel direction and the current's direction $\vec{R_k}$ as illustrated in Fig. 5.

The energy cost for this cell $e_k, k \in \{1, \ldots, N\}$ is linear with the travel time of the mobile charger,

$$e_k = \frac{c\,||p_i(t_m) - p_j(t_n)||}{N\|\vec{v_k}\|}, \tag{3}$$

where c is a constant specifying the relation between operation time and consumed energy. The total energy cost for a mobile charger spent on traveling through the edge is $E_{m,n} = \sum_{k=1}^{N} e_k$.

An edge is feasible if the mobile charger has enough time to travel from $p_i(t_m)$ to $p_j(t_n)$ with the maximum velocity $\|\vec{S_c}\|$ considering the charging period Δt. A feasible edge meets the constraint

$$E_{m,n}/c \le t_n - t_m - \Delta t, \tag{4}$$

otherwise, a large penalty will be added to the edge cost.

In addition to energy expenditure for traveling from one point to another, a mobile charging station also needs to spend energy to hold its position in currents while awaiting the AUV. After arriving at the designated rendezvous location, a mobile charging station needs to operate in the opposite direction of currents periodically to compensate the effect of currents. We call this station keeping energy, which is calculated as

$$F_{m,n} = \sum_{\tau = t_m + \Delta t + E_{m,n}/c}^{t_n} \|\vec{R_\tau} / \vec{S_c}\|. \tag{5}$$

Finally, we find the estimated energy cost $U_{m,n}$ for this edge by adding up all energy costs

$$U_{m,n} = E_{m,n} + F_{m,n}.$$

With all the energy costs calculated for every edge, the LKH can be applied to the converted TSP in $\mathbb{G}'(V', A', \mathfrak{R}(x,y,t), \mathfrak{B}(x,y))$ to find the paths with the lowest energy cost.

B. Multi-Cycle Recharging Scheduling

In this section, we propose an iterative method to solve the multi-cycle recharging problem. When the pre-defined trajectories for AUVs require more than one recharge cycle scheduling, the upcoming charging windows depend on the the previous rendezvous time. The multi-cycle recharging problem can be solved by switching between a planning and a re-scheduling processes iteratively. In the planning process, we solve the planning problem with estimated charging windows. In the re-scheduling process, we re-define the charging windows based on optimized paths.

In the first iteration, we schedule all the charging windows of AUVs required for the large-scale problem assuming every rendezvous happens in the middle of the charging window. In the planning process, the rendezvous planning method in Sec. II-A is applied to find the paths and schedule of mobile chargers visiting those charging windows. The result of this process will be used in the scheduling process.

In the scheduling process, we first estimate the charging windows based on the rendezvous duration, and then verify them by simulation to check if all the rendezvous are feasible. For each AUV, the rendezvous time is checked from the first one to the last one. If an estimated charging window does not hold the simulated rendezvous, we modify the estimated charging window and re-schedule accordingly. The iterations will repeat until all the rendezvous are properly planned and scheduled for all AUVs.

In the event that one of the AUVs or mobile chargers encounters an error in operation, such as drift, the planned rendezvous may become infeasible due to delays. In this scenario, the optimization is completed again to re-plan new feasible rendezvous using the same pre-defined AUV trajectories. New charging locations and times can be planned based on an updated current and obstacle model collected during the operation.

III. Rendezvous Planning Verification

For validating the algorithms developed in this work, we simulate the missions of mobile power delivery vehicles to extend AUVs operation in a dynamic underwater environment. The simulation uses current models built from real data gathered in Lake Michigan. The current data provides information on current direction and magnitude in a 40 km by 40 km area during a one-week time period, with spatial resolution of 1 km and temporal resolution of 1 hour (Fig. 6). Currents are magnified in simulation for presentation. The simulated mission area also has obstacle areas in trajectory planning based on the prior knowledge. In this work, we assume that only mobile charging stations need to avoid obstacles. For example, obstacles can be buoys and crowded area with boat traffic, which only affects surface vehicles.

We simulate four AUVs that follow pre-defined trajectories to perform a coverage mission. In these simulations, AUVs have a 16 hours endurance at a speed of 6 km/h. The charging window is configured as 6.3–34.4% to have a one-hour safety battery level. The mobile charging stations have a speed of 4 km/h. Each rendezvous takes 1 hour. Using four AUVs,

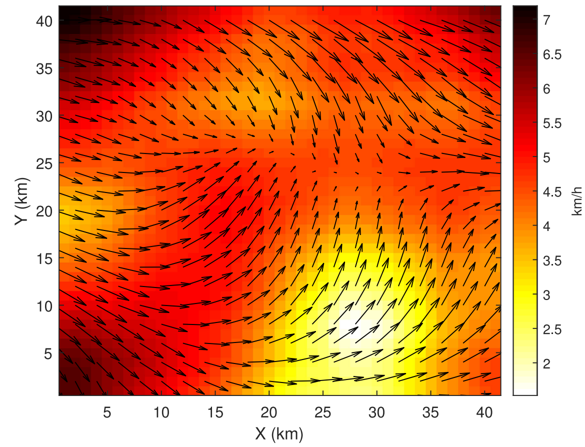
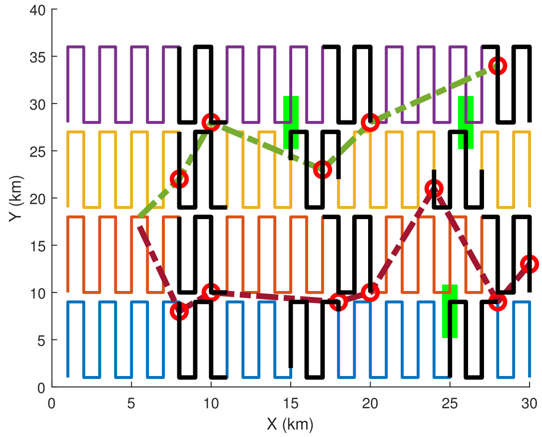


Fig. 6. Illustration of a current model in the mission area. The directions of arrows indicate the directions of currents, and the magnitudes of the currents are represented by the heat map. The resolution of the model is reduced for clarity, and current magnitudes are magnified 13 times in simulation.

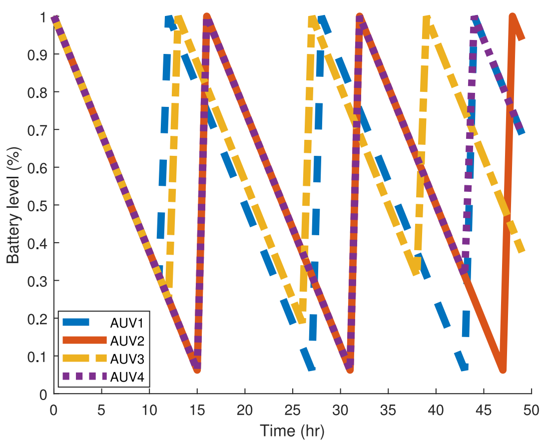
we first present the results for a sample scenario with dynamic currents and obstacles. Next, we apply the planning method to a scenario that requires a large number of chargings. Finally, the proposed method is statistically evaluated by simulating scenarios under different current conditions. We compare the statistical results of our proposed method that works based on energy minimization with the results calculated for the distance minimization method that does not consider currents in planning [8].

Fig. 7a illustrates an example mission scenario and the planned trajectories for energy delivery. The AUV trajectories are pre-defined as lawnmower paths, represented by colored solid lines. The trajectories generated by the proposed method for mobile charging stations are represented by colored dashed lines. The optimized rendezvous locations are shown as red circles. The charging windows are indicated by black lines portions along AUV trajectories. Obstacle areas are shown as green rectangles in Fig. 7a. Since the energy cost is linearly proportional with the operational time of mobile charging stations, the energy costs presented in this section have a unit of operation time. The simulation results show that the two mobile chargers are required to spend a total time of 54.4 hours for traveling and station keeping, 25.2 hours and 29.2 hours respectively. The result shows that the resulting trajectory successfully visited all the AUVs during their charging windows by overcoming the obstacles and dynamic currents in the environment (Fig. 7b). The total mission time is 49 hours to finish covering 1080 km^2 area in this simulation.

In the simulated scenario presented in Fig. 7, each AUV needs to rendezvous with a mobile charging station for three rechargings. To demonstrate planning more recharging cycles, we also simulated the same number of AUVs and mobile charging stations having ten rendezvous considering a larger area coverage mission. The mission is planned without considering any currents and obstacles. The results show the total mission time is 160 hours to cover an area of 3600 km^2. All the rendezvous are planned within the charging windows, and the AUV gets



(a)



(b)

Fig. 7. (a) Rendezvous planning for energy minimization with four AUVs and two mobile charging stations considering the effect of dynamic currents and obstacle areas. (b) Battery level of AUVs during the mission.

recharged at 12.7% battery level on average with a standard deviation of 8.7%.

For statistical analysis, we simulate the same mission area as in Fig. 7 with ten different current models. The currents have a maximum magnitude of 3.6 km/h, which makes the mission challenging for the mobile charging stations (4 km/h speed). Using the same pre-defined trajectories, we generate the paths of the two mobile charging stations using two approaches. One is the energy optimization method proposed in this work, and the other one is a distance minimization considered in [8]. We compare the two approaches by analyzing the energy cost of two mobile charging stations under dynamic currents and the success rate. The success rate is measured by whether or not the AUV can get recharged during the charging windows.

The results show that compared to distance minimization, the proposed method can save the total energy cost of the mission by about 10% (Table I). The mission has a higher chance to succeed if the proposed energy optimization method is used. This improvement is the result of integrating environmental conditions into planning with consideration for energy requirements.

To further evaluate our method and demonstrate the effectiveness of adapting to different types of vehicles, another

TABLE I
COMPARISON BETWEEN DISTANCE AND ENERGY MINIMIZATION USING SLOW MOBILE CHARGING STATIONS

Mission objective	Energy cost (hr)		Mission time (hr)	Success rate
	Travel	Station keeping		
Distance	20.1	32.1	49	40%
Energy	19.8	27.4	49	100%

TABLE II
COMPARISON BETWEEN DISTANCE AND ENERGY MINIMIZATION USING FAST MOBILE CHARGING STATIONS

Mission objective	Energy cost (hr)		Mission time (hr)	Success rate
	Travel	Station keeping		
Distance	36.3	102.5	49	100%
Energy	56.3	60	49	100%

evaluation is performed using different charging agents specifications (Table II). In this case, mobile charging stations with higher speed of 10 km/h are considered, where the currents have less impact. Faster mobile charging stations spend higher energy cost by a factor of 6.25. The results show that both approaches can successfully plan the mission. Using the proposed method, the total energy cost is reduced by about 16% compared to distance minimization. The travel energy cost for distance minimization is less than the proposed method, because it ignores the station keeping energy cost.

The results presented in this section suggest that the consideration of dynamic currents and directly optimizing the energy cost can significantly improve mission efficiency and feasibility. The proposed method is scalable for multiple number of working vehicles, mobile charging stations, and multiple recharging cycles. It is also independent from the characteristics of the performing vehicles.

The simulations in this section were performed in MATLAB environment on a desktop computer running a 64-bit Windows 10 Home operating system with a 3.20 GHz AMD A8-5500 APU processor. The computational time of the proposed algorithm is related to the consideration of currents and number of charging points. The computational time of energy minimization is 19.2 seconds in the sample scenario and statistical simulations, where a total of 360 charging points are considered. Without considering currents, the computational time is 4.4 seconds for 360 charging points, and 51.2 seconds for 1200 charging points.

IV. RENDEZVOUS PLANNING IMPLEMENTATION

Multiple field experiments were carried out in Lake Superior in the Summer 2018 to evaluate the performance of the proposed method. The method was applied to plan real-world missions carried out by AUVs in open-water with multiple rendezvous with surface crafts serving as a mobile power delivery system. In the first experiment, a small Bluefin SandShark AUV is tasked with navigating a lawnmower trajectory covering a 270 m by 150 m area featuring multiple rendezvous for recharging.

A small Unmanned Surface Vehicle (USV) is used as mobile charger. The USV should meet the AUV at the rendezvous location and loiter for the duration of charging period. Rendezvous is considered to happen when both vehicles are within 8 m of the target waypoint. The second experiment used an OceanServer Iver3 equipped with an enhanced navigational suite to perform the pre-defined AUV trajectory while a manned surface vessel followed the planned rendezvous trajectory.

The rendezvous locations are generated by the developed method with the length of the USV's path as the cost objective. The AUV is assumed to have a 12 minutes battery life at a speed of 1.8 km/h. The mobile charging station has a maximum speed of 2 km/h. We assume that the rendezvous time is 2.5 minutes. The mission time for the generated trajectory is 1.05 hours.

The Bluefin SandShark AUV used in the first experiment is a 1 m long, 12.4 cm diameter torpedo style AUV with onboard dead-reckoning navigation. It navigates based on GPS when surfaced and uses inertial estimates while submerged. It is capable of traveling at 3.96 km/h at depths up to 200 m. The AUV is commanded to follow a traditional lawnmower pattern at 2 m depth with surfacing at each waypoint for GPS fix. In addition, four rendezvous locations are included in the trajectory where the AUV surfaces to meet with the USV. Due to the nature of inertial navigation, discontinuities in localization are expected when surfacing, especially after long transits.

The USV used as mobile charging station is a custom-made autonomous cataraft style inflatable boat developed by the NASLab team at Michigan Tech. The boat is 2.7 m long and 1.4 m wide equipped with custom trolling motor and autonomy package onboard. It features three, 12 V deep cycle batteries onboard for a combined capacity of 300 Ah capable of driving the USV for 12 hours at a speed of 1.7 m/s. Navigation and autonomy is achieved with an ODROID running a custom navigation suite based on standard waypoint navigation. The ODROID is able to independently control steering angle of the thruster and thruster speed. The USV is commanded to achieve the start, and four rendezvous locations with a brief (60 seconds) loiter at each rendezvous.

The trajectories of the working AUV and mobile charging USV are illustrated in Fig. 8a. The trajectories are 700 m offshore in Lake Superior near McLain State Park, Michigan. During the testing window, winds were 10 knots with 30 cm waves. The working AUV completed the trajectory in 41 minutes as no loiter time was commanded for the AUV at the rendezvous locations. During the loiter maneuver, the charging USV maintained its location about the target waypoint while disturbed by the surface conditions.

In Fig. 8a, the AUV was beach launched roughly 700 m away from the testing area. It transited towards the test area at an altitude of 3 m from the bottom. Significant drift was encountered on the 700 m initial transit from the launch location to first waypoint. This drift is due to localized currents in the area, magnetic anomalies common in Lake Superior, and drift of the inertial navigation system. This drift was reduced during the rest of the trajectory as the vehicle was able to fix its location more frequently with GPS. While the planned and experimental AUV trajectories are not direct matches, the feasibility of the planned trajectories is confirmed here. The SandShark relies on a MEMS inertial navigation unit and does not have any other underwater navigation tools available, causing it to suffer from significant drift on long duration trajectories. Higher grade inertial navigation, particularly aided by acoustic localization methods or with a Doppler Velocity Log (DVL) can help improve the relative performance of AUVs on path following missions. Additionally, the SandShark AUV navigation controller is still being developed by General Dynamics, so the dynamic controller used here is being continuously refined to more accurately follow planned trajectories.

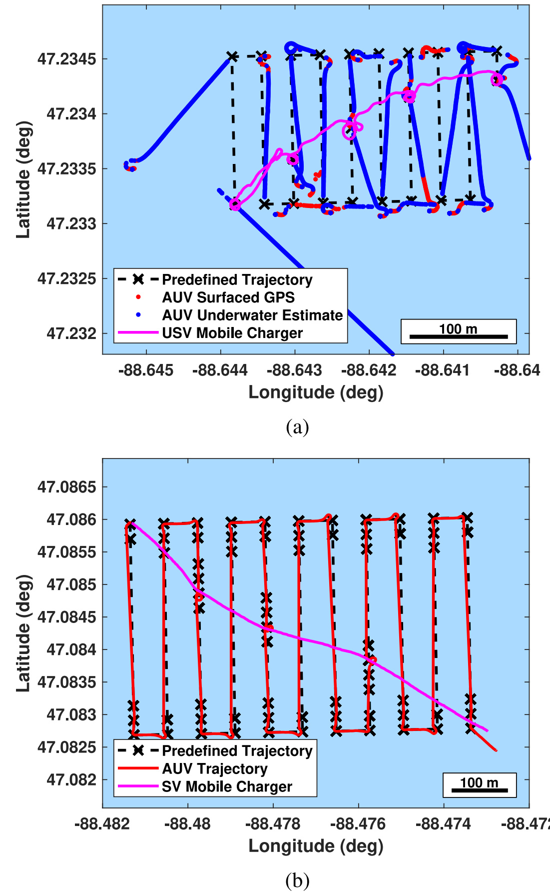


Fig. 8. (a) Overview of trajectories followed by SandShark AUV and USV during the coverage mission. (b) Trajectories followed by the Iver3 AUV and manned surface vessel. The additional navigational capabilities of the Iver enable it to follow the prescribed path more closely.

As additional validation of the planned trajectories, the Michigan Tech OceanServer Iver3 was deployed on a 600 m by 300 m lawnmower survey. The Michigan Tech Iver features a DVL and higher quality inertial navigation system over the low cost SandShark. The automatically generated lawnmower was augmented with midpoint surfacing where commanded by the planning algorithm. At these rendezvous locations the Iver parked for 5 minutes with a capture radius of 10 m. Additionally, to mimic the automatically generated lawnmower trajectory and improve performance, GPS alignment legs were added. The planned rendezvous locations were achieved using the SV Osprey, a 7.3 m manned support boat.

Fig. 8b shows the trajectory followed by the Iver and the manned surface vessel. Testing was completed near Grosse

Point on Portage Lake, Michigan. The testing area is consistently sheltered from prevailing winds and waves. It is 10 m deep with a flat, sandy bottom. During operation, the Iver was commanded to operate at a 2-meter depth during the long survey legs and surfaced during the shorter transit legs. The mission was started with the AUV in the water at the bottom right of the map and a short transit to the start of the mission before progressing through the mission towards the upper left. With the additional sensor capability onboard the Iver, it was able to navigate the entire trajectory with an average of 1.2 m of cross track error.

The proposed method is computationally efficient enough to run constantly during the mission and keep the mission plan updated with the newest current models to further improve the performance of the network.

V. Conclusion

In this letter, we presented a rendezvous planning method for multiple underwater mobile charging stations under dynamic environments. The integration of dynamic environments into the energy cost calculation is presented in detail. The energy cost calculation allows the proposed path planning method to consider obstacles and dynamic currents, which may cause failures if ignored. Additionally, the strategy extends the single charging cycle problem to a multi-cycle charging problem. A realistic non-instant charging process is also included in our method. The simulation results show that our method is more reliable and energy efficient compared to distance minimization without considering the effect of currents in path planning. To verify the proposed method, field experiments are conducted using an AUV and a USV performing rendezvous multiple times as well as an AUV and manned support vessel. The experiments show the potential of an integrated planning and charging infrastructure to enable undersea persistence.

With the developed method, it is now possible to plan underwater robotic missions for areas that extend far beyond the manual recharging limits and perform long endurance missions without human intervention. In the future, we will introduce our findings on development of online re-plan algorithms that can adjust to unforeseen disturbances and updated environment and vehicle information. This work will also marry our research direction on development of a mobile energy delivery vehicle, continuing integrated field experiments, and transitioning our findings into real-world applications.

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