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Collaborative Mission Planning for Long-term Operation Considering Energy Limitations

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Abstract— **Mobile robotics research and deployment is highly challenged by energy limitations, particularly in marine robotics applications. This challenge can be addressed by autonomous transfer and sharing of energy in addition to effective mission planning. Specifically, it is possible to overcome energy limitations in robotic missions using an optimization approach that can generate trajectories for both working robots and mobile chargers while adapting to environmental changes. Such a method must simultaneously optimize all trajectories in the robotic network to be able to maximize overall system efficiency. This paper presents a Genetic Algorithm based approach that is capable of solving this problem at a variety of scales, both in terms of the size of the mission area and the number of robots. The algorithm is capable of re-planning during operation, allowing for the mission to adapt to changing conditions and disturbances. The proposed approach has been validated in multiple simulation scenarios. Field experiments using an autonomous underwater vehicle and a surface vehicle verify feasibility of the generated trajectories. The simulation and experimental validation show that the approach efficiently generates feasible trajectories to minimize energy use when operating multi-robot networks.**

I. INTRODUCTION

Robots have played an important role in long-term missions such as search and rescue, surveillance, and environmental studies. One of the main limiting factors in the deployment of robots is the energy limitation. Although static charging technologies have shown success in extending operational life by providing recharging opportunities [1]–[3], their static nature limits their use in large area missions. This limitation is due to the interruption in operation and energy lost while traveling to and from a charging station.

Deploying mobile charging agents in the robotic network has become one of the main approaches to ensure continuous robotic operation. Research has been conducted to find mobile charger paths and schedule rendezvous to extend robots' operational life given pre-defined robot paths [4]–[7]. Simultaneous planning of both working robots and mobile charging agents has the potential to further improve overall mission performance. Fig. 1 illustrates a scenario where three Unmanned Surface Vehicles (USVs) support three Autonomous Underwater Vehicles (AUVs) in mapping applications.

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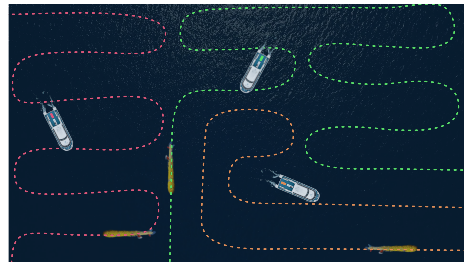

Fig. 1: Sample scenario where three grey USVs serving as mobile chargers respond to the energy limitations of three yellow AUVs (working robots) in a large field.

Another limiting factor in robot deployment for long-term missions is environmental disturbances. Unforeseen disturbances during a mission usually have negative impacts on robotic operations. This limitation becomes more critical in applications where robots have limited communication, such as underwater missions using AUVs. The key to solving long-term mission planning problems with this uncertainty is to have a mission planner that efficiently allocates resources in the overall robotic network and recharging system while having the capability to re-plan during a mission.

Long-term missions such as mapping, inspection, and monitoring missions are generally considered as a Coverage Path Planning (CPP) problem. Traditional methods for solving CPP problems such as the wavefront algorithm [8], spanning trees [9], neural network-based approaches [10], and other methods [11] can optimize the path length of working robots. Although mission efficiency is improved, these methods fail to consider the energy limitations of robots restricting their use in the real world. Several methods manage to plan mission scenarios efficiently in a limited area considering energy limitations [12]–[14]; however, these methods are not adaptable to the wide range of long-term, large-scale missions.

To address the energy limitation of working robots, multi-robot energy cycling utilizing mobile chargers has been studied extensively [15]–[18]. Without introducing a trajectory planning strategy, it is difficult to implement the mobile charger proposed in [18] into missions since the energy consumption of the whole system is not optimized. Further, optimal methods [15] and heuristic algorithms [16], [17] that generate paths and charging schedules for mobile chargers do not account for disturbances and uncertainty during the mission. This is generally due to the increased computational cost when solving the combinatorial optimization problem. An alternative used in this paper is to utilize a Genetic

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Algorithm (GA) to find global, sub-optimal results in minutes to hours, such that the proposed method can be used to re-plan during the mission. The GA-based approach can also be customized to consider different mission scenarios.

Prior knowledge of the environment including obstacles [19], disturbances [20], [21], and adversary areas [22] have been considered in pre-planning methods. However, these methods are not scalable in size of the mission area and the number of robots at the same time. Long-term mission robustness requires consideration of unforeseen conditions [6], [23], [24]. A multi-robot scheduling problem combined with a collision avoidance routing problem was solved by a hybrid approach using constraint programming and mixed integer programming in [25]. Still missing is an approach that simultaneously plans the working robots and mobile chargers trajectories in the presence of a challenging environment.

In this paper, a mission planning method for multi-robot systems on long-term coverage missions is proposed. This work greatly extends our previous work on CPP trajectory generation by simultaneously solving for worker and charger trajectories with the possibility of re-planning. We have previously generated trajectories for working robots given static chargers with predictable disturbances in [1] and mobile charger trajectories given predefined working robot trajectories in [7]. In [26], we presented the concept of using a GA approach to generate working robot trajectories and a single mobile charger at great computational cost.

In this paper, we present a planning method to generate trajectories for a team of mobile chargers and multiple working robots deployed in an environment with unforeseeable disturbances. The trajectories of mobile chargers and working robots are planned together by a GA-based method, considering energy and environmental constraints. The GA in this paper fundamentally extends the planning method to optimize mission time through efficient charger scheduling. Further, the re-developed GA method is computationally efficient and capable of supporting re-planning to accommodate unforeseeable disturbances. The specific trigger for the re-planning used in this work is set based on expected rendezvous times. Capabilities of the proposed approach are demonstrated through simulation results. Field tests using an AUV and a surface vehicle verify the feasibility of the approach.

The paper is organized as follows, we define the problem and present our approach in detail in Sec. II. The simulation results and experimental validation are illustrated in Sec. III. Finally, we conclude this paper and point out some future work in Sec. IV.

II. MISSION PLANNING PROBLEM

In this section, we formulate the mission planning problem for a multi-robot area coverage mission to be undertaken by a team of primary working robots and a collaborating team of mobile chargers. A Genetic Algorithm (GA) based approach is introduced to solve the optimization problem.

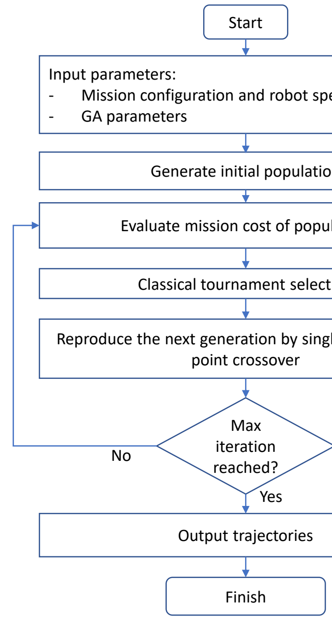


Fig. 2: The steps of GA solving the mission planning problem by finding trajectories of working robots and mobile chargers.

A. Problem Statement

Consider a mission where multiple working robots cover a large area, the problem is to find the optimized working robot trajectories to cover the whole mission area in the presence of uncertainty with support from a team of mobile chargers. We construct a 2D grid map to represent the mission area. The constructed map has N uniform cells. Each cell needs to be visited by one of the working robots at least once to complete the mission. The center of the cells are defined as mission points. The mission area is numbered arbitrarily.

We assume that disturbances such as currents will reduce along track velocity of working robots but will not remove them from their assigned trajectories. However, if the disturbance is too strong to overcome, the robot will be pushed off track and will be removed from the working robot list as safe operations are not possible. The robot will wait for recovery until after the mission is completed. Disturbances do not impact mobile chargers.

The number of working robots is represented by W and the number of mobile chargers is represented by C. The working robots can operate G hours at a speed of V relative to the surroundings. We assume that all working robots have identical energy capacity and maximum velocity, and G is smaller than the actual battery capacity to account for a level of safety. Before a working robot runs out of battery, it needs to be recharged by docking into a mobile charger. Mobile chargers have a maximum speed of V_c with unlimited energy. Recharging procedures take a period of time, ΔT, for each rendezvous. Each mobile charger can charge only one working robot at a time.

For a working robot indexed by w, its mission time, T_w, is the summation of the trajectory following time, L_w, the waiting time for mobile chargers, Y_w, and the total charging time. The trajectory following time, L_w, can be expressed as

$$L_w = D_w / V$$

where D_w is the total travel distance. The waiting time, Y_w, is considered when the mobile charger reaches the designated rendezvous location later than the working robot. The total charging time is calculated by the charging period, ΔT, multiplied by the number of chargings, $\mathfrak{N}_w$. The total mission time is represented as

$$T = \sum^{w} (L_w + Y_w + \mathfrak{N}_w \Delta T), w \in \{1, \ldots, W\} \qquad (1)$$

The mission planning problem can be defined as finding and updating the trajectories of W working robots and C mobile chargers while considering the energy limitation of working robots such that the total mission time, T, is minimized. During the mission, the operation of working robots can be delayed by unpredicted environmental disturbances or mechanical failures, which may increase the total mission time. The trajectories can be re-planned by re-running the optimization using updated information.

B. GA Based Mission Planning Approach

Given mission specifications and available resources, the mission planning problem is solved by a GA-based method. The proposed GA uses discretized mission points with number of working robots and mobile chargers and robot configurations (including starting locations, battery capacity, maximum speed, and charging period) as inputs to find trajectories of working robots and mobile chargers. The proposed optimization process can be repeated multiple times during a mission to compensate for errors caused by environmental uncertainty. In each repeated optimization process, the inputs to the GA (number of working robots, starting locations and times, and uncovered mission points) are updated.

Having been widely used in the robotic path planning fields [19], [26], [27], GAs utilize evolutionary operations to produce new solutions through generations. An illustration of GA design is presented in Fig. 2.

In the initialization process, the initial population is randomly generated. We use a fixed-length decimal chromosome to represent N mission points as N genes. The order of the genes in the chromosome represents the trajectories of working robots. Each chromosome is evenly divided by the number of working robots (Fig. 3).

In the evaluation process, we calculate the cost of each chromosome. The objective is to minimize the total mission time, T, considering the energy limitation of the working robots. The travel time of working robots, as well as rendezvous locations and times, can be obtained by analyzing the chromosome. For each segment of a chromosome that represents a working robot trajectory, we analyze the trajectory based on the order of genes. We keep track of the remaining battery level by calculating the travel time from one mission point to the next. If traveling to the next mission

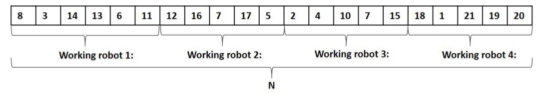


Fig. 3: Each chromosome represents trajectories of all working robots.

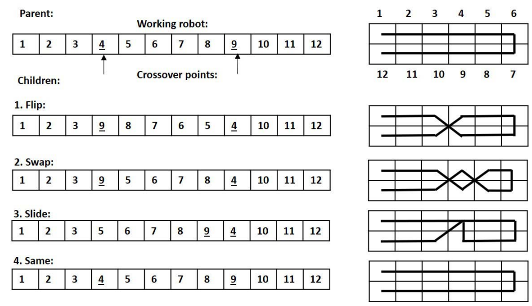


Fig. 4: The population reproduction uses a single parent two-point crossover process [28]. The illustrations of the decoding of each offspring are shown on the right.

point requires the remaining battery level to drop below the minimum safety level, then the current mission point of this working robot is marked as a rendezvous location, and its remaining battery level is reset to G.

Using the known rendezvous locations, the trajectories of mobile chargers are created. Each mobile charger is only able to rendezvous with one working robot at a time, causing it to become unavailable for a period of time ΔT. The rendezvous locations are assigned to mobile chargers such that the first available charger goes to the first rendezvous location. If multiple chargers are available, the closest charger is assigned. If the working robot arrives at the rendezvous location before the charger, the working robot will have a waiting time, Y_w. This rendezvous scheduling and assignment strategy satisfies the battery capacity constraint.

After calculating the costs based on total mission time, Eqn. 1, all chromosomes are randomly grouped. Each group has four chromosomes. A tournament selection is used to choose the best chromosomes from the chromosome groups as parent chromosomes of the next generation. A single parent crossover is used to prevent duplicated genes (Fig. 4) in the crossover process. The child chromosomes are obtained by performing two point flip, swap, slide, and same to the selected parent chromosomes [28]. Flip reverses the order of genes between two points; slide moves the gene from the first point to just behind the second one, then shifts all genes in between to the left to fill the gap; swap exchanges the genes at the two crossover points; same copies the parent chromosome. The crossover grows the number of chromosomes four times, keeping the size of the population constant from one iteration to the next.

The algorithm stops when it meets the maximum number of iterations. The chromosome representing the trajectories of working robots and mobile chargers with the lowest cost is the output of the algorithm.

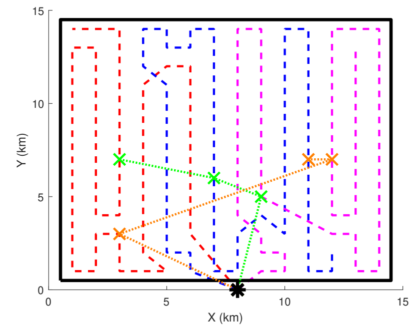
In the event that a working robot encounters a disturbance in operation, the total mission time may be delayed. In the worst case scenario, the mission can become infeasible due to the failure of a working robot. To reduce the impact of disturbances, the optimization can be performed again to find new feasible trajectories for working robots and mobile chargers. To re-plan, the GA updates the number of available working robots with their current battery levels, starting locations and times of all robots, and uncovered mission points in the initialization process. The updated information is used to change the length of the chromosomes and generate a new workload distribution for the working robots. The new chromosome's length is shorter than before as it is equal to the number of uncovered mission points.

The re-plan GA operates the same way as the pre-plan GA by evaluating the mission cost in the evaluation process and choosing the most fit chromosomes to produce the next generation. The re-plan GA has a smaller population size and number of iterations due to the reduced size of the remaining mission area. Re-planning of the mission is triggered by the detection of a robot that is no longer in communication with the central node due to an environmental disturbance or mechanical failure. For mobile chargers, the communication is continuous and any sustained lack of signal causes that mobile charger to be removed from the list of available chargers. Working robots are limited to communicating with the central node while docked. Since it can be estimated when the working robots will arrive at the rendezvous points, the lack of communication received by the central node during the expected time window indicates that the working robot is no longer available. In either of these cases, the GA will re-initialize with the updated parameters to solve the new trajectory optimization problem and send the updated trajectories to the robots while at the rendezvous points. Since the working robots may rendezvous at different times, it is assumed that they are working as planned until shown otherwise. At that point, the GA would then be re-initialized again to solve the optimization problem.

Other strategies for triggering re-plans exist, such as scheduled re-plans. In a scheduled re-plan scenario, the planned trajectories could evolve to more efficiently manage disturbances in the mission area.

III. MISSION PLANNING METHOD VERIFICATION

In this section, we demonstrate performance of the presented method using Autonomous Underwater Vehicles (AUVs) as working robots with the support of Unmanned Surface Vehicles (USVs) as mobile chargers. During the mission, USVs carry batteries to the rendezvous locations, where the AUVs will dock and replace their batteries. The AUVs deployed in the mission can travel at the maximum speed of 3 km/h for 12 hours with a safety level of 2 hours. The USVs have a speed limit of 16 km/h. For each rendezvous, the battery charging process takes 8 hours. We apply the proposed method to minimize total mission time.



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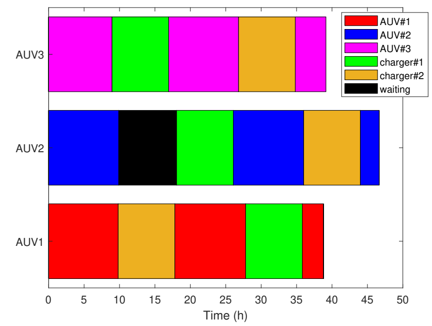


(b)

Fig. 5: Pre-plan simulation results with 8 hour charging period: (a) Pre-plan GA optimizes trajectories of three AUVs and two USVs to cover the whole mission area. (b) Timeline of the mission including operation time, charging time, and waiting time. The colors of the bars match the colors in (a).

We first present trajectories of AUVs and USVs optimized by the pre-plan GA for the whole mission area in Sec. III-A. Complete failure caused by environmental disturbance is then applied to one AUV. The re-plan GA is used for the uncovered mission area to reduce the impact of environmental disturbances on overall mission performance in Sec. III-B. Experimental verification of trajectory feasibility is completed with a small test area in Lake Superior in Sec. III-C.

A. *Pre-plan GA Evaluation*

An underwater coverage mission scenario in a square mission area of 14×14 km^2 of Portage Lake, Michigan is simulated. We use 1×1 km uniform cells to grid the mission area to ease visualization. In this mission, three AUVs are deployed with the support of two USVs. The GA is configured as having a maximum iteration of 1200 with the population size of 1200. The pre-plan GA is repeated 100 times with the same inputs and GA configurations. The best pre-plan GA result for completing the coverage mission is presented in Fig. 5a. The mission timeline and rendezvous schedule of robots is shown by the bars in Fig. 5b.

The mission area is within the black square. Three AUVs and two USVs are deployed from the asterisk point in Fig. 5a. This point can be outside of the mission area. We indicate the optimized trajectories of AUVs with colored dashed lines.

The planned rendezvous locations of mobile chargers (USVs) are shown as ‘X’s. The mission time for three AUVs is 38.8, 46.5, and 39.1 hours with the total travel distance of 205.3 km. In this mission, the two USVs need to travel 28.1 km between all assigned rendezvous locations. Black bars in Fig. 5b are the time that the second AUV is waiting for the next available USV. The user can choose to deploy the second AUV later to avoid this waiting period without changing the mission performance.

We measure the mean values and standard deviations of mission time and travel distance of vehicles to show the reliability and efficiency of the pre-planning by analyzing the 100 randomly initialized GA runs. The average mission time for 100 results is 126.4 hours, with standard deviations of 0.8 hour. The average travel distance is 210.3 km with standard deviations of 2.3 km. The results indicate that the proposed pre-plan GA is consistent with all results being within 3% of the best result.

Considering a case with a 3 hour charging period, as opposed to 8 hours, and running the simulation, the mission time for three AUVs is 29, 31.3, and 30.3 hours with the total travel distance of 205.4 km. The two USVs need to travel 39.5 km between all assigned rendezvous locations. The average mission time for 100 results is 91.4 hours with a standard deviation of 0.9 hour. The average travel distance is 210.2 km with a standard deviation of 2.7 km.

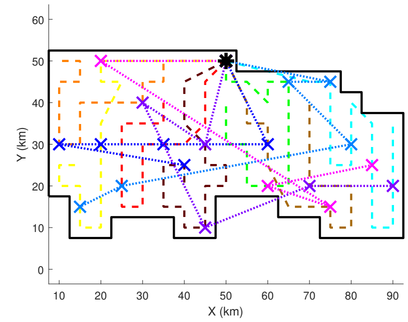
To show the scalability of our model, another mission scenario with a much larger area (3496 km^2), seven AUVs, four USVs, and a 3 hour charging period was simulated. The mission was discretized into 124, 874, and 3496 uniform cells. For the 124 mission point case, the GA was configured with 2400 maximum iterations and a population size of 2400. The optimization was completed in 4.9 minutes, Fig. 6. The average mission time for 100 results was 316.2 hours, with a standard deviation of 6.6 hours. The average travel distance was 730.6km with a standard deviation of 15.5 km. In all our simulated scenarios, the mission represents the area of interest. In this more complex mission, both working and charging robots sometimes leave the boundaries as it can be more efficient for a working or charging robot to traverse between points by going outside the mission area.

In the higher resolution cases (874 and 3496 points), the GA was configured with 9000 and 12000 maximum iterations and a population size of 12000 and 16000. Due to computational complexity, the simulations were completed with computational times of 328.9 minutes and 512 minutes respectively. A statistical study was not completed due to computational cost. The total travel distances for these two higher resolution missions were 2460 km and 4021.6 km with total mission times of 1272 hours and 1844 hours. Fig. 7 and Fig. 8 show the generated trajectories. A summary of all results is presented in Table I.

The mission planning method presented here is capable of efficiently finding sub-optimal solutions for complex missions. As a comparison, we applied an approach based on the Lin-Kernighan heuristic (LKH) solver to the trajectory optimization problem [7]. The LKH-based approach only optimizes charging robot trajectories with given working robot trajectories, if able to find a feasible solution, and the result is slightly better than the GA method and close to an optimal solution [4]. In general, we cannot always find optimal solutions, especially as problem size and complexity scales. The presented GA approach generates feasible trajectories with greater flexibility than optimal methods. By simultaneously distributing working robots and charging robots, manual distribution of workers in unstructured mission areas can be avoided. The working robot distribution is critical for overall mission success and will cause the LKH method to fail if not appropriately distributed. One of the main limitations of LKH is that it does not provide solutions when the charging period is not short enough, where the presented GA method can consider realistic long charging

TABLE I: Pre-plan results

	Area (km^2)	Resolution (km^2)	W	C	Δ T (hour)	Average T (hour)
Mission 1	196	1	3	2	8	126.4
Mission 2	196	1	3	2	3	91.4
Mission 3	3496	28	7	4	3	316.2
Mission 4	3496	4	7	4	3	1272
Mission 5	3496	1	7	4	3	1844



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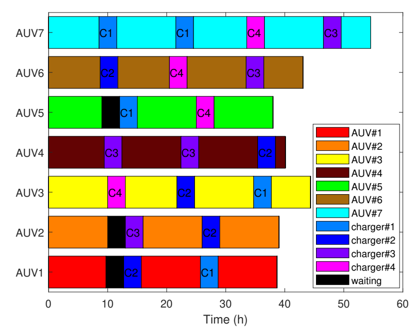

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Fig. 6: Pre-plan simulation results with 3 hour charging period: (a) Pre-plan GA optimizes trajectories of seven AUVs and four USVs to cover the whole mission area. (b) Timeline of the mission including operation time, charging time, and waiting time.

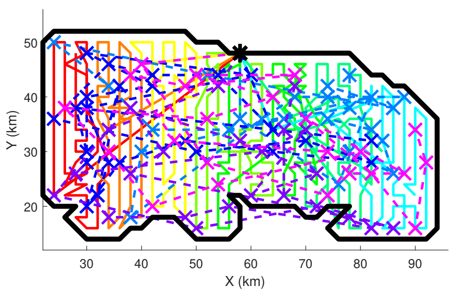


Fig. 7: Sample result of pre-plan GA optimized trajectories for seven AUVs and four USVs with 874 cells in the mission area.

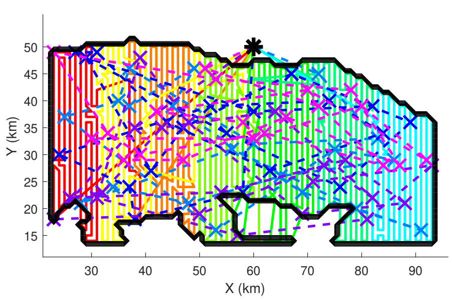
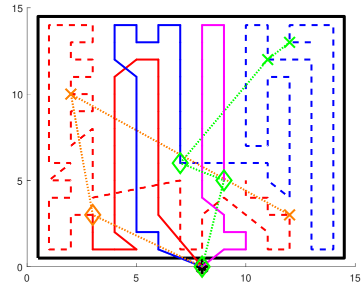


Fig. 8: Sample result of pre-plan GA optimized trajectories for seven AUVs and four USVs with 3496 cells in the mission area.



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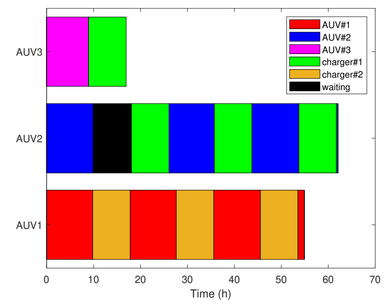


(b)

Fig. 9: Re-plan simulation results with 8 hour charging period: (a) Re-plan optimizes trajectories of first and second AUVs and two USVs to complete the mission area with the failure of the third AUV. (b) Timeline of the re-plan mission including operation time, charging time, and waiting time. The colors of the bars match the colors in Fig. 9a.

periods. These constraints are generally not within the user's control, making the inherent flexibility of the proposed GA method more robust for real-world implementation.

B. Re-plan GA Evaluation

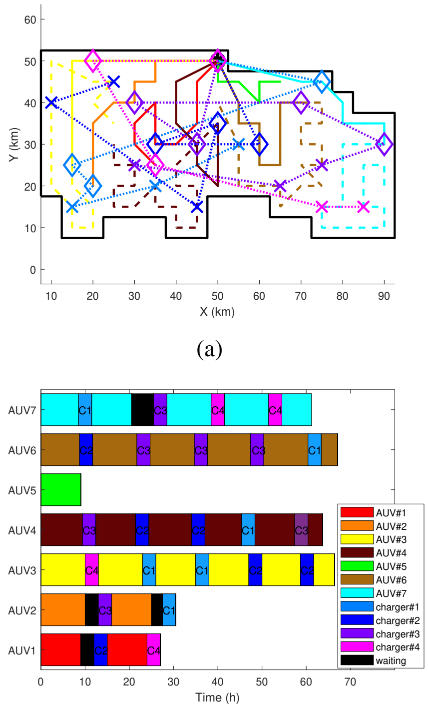
Scenarios involving AUV failure are presented here to show the capability of the proposed algorithm to adapt to changing conditions by re-planning. Due to limited underwater communication, in the presented scenarios re-plans are only considered to be possible at rendezvous locations. Therefore, we assume that AUVs will successfully cover their trajectories up to their next rendezvous location in the event of disturbance.

The result of the failure scenario with an 8 hour charging period is presented in Fig. 9a. The mission area covered by the three AUVs is indicated by colored solid lines. Waypoints traveled by two USVs are represented by diamonds. In this case, the third AUV (shown by pink lines) stops working and fails to follow the rest of its assigned trajectory. We implement the re-plan GA in this scenario with two AUVs and two USVs to cover the rest of the mission area. The uncovered mission area has 116 mission points. The results show mission times for the three AUVs to be 54.9, 62.1, and 8.9 hours when the first and second AUVs continue to cover the rest of the mission area following the re-planned trajectories. The mission timeline and schedule are shown in Fig. 9b. Without the re-plan GA, the mission area would not be completely covered.

In the 3 hour charging period case, if the third AUV stops working and fails to follow the rest of its assigned trajectory, we implement the re-plan GA with two AUVs and two USVs to cover the rest of the mission area. The uncovered mission area has 119 mission points. The results show mission times for the three AUVs to be 40, 42, and 8.8 hours when the first and second AUVs continue to cover the rest of the mission area following the re-planned trajectories.

In the 3496 km^2 mission area, we assume that multiple vehicles will fail during the same mission to evaluate the algorithms capabilities. AUV 5 fails at the first rendezvous, followed by both AUV 1 and AUV 2 later in the mission. Re-planning is performed after each detected failure. The final trajectories for the re-plan scenario are presented in Fig. 10a. Re-plan results are presented in Table II.

The simulations were performed in a 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 and 12GB memory. The computational time for the 196 km^2 Portage Lake scenario is 2.3 minutes in pre-



(a)

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Fig. 10: Re-plan simulation results with 3 hour charging period. Fifth AUV (green) fails at the first rendezvous location, and first (red) and second (orange) AUVs fail at their second rendezvous locations.

TABLE II: Re-plan results

	Δ T (hour)	Failed Robots	Average Mission Time (hour)
Mission 1	8	#3	125.9
Mission 2	3	#3	90.8
Mission 3	3	#1, 2, 5	324.9

planning and 0.3 minutes for re-planning. The computational time for the re-plan GA is related to the size of the remaining mission area. The computational speed of the re-plan GA is fast enough to be executed multiple times during charging of the vehicles.

Based on the pre-plan simulation, the proposed method successfully finds the trajectories of working robots and mobile chargers to minimize the mission time with high reliability. The approach is also capable of handling mission uncertainty through a re-planning method. A mission with robot failures and other disturbances can still be completed using the re-plan method, as opposed to the pre-plan method.

C. *Experimental Evaluation*

Field experiments were completed for a small test mission on Lake Superior using an AUV and a manned Surface Vehicle (SV) to evaluate feasibility of the planning algorithm. The test mission is 800 meters by 400 meters with a point

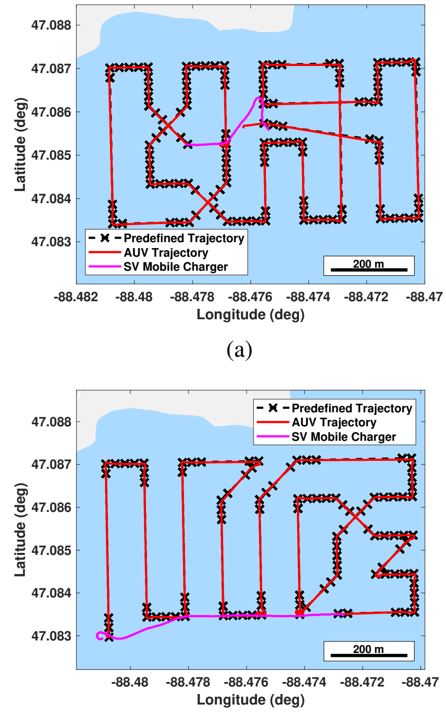

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Fig. 11: Experimental feasibility verification of the planned trajectories using an OceanServer Iver3 and the manned SV Osprey. The planned trajectory is shown as the black dashed line with waypoints marked as ‘X’s. The actual trajectory followed by the AUV is shown in red. The actual trajectories were accurate enough that they appear overlaid over the planned trajectories. The trajectory followed by the SV is shown in magenta.

resolution of 100 meters. The AUV used is an OceanServer Iver3 while the manned boat is the 7.3 meter SV Osprey. The Iver3 AUV has a Doppler Velocity Log (DVL) to help it navigate accurately underwater. Two trajectories are generated including three rendezvous. Mission waypoints are generated by the genetic algorithm and converted into an Iver3 mission using a custom MATLAB script. The waypoints are augmented with additional points for GPS alignment, diving, surfacing, and sensor control. Two missions are completed using the Iver3 and SV Osprey on Portage Lake near Grosse Point. The testing area is consistently sheltered from wind and waves and is 10 meters deep with a flat, sandy bottom. Fig. 11 shows the two trajectories.

In the first test (Fig. 11a), the AUV took 74 minutes to complete the mission. Between surfaced GPS waypoints, the AUV dove to 2 meters. The AUV had three virtual rendezvous with the mobile surface charger during the trajectory. At each of these rendezvous, the AUV parked for 5 minutes with a 10 meter capture radius. The AUV averaged 0.51 meters of cross track error over the entire trajectory. The second test (Fig. 11b) took 75 minutes to cover the same 800 by 400 meter area with similar configuration and testing conditions to the first trajectory. The AUV maintained an average cross track error throughout the operation of 0.71 meters.

For both tests, the manned SV Osprey was manually piloted to achieve the rendezvous waypoints as commanded by the planner. The SV operation was completed following the conclusion of the AUV operation to minimize risk of collision. Coordination of the two platforms is outside the scope of this work and is an ongoing project.

IV. CONCLUSIONS

In this paper, we introduced a robotic network planning architecture for long-term missions using mobile chargers. A GA-based optimization algorithm was developed to optimize the trajectories of working robots and mobile chargers, with the capability of re-planning during a mission to compensate for the impact of environmental or operational disturbances. Simulation results demonstrate the reliability and efficiency of the proposed method in a realistic underwater coverage mission scenario. The ability to limit the impact on overall mission time caused by individual robot failures with the re-plan GA is also presented. Evaluation of the method is conducted by numerical studies. Experimental validation of the method is also presented that validates the feasibility of the planned routes when implemented onto an AUV platform and manned SV.

In the future, more constraints on robots and the environment will be considered. These constraints can include energy limits on charging stations, obstacles in the environment, and collision avoidance between the robots. Additionally, the developed method will be used to generate efficient mission trajectories for real-world field tests. We will deploy teams of aerial and ground robots to undertake planned missions in test areas. This future implementation will provide a better understanding of challenges and considerations needed for applications such as air sampling or search and rescue. Further, the actual docking and recharging process is being explored between USV and AUV. A full experimental validation of pre-plan and re-plan is being prepared using multiple AUVs as working robots and multiple USVs as chargers.

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