Mission Planning for Multiple Autonomous Underwater Vehicles with Constrained In-Situ Recharging

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***Abstract*— Persistent operation of autonomous underwater vehicles (AUVs) without manual interruption for recharging saves time and total cost for the mission. In order to facilitate AUVs for longer mission durations, they can be equipped with docking capabilities to recharge at on-site Wave Energy Converter and dock hybrid type recharging stations. However, the power generated at the recharging stations could be constrained depending on the sea conditions. Therefore, a robust mission planning framework is proposed using a centralized and decentralized scheme that incorporates the power availability constraint at the recharging station in addition to the limited battery capacity of each AUV. The planner generates efficient mission plans for all AUVs by optimizing their time to visit the dock based on the imposed constraint. The effect of increasing the number of AUVs and number of mission points is studied on the mission duration. The effect of sea state on mission performance is also analysed in a particular mission scenario.**

I. INTRODUCTION

Multiple autonomous underwater vehicles (AUVs) have the ability to navigate autonomously for prolonged periods in potentially hazardous environments that are otherwise unsafe or time consuming for human divers by utilizing in-situ recharging strategies. Continuous operation of AUVs is essential for missions to carry out continuous data collection, exploration, or monitoring in underwater environments. Hence, AUV's can be equipped with docking capabilities that allow them to recharge at a docking station and resume it's mission without manual intervention.

Some missions allow tethered charging where AUVs are connected to an external power source using a tether cable. However, they can impose physical limitations on the maximum range covered by the AUV based on the cable length. On the other hand, docking stations can allow higher flexibility for AUV as these docking stations are often positioned at one or more fixed locations in the mission area allowing the AUVs to dock, recharge their batteries and resume their mission. The power available at the docking station can be sourced from Wave Energy Converters (WECs). WECs capture energy from ocean waves and convert it into electricity which is then used to power the docking stations. The power generated at WECs is determined by the characteristics of the incident waves defined by the sea state as well as the design and efficiency of the converter [1].

Much of the existing work [2] in generating efficient mission plans for AUV fails to account for the energy constraint at the docking station, as it is assumed that the docks would always have surplus energy to completely recharge the AUVs. In other scenarios that account for energy constraints at the dock [3] mission plans are executed such that AUVs visit the dock at periodic intervals and recharge completely. The time between subsequent recharge ensures that the dock has sufficient power available. However, these assumptions come at the expense of higher mission time and energy consumption as it might not be essential for an AUV to recharge completely or periodically.

Hence, efficient mission planning would ensure optimal utilization of vehicle energy resource as well as power generated by WECs. Based on the specific mission goals and the power availability at the docking stations, a mission planner can generate waypoints or routes for the AUV by efficiently minimizing energy consumption and travel time and at the same time maximizing mission coverage.

In this paper, a robust mission-planning algorithm is designed for multiple AUVs that minimizes the mission duration while adhering to the energy constraints of both the AUVs as well as the docking station. A mission planning framework incorporating the energy constraints is provided using a centralised and decentralised algorithm. An empirical evaluation is carried out to compare the performance of the two algorithms with respect to total mission time on randomly generated maps with varying number of AUVs and mission points. The effect of low and high sea states on the mission time is also analyzed using both of the algorithms.

II. RELATED WORK

A. AUV Docking and Recharging Systems

Underwater docking infrastructure provides a platform for AUV recharging and data transfer. The existing dock designs are classified as unidirectional and omnidirectional [4] based on the direction in which AUV can approach the dock. They are further categorized into fixed or floating type.

A WEC-dock hybrid system design [5] allows on-site energy harvesting and AUV recharging capabilities. The type of docking mechanism decides the AUV navigation and undocking strategies.

B. Marine Energy Harvesting Model

Wave energy can be modelled using linear wave theory or models that take into account nonlinear waves effects and interactions. A simplified linear energy model based on sea state for regular waves [3] is a function of wave height H_m and wave period T_m as given by Equation (1), where ρ is the water density and g is the acceleration due to gravity. Assuming a WEC-dock hybrid system, the power generated at WEC can be computed using Equation (2), where B represents the WEC dimension, η is the hydrodynamic efficiency and ϵ, ϵ_2 are generator efficiency and power transfer efficiency respectively.

$$J_{wave} = \frac{\rho g^2}{64\pi} T_m H_m^2 \quad (1)$$

$$P_{WEC} = J_{wave} B \eta \epsilon_1 \epsilon_2 \quad (2)$$

The wave spectral density function provides the significant wave height and energy period for irregular waves. The power matrix [6] for a particular WEC type provides a mapping of the mean power available for a given sea state.

Wave Energy Converter Simulator (WECSim) [7] is an open source tool that incorporates complex wave energy modelling involving numerical simulations or empirical relationships that include additional factors such as wave steepness, water depth, wave spectra, and nonlinear wave interactions and generates power output based on the chosen WEC construction.

Additionally, the power generated from WEC recharges the energy storage device at the dock such as batteries. The charging and discharging of the batteries can be modelled using the function as given in Equation (3), where β is the rate of charging and discharging.

$$\dot{q}(t) = \beta \quad (3)$$

C. Mission Planning Algorithms

Existing methods on mission planning for multiple autonomous vehicles mostly fall under the categories of centralised or decentralised approaches. In [8] and [9], a taxonomy for multirobot task allocation problems with inter-task dependencies is provided along with a mathematical formulation for each class of problems.

A multi-objective genetic algorithm (GA) is utilised in [2] that generates energy efficient trajectories while accounting for obstacles and ocean currents. Such population based optimization approaches generate a candidate pool of possible solutions and iteratively improve upon them to converge to an approximate solution. In [10], Multi-Robot Long Term Persistent Coverage Problem (MRPCP) is formulated as MILP that accounts degree constraints, capacity and flow constraints and fuel constraints. The method can also handle dynamic costs between the targets.

A policy gradient based search [11] is utilised to train all the robots independently, and is deployed in a decentralized manner where the robots are allowed to communicate about their completed tasks. Other reinforcement learning approaches such as actor-critic based methods incorporate centralised learning and decentralised execution as those discussed in [12].

An online multiagent Monte Carlo Tree Search (MCTS) approach [13] is applied in multi-drone delivery problem using dynamic coordination graphs. The decentralised variant of MCTS is presented in [14] where every autonomous vehicle grows its own search tree and iteratively optimizes upon the action-sequence probabilities by communicating with other autonomous vehicles. [15] presents an online distributed method for coordinating heterogeneous multirobot systems for task allocation.

However, all the above methods assume unlimited power at the recharging stations, hence they do not account for power availability at the dock that can generate more informed mission plans for the autonomous vehicles.

III. METHODOLOGY

A. Problem Formulation

There are $R = \{r_1, r_2, ..., r_n\}$ AUVs that are assigned to cover a mission area in minimum time. The mission area is represented as a undirected graph $G = (V, E)$, where V represents the mission points and recharging station nodes such that $V_{dock} \subset V$, and E represents the edges connecting any two nodes in V. The mission planning algorithm is formulated as given in Equation (4). The paths of all AUVs that minimizes the total mission duration is given by $P_M = \{p_1, p_2, ...p_n\}$. $p_i = \{v_1^i, v_2^i, ...\}$ is the sequence of nodes traversed by an i^{th} AUV, $v^i \subset V$ represents the points covered by i^{th} AUV. p_i determines when the i^{th} AUV would visit the recharging station. T_i represents the individual mission time of an i^{th} AUV in R. AUVs are assumed to be traveling at a specific constant speed s_i between two mission points.

Equation (5) defines that set V is equal to the total mission points covered by all the AUVs. No overlapping constraint between the mission plans $p_i,\ p_j$ of any two AUVs is given by Equation (6). The current charge $C_i(t)$ of the i^{th} AUV at any given time is bounded by its maximum charge capacity B_i as given in Equation (7). The charge available at the dock $q_{dock}(t)$ is bounded by its maximum charge capacity of B_{dock} as given in Equation (8). The current dynamic state of charge available at the dock is given by a function f in Equation (9).

$$P_M = \operatorname{argmin} \max_{i \in R} T_i \quad (4)$$

such that,

$$V = \bigcup_{i \in R} p_i \quad (5)$$

$$\forall_{i \neq j} \{p_i \setminus V_{dock}\} \cap \{p_j \setminus V_{dock}\} = \emptyset \quad (6)$$

$$0 \leq C_i(t) \leq B_i \quad (7)$$

$$0 \leq q_{dock}(t) \leq B_{dock} \quad (8)$$

$$q_{dock}(t) = f(C_{i \in R}(t), P_{WEC}, \beta) \quad (9)$$

B. Algorithm

To solve the optimization problem formulated in Equation (4), a decentralised scheme using Monte Carlo Tree Search as given in Algorithm 1 and a centralised scheme using a Genetic Algorithm as given in Algorithm 2 is applied.

In Algorithm 1, the selection starts from a root node in each AUV's tree and terminates at a leaf node, and at every step a node in the tree is selected using a tree policy. The expansion phase expands over the leaf node if the leaf node is not the terminal state. The simulation phase executes possible future scenarios in order to select best state-action pair in the subsequent iterations. At every step in the selection/expansion/simulation phases, the AUV charge is updated based on the distance traveled. If the destination

Algorithm 1 Decentralised Mission Planning Scheme using Monte Carlo Tree Search for Multiple Underwater Vehicles

Input: Graph G
Output: Mission time T_M, Path traced by each AUV p_i
for each episode **do**
  Initialize $V_{unvisited} = V$, $root^i = \{v^i_{start}\ \forall i \in R\}$
  STEP 1 Perform selection for each AUV simultaneously until reaching a leaf node. Update the AUV charge and branch cost based on the distance traversed.
  STEP 2 Perform expansion in each AUV's tree and select a child for rollout if $V_{unvisited} \neq \emptyset$. Update the AUV charge and branch cost based on the selected child node.
  STEP 3 Perform simulation in each AUV's tree until $V_{unvisited} = \emptyset$.
  STEP 4 Backpropagate $\max_{i \in R} cost_i$ in each tree.
  STEP 5 Evaluate the policy and return the best sequence of points traversed by each AUV p_i if $V_{unvisited} = \emptyset$
end for
The charge and branch cost are updated as follows:
Function: $ChargeUpdate()$
$c^i_{v_{next}} \leftarrow c^i_{v_{curr}} - c_i(v^i_{next},\ v^i_{curr})$
if $v^i_{next} \in V_{dock}$ **then**
  $c_{source} \leftarrow c_{source} + \sum f(t)$
  $c^i_{v_{next}} \leftarrow c^i_{v_{next}} + \min\{c_{source},\ B_i - c^i_{v_{next}}\}$
  $c_{source} \leftarrow \max\{0, c_{source} - \min\{c_{source},\ B_i - c^i_{v_{next}}\}\}$
end if
$cost^i = -\frac{d(v_{next},\ v_{curr})}{s_i} - \{c^i_{v_{next}} - c^i_{v_{curr}}\}$

is a docking location, the AUV is recharged based on the current charge available at the docking station using the $ChargeUpdate()$ function. Based on the outcome of the simulation, the computed branch cost is backpropagated from the starting node in the simulation to the root node.

In Algorithm 2, a population of possible solutions is randomly generated. Each state is encoded such that each AUV's path has nodes corresponding to starting node, docking node and a random distribution of mission points. The index of the starting node remains fixed with respect to the starting gene for each AUV's path. The index of docking location in each AUV's path is non-interchangeable during mutation with any other AUV's path. All other mission points are interchangeable across the entire chromosome length during mutation. The fitness of each chromosome in the population is evaluated using a cost function that penalizes cost of traveling between two points and an added penalty for reaching the docking station when the dock has no charge left. Any incremental change in AUV's charge at the dock is added as a reward to the cost function. A fraction of individuals are selected based on Roulette selection for continuing in the next generation. The remainder of the next generation of population is formed by mutating the selected nodes obtained through roulette selection. The process is repeated until the fitness value converges.

Algorithm 2 Centralized mission planning framework using evolutionary algorithm for multiple AUVs

Initialize population P
Each state in the population is represented as
$p = \{v_{start}, v^{r1}_1, v^{r1}_2, ..., v_{dock};$
$v_{start}, v^{r2}_1, v^{r2}_2, ..., v_{dock}; ...\}$ where, $v \in V$
for each episode **do**
  STEP 1 Evaluate Fitness F:
  {▷`Update dock` & `AUVs current charge`}
  $c^i_{v_{next}} \leftarrow c^i_{v_{curr}} - c_i(v^i_{next},\ v^i_{curr})$
  $c_{dock} \leftarrow c_{dock} + \sum f(t)$
  $F \leftarrow F + c^i_{v_{next}}$
  if ($v_{next} \in V_{dock}$ & $c_{dock} > 0$) **then**
    $\Delta c^i = \max\{c_{dock}, B_i - c^i_{v_{next}}\}$
    $F \leftarrow F + \Delta c^i$
  else if $c_{dock} = 0$ **then**
    $F \leftarrow F - B_{dock}$ {▷`Add penalty`}
  end if
  STEP 2 Perform Roulette Selection and save k candidates for next generation.
  STEP 3 In the remaining $P - k$ candidates, perform mutation by selecting a state from each robot path such that the current state $\notin \{v_{start}, v_{dock}\}$
end for

The converged policy using both algorithms provides the sequence of mission points traversed by each AUV which also dictates when the AUV would visit the dock through the course of a mission.

IV. EXPERIMENTAL SETUP

The above algorithms are evaluated using maps with a random distribution of nodes in a 600×600 area. Every AUV starts from the same point in the map assumed to be the starting index. The dock is represented by one of the points in the map, that has maximum energy capacity equivalent to a single AUV and can only charge one AUV at a time. The performance is evaluated using mission duration by increasing the number of AUVs as well as by increasing the number of mission points in the same area.

In our experiments, it is assumed that all the AUVs would start from the same starting location and would need to recharge once for completing the entire mission in the least amount of time. The dock is assumed to have a constant mean power value for a given sea state obtained from a power matrix of a particular WEC type. The charging of the dock and discharging of the AUVs changes linearly with time as shown in Figure 1.

V. RESULTS & DISCUSSIONS

The total mission time is evaluated against an increasing number of AUVs as well as an increasing number of mission points using both algorithms as shown in Figure 2, and 3 respectively. The computed mission time was also analysed for a low and high sea state scenario as shown in Figure 4. In the high sea state scenario, the WEC is assumed to generate

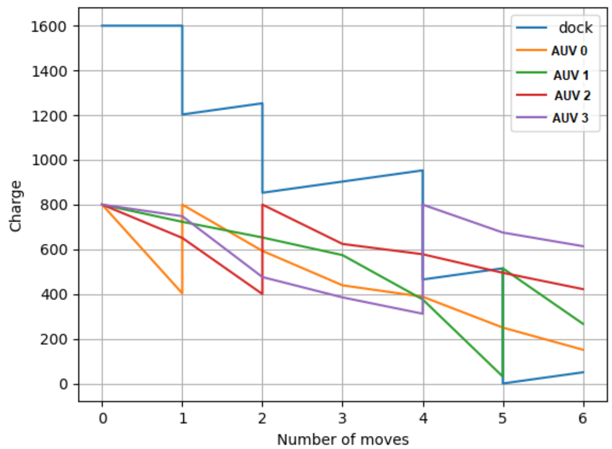

Fig. 1. Charging and discharging profile for four AUVs $\{0, 1, 2, 3\}$ and the *dock* node through the course of mission in a 600×600 area with 18 randomly distributed mission points.

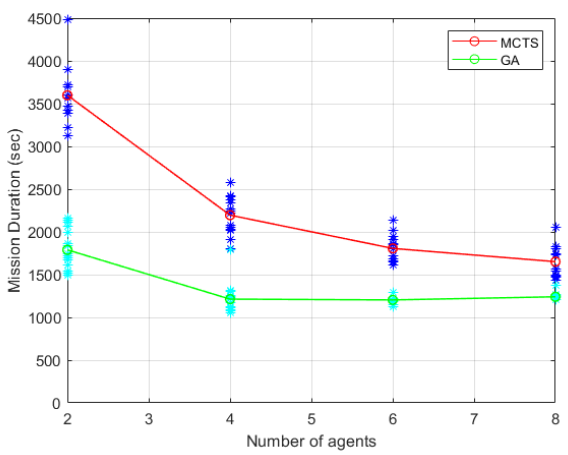

Fig. 2. Mission duration with an increasing number of AUVs on a 600×600 area with 26 randomly distributed mission points. The centralised GA scheme generates better mission plans than the decentralised MCTS scheme for the constrained energy source problem.

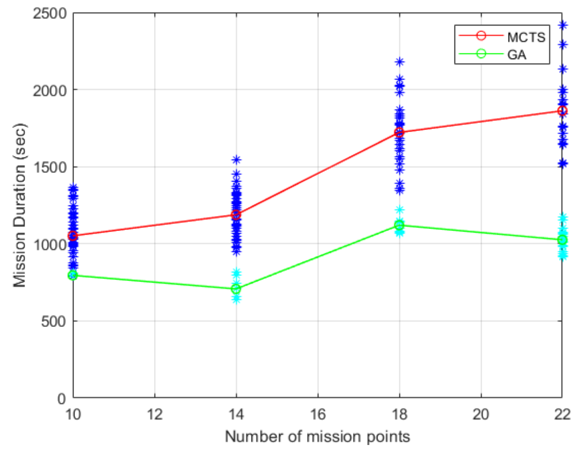

Fig. 3. Mission duration using four AUVs with an increasing number of mission points on a 600×600 area. The centralised GA scheme generates better mission plans than the decentralised MCTS scheme for the constrained energy source problem.

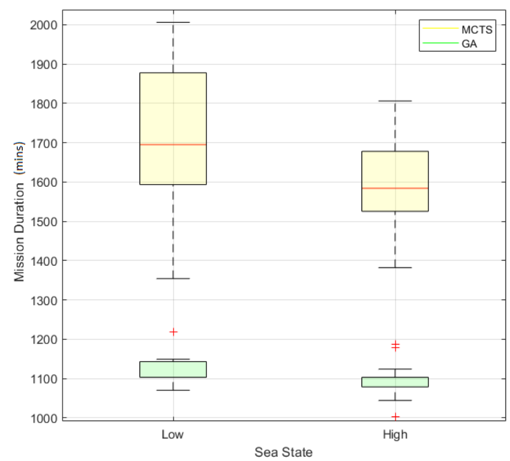

Fig. 4. Mission duration for a low and high sea state condition with four AUVs and one dock in a 600×600 area with 18 randomly distributed mission points. In this mission scenario, higher sea state generates more efficient mission plans that at low sea state and the impact can be seen from reduced mission time.

double the power than the power generated in the low sea state scenario.

It is observed that Algorithm 2 (GA) provides better estimate of mission time for the constrained energy source problem than Algorithm 1 (MCTS). However, the centralised GA scheme has a higher computational overhead than the decentralised MCTS scheme as it requires one central planner that generates the sequence of mission points to be traversed by each AUV in the entire fleet. On comparing the mission duration in low and high sea state scenarios as shown in Figure 4, it is observed that the mean value of mission duration obtained over multiple episodes decreases for a high sea state condition. The observation indicates that the AUVs were able to optimize their visit time to the recharging station more efficiently in the high sea state condition as the maximum power availability constraint at the dock is relaxed as compared to the low sea state condition.

VI. CONCLUSIONS

A centralized and decentralized framework is provided for the mission planning of multiple underwater vehicles that take into account the charge available at the recharging station in addition to the charge capacity of AUVs. The impact of an increasing number of AUVs and an increasing number of mission points on the overall mission duration was compared against the two algorithms. The mission performance was also analyzed with respect to changing sea state conditions.

In the future, mission performance can be studied by incorporating charging time delays at the recharging station. Also, the continuous communication dependency of a central planner during online replanning can be overcome with a decentralized scheme. Hence, the mission performance can be analyzed for online replanning scenarios as well as AUV failure scenarios.

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