Article

# Implementing Path Planning for Robotic Aquaculture Monitoring

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**Abstract:** Marine food chains are highly stressed by aggressive fishing practices and environmental damage. Aquaculture has increasingly become a source of seafood which spares the deleterious impact to wild fisheries. However, continually monitoring water quality to successfully grow and harvest fish is labor intensive. The Hybrid Aerial Underwater Robotic System (HAUCS) is a swarm of unmanned aerial vehicles (UAVs) and underwater measurement devices designed to collect water quality data of aquaculture ponds. Three methods of path planning for the UAVs are simulated and experimentally verified at Southern Illinois University's Aquaculture Research Center to demonstrate the feasibility of HAUCS.

**Keywords:** aquaculture; robotics; monitoring; machine learning; path planning; vehicle routing problem; drones

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## 1. Introduction

Global fish stocks in every ocean have been declining for decades, primarily due to overfishing [1,2]. Changes in the marine environment from human pollution have also brought about further reductions of fish populations and the bioaccumulation of pollutants such as heavy metals in wild fish [3,4]. Since 1990, fish consumption has doubled, while capture fishery production has remained constant. The rising demand has been met by the explosive growth of aquaculture, which has grown exponentially over the last few decades, producing more fish than capture fisheries for the first time in 2012 [5].

Aquaculture is a labor intensive activity, with the most burdensome task being maintaining appropriate water quality levels. Of particular importance is the level of dissolved oxygen (DO), which, if mismanaged, will result in the sudden collapse of a fish pond. Fish farmers typically measure DO by attaching a sensor to a vehicle which is manually driven to each pond. This process is repeated multiple times a day, and is particularly important to measure at night, when DO levels typically drop due to the lack of photosynthesis and subsequent plant respiration. Because DO measurement is a repetitive and relatively simple task, it is a prime target for automation.

### 1.1. Previous Work

Much advancement has been made toward the use of AI and drones to help manage production and maintenance on aquaculture farms. Besides monitoring water quality levels, methods have been proposed to automate activities such as fish counting, fish length estimation, and facility surveillance [6,7]. Two distinct approaches have been used to approach the problem of automating the task of monitoring DO levels. The first approach consists of using stationary DO sensors, wireless communications and a power source installed into each pond [8–10] to constantly monitor water quality levels. While this type of solution does reduce labor costs, equipment and installation costs do not scale well for industrial sized farms which have thousands of ponds. Additionally, sensors which remain in water will biofoul if they are not regularly maintained. These hardware and maintenance requirements will detract from the goal of reducing overall costs.

The other type of approach to automatically monitor DO levels involves the design of sensor packages [11,12] and vehicles [13,14] to travel between ponds on a regular basis to collect their water quality data. This reduces the maintenance burden and eliminates the need to install sensors for each pond. Remote sensing techniques have also been proposed to predict DO levels using multispectral images of the pond surface [15]. While remote sensing would greatly simplify the task for the drones, it introduces the risk of poorly predicting the DO due to the unknown level of oxygenation beneath the surface.

While studies of autonomous aquaculture systems are relatively common, work regarding robotic motion planning for autonomous aquaculture management has been sparse. Motion planning for oyster farm maintenance [16], fish net cleaning [17], and mesh networks [18] are some of the few examples. The rising demand for aquaculture products, the short supply of laborers, and so far limited research interest makes this a prime topic for further investigation.

### *1.2. The Hybrid Aerial Underwater Robotic System*

Research into this approach of using autonomous vehicle mounted sensors works has demonstrated that DO measurement using drones is feasible, but it has not yet demonstrated the ability to automate their data collection. Our proposed solution is the Hybrid Aerial Underwater Robotic System (HAUCS) [19,20]. In this system, DO sensors and radio modules are installed on a set of GPS navigated drones which take in situ measurements before returning to be recharged. The drones conduct a direct, full depth measurement of DO, temperature, and pressure to gain a full understanding of the state of each pond.

The routing of the drones in a safe and efficient manner is a complex problem. Multi-robot navigation is a well-studied topic of research, with many differing constraints and requirements [21,22]. Devising the path for each drone is an example of the Vehicle Routing Problem (VRP), a generalization of the Traveling Salesman Problem (TSP). In the VRP, a group of vehicles must visit each node of a graph with the minimal longest route. This ensures the most equal distribution of distance required to be traveled by each drone, which allows the fewest possible of drones needed to adequately monitor the farm. Considerable research has been invested in TSP, VRP and its numerous variants [23–25], and as a result many solutions to this routing problem are available. More specifically, this environment is an example of Distance Constrained VRP (DVRP) due to the limiting factor being the range of the drones.

Most VRP research consists of node graphs which are highly idealized. While most studies focus on randomly generated node locations with 100 nodes or fewer, the reality of aquaculture farms is they may have hundreds of ponds. Aquaculture farms also dig their ponds in a regular, grid-like manner, which would facilitate repetitive paths. There are relatively few VRP methods which are intended for calculating routes for more than 100 nodes [26,27], and fewer methods for calculating paths in a grid space [28,29]. Another factor to consider is the drones will be required to fly in inclement weather. The impact of wind on their path planning may be highly significant, yet there is very little research regarding its impact on drone path planning [30,31]. These unique conditions require special consideration that are not sufficiently studied in the literature.

### *1.3. Simulation*

To create a realistic distribution of fish ponds, an algorithm was devised using some basic assumptions of how a typical fish farm is organized. First, a randomly generated convex polygon is created to replicate the farm's available land and a grid of points is filled inside it. Then, 20% of the points are removed in order to replicate empty ponds and add additional variation. This creates a pattern of points which are not completely regular yet not random, and is a reasonably accurate generalization of the spacial distribution of typical fish farms.

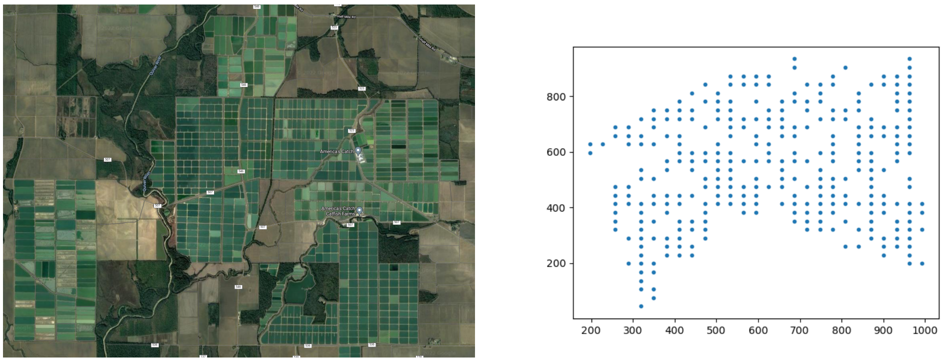


**Figure 1. Left:** America's Catch Catfish Farm with approximately 700 ponds. **Right:** Example of 300 pond simulated aquaculture distribution. Adapted from [32].

Our previous work investigated three different VRP approaches for this problem using these simulated fish farms [32]. These approaches were the Google Linear Optimization Package (GLOP) [33], Graph Attention Model (GAM) [34], and our heuristic solution, the HAUCS Path Planning algorithm (HPP). These methods were selected because they represent high performing methods with different approaches.

GLOP is a linear optimization Python package which computes the most optimal or nearly optimal solution for a set of node locations given certain linear relationships [33]. Linear programming is a method used to optimize a linear objective function, subject to a set of linear inequality or equality constraints. In the context of the vehicle routing problem, GLOP can be used to minimize the maximum route length for a given set of node coordinates. It does this by using a primal-dual simplex algorithm, which works by starting with a feasible solution to the problem, called the primal solution, and finding a corresponding feasible solution to a related problem called the dual problem. The algorithm then iteratively improves both the primal and dual solutions until an optimal solution is found. At each iteration, the algorithm chooses a direction to move in, called a pivot, that improves the objective function. The pivot is chosen based on the values of the objective function and the constraints at the current iteration. One potential disadvantage of using GLOP for the vehicle routing problem is that the complexity of the algorithm grows exponentially with the size of the problem, making it inefficient for large-scale problems.

Kool et al. proposed a machine learning approach to solving routing problems using a graph attention model (GAM) and reinforcement learning [34]. They use GAM to encode a learned representation of the locations and their relationships, which is then used in conjunction with reinforcement learning to identify the most optimal routes. GAM is a type of graph neural network that uses attention mechanisms to weigh the importance of different parts of the input data, allowing it to focus on the most relevant information when making predictions. To train the GAM, Kool uses a dataset of synthetic routing problems with known optimal solutions, and uses reinforcement learning to learn a policy for selecting actions that lead to the most optimal routes. GAM is trained using a variant of the actor-critic algorithm, which involves learning both a policy for selecting actions and a value function that estimates the expected future reward. The results of the experiments in the paper show that GAM is able to learn the highly optimal routes for the synthetic routing problems, and outperforms many traditional optimization methods in terms of both accuracy and speed.

HPP is a path planning strategy that enables drone platforms to monitor aquaculture farms in a back-and-forth pattern using a geometric approach. It consists of two phases: clustering and routing. In the clustering phase, k-means is used on the set of nodes to produce evenly spaced clusters. Convex polygons are then created around each cluster, and the antipodal pairs of these polygons are calculated using the Shamos algorithm [35]. In the routing phase, the Optimal Coverage Algorithm (OCA) is used to determine the shortest optimal back-and-forth path that starts and ends at one of the antipodal point

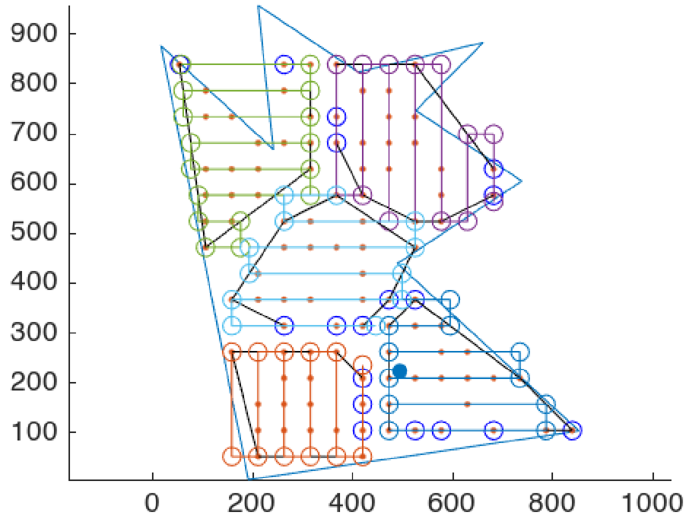


**Figure 2.** Plot of HPP clusters and their associated route plans. The blue dot signifies the depot location.

pairs [36]. The route is then assigned to follow the optimal back-and-forth pattern as closely as possible. If a cluster is too small to form a polygon, it is expanded by adding the closest nodes from neighboring clusters until all clusters have a valid size and shape. The performance of HPP is demonstrated by the evenly spaced clusters of approximately equal size shown in 2, despite the irregular outline shape of the node locations. The effectiveness of this approach is dependent on the assumption that the distribution of nodes is generally even. If nodes are placed randomly or have areas of higher density, this assumption may not hold, and the method may be less effective in producing efficient routes. Further details of the HPP implementation can be found in our previous works [32,36,37].

The results for these three methods differed depending on the scale of the simulated farm as show in tables 1, 2, and 3. For small farms, which consist of 50 to 200 ponds, GLOP was the most efficient router with the lowest average maximum route length. For larger farms, which were simulated as 200 ponds to 700 ponds, HPP provided the best routing. GLOP is not able to compute routes for farms that large due to the high computational complexity of the method, so the most optimal solutions cannot be found in a reasonable amount of time. While GAM was unable to outperform GLOP in small farms or HPP in large farms, it achieved comparable quality of results for large and small farms in a fraction of the time.

**Table 1.** Average Total Distance

| Ponds | HPP | GAM50 | GAM100 | GLOP |
|---|---|---|---|---|
| 50 | 7.62 | 7.19 | 7.6 | **6.37** |
| 100 | 9.94 | 9.45 | 9.85 | **7.72** |
| 200 | 12.66 | 13.06 | 12.95 | **9.12** |
| 300 | **15.37** | 17.22 | 16.47 | — |
| 500 | **19.02** | 25.46 | 22.79 | — |
| 700 | **21.72** | 35.35 | 29.74 | — |

**Table 2.** Average Maximum Route Length

| Ponds | HPP | GAM50 | GAM100 | GLOP |
|---|---|---|---|---|
| 50 | 2.01 | 1.75 | 1.82 | **1.47** |
| 100 | 2.53 | 2.27 | 2.39 | **1.65** |
| 200 | 3.14 | 2.73 | 3.27 | **1.9** |
| 300 | **3.79** | 4.02 | 3.89 | — |
| 500 | **4.58** | 5.57 | 6.32 | — |
| 700 | **5.28** | 12.77 | 7.66 | — |

**Table 3.** Average Run Time (ms)

| Ponds | HPP | GAM50 | GAM100 | GLOP |
|---|---|---|---|---|
| 50 | **.013** | 1.1 | 1.2 | 735 |
| 100 | **.030** | 3.5 | 3.1 | 6581.5 |
| 200 | **.047** | 9.0 | 10.7 | 54352.6 |
| 300 | **.095** | 21.5 | 23.9 | — |
| 500 | **.110** | 59.7 | 64.9 | — |
| 700 | **.115** | 179.7 | 185.1 | — |

### *1.4. Wind Considerations*

Whenever planning flights for any aircraft, it is important to take weather conditions into consideration. Significant wind can dramatically change the optimal flight path by increasing the cost of flying upwind. Some research has been done to investigate the effect of wind on path planning for aerial drones, but this research is divided into fixed wing [30,31] and multicopter [38,39] configurations. The so-called Windy Routing Problem (WRP) [40–42] addresses multicopter flight planning in windy conditions, as it is not constrained by the turn radius of a fixed wing aircraft, which requires additional consideration [30]. WRP assumes steady wind in a single direction and no complex wind phenomena such as turbulence and pressure or density changes.

To model this for our aquaculture dataset, we simply increase the cost of travel in upwind directions and reduce the cost in downwind directions. A random direction and wind speed is chosen, with the maximum wind speed being just less than the top speed of the drone. We repeat the aquaculture simulation path planning with this added factor and report the results in 4, 5, and 6. GAM did not perform as stably when wind conditions were factored in, and much of its increase is attributed to its total failure to plan efficient routes for a few samples, while performing reasonably well for the majority of samples. HPP and GLOP performed similarly as in non-windy conditions, with GLOP providing the most optimal routes but being unable to produce results in a reasonable amount of time for real-time operations.

**Table 4.** Average Total Distance in Wind

| Ponds | HPP | GAM50 | GAM100 | GLOP |
|---|---|---|---|---|
| 50 | 8.69 | 9.28 | 10.69 | **7.017** |
| 100 | 10.41 | 11.65 | 14.79 | **7.71** |
| 200 | 13.99 | 16.99 | 24.02 | **8.95** |
| 300 | **15.02** | 21.31 | 35.95 | — |
| 500 | **19.10** | 32.16 | 63.57 | — |
| 700 | **22.93** | 41.57 | 84.75 | — |

**Table 5.** Average Maximum Route Length in Wind

| Ponds | HPP | GAM50 | GAM100 | GLOP |
|---|---|---|---|---|
| 50 | 2.26 | 2.28 | 3.14 | **1.65** |
| 100 | 2.71 | 2.89 | 6.18 | **1.72** |
| 200 | 3.45 | 6.63 | 10.29 | **1.88** |
| 300 | **3.75** | 7.99 | 9.34 | — |
| 500 | **4.66** | 13.21 | 15.88 | — |
| 700 | **5.64** | 16.89 | 17.21 | — |

**Table 6.** Average Run Time in Wind (ms)

| Ponds | HPP | GAM50 | GAM100 | GLOP |
|---|---|---|---|---|
| 50 | **0.03** | 0.94 | 1.03 | 748.79 |
| 100 | **0.04** | 2.96 | 3.31 | 6091.04 |
| 200 | **0.06** | 9.10 | 10.67 | 58157.81 |
| 300 | **0.09** | 22.31 | 28.76 | — |
| 500 | **0.21** | 76.28 | 72.36 | — |
| 700 | **0.21** | 151.22 | 162.92 | — |

This work is intended to validate the conclusions derived from our simulations by implementing these algorithms onto drone hardware. We apply the three methods to pond coordinates in the Southern Illinois University Aquaculture Research Center and return a set of routes for each method. These routes are then loaded onto a set of three drones, and power measurements from the drones are recorded after they fly their missions to conduct their measurements.

## 2. Materials and Methods

The drones used to facilitate this study were the SwellPro Splashdrone 4. They are IP67 waterproof drones meant for hobbyist photography and aquatic activities which include waterproof connectors for payload, camera and gimbal controls. Three drones were used to conducted our experiment. Attached to the underside of the drone is a housing for communication equipment and the winch release mechanism, see figure 3. The winch holds the sensor payload, which is released into the pond upon landing on the surface of the water down to a depth of 2 meters. The payload consists of a Seeed Studio XIAO nRF52840 Sense board which is used to collect DO, temperature and pressure data and send it over Bluetooth Low Energy wirelessly to an ESP32 Wi-Fi LoRa V2 board contained in the winch mechanism, where it is then forwarded over LoRa to an identical ESP32 board functioning as the base station. The base station receives the sensor data and uploads it to a cloud Firebase instance to automatically update an android app with the water quality status of each pond, see figure 4.

The SwellPro Software Development Kit (SDK) was used as the interface between the path planning methods and the flight controllers. Custom flight control software was created in python to load these routes into the drone and to facilitate the communication between the drones and the base station. A laptop was connected to each of the drones' hand-held controllers via dual band 802.11 Wi-Fi, switching connections as necessary to send commands to each of the drones. Mission commands with the planned route coordinates and necessary take off and landing commands were sent over TCP/IP to each controller and were then forwarded to its respective drone over a proprietary SwellPro radio link. Once the mission plan was successfully received by the drone, no further radio communication was necessary for flight control, and they could fly out of radio range. However, the LoRa link to the base station still required a stable connection to upload the pond data as it was collected. This shortcoming can be addressed in future iterations by either developing a mesh network with the drones to forward messages to the base station, or storing the sensor data until a radio connection with the base station is reestablished.

**Figure 3. Top Left:** SwellPro Splashdrone 4 with orange payload visible underneath. **Top Right:** Side view with the winch release mechanism and radio housing in black. **Bottom Left:** Underside with the orange winch drum visible. **Bottom Right:** Payload which contains BLE transmitter and DO, temperature and pressure sensors.

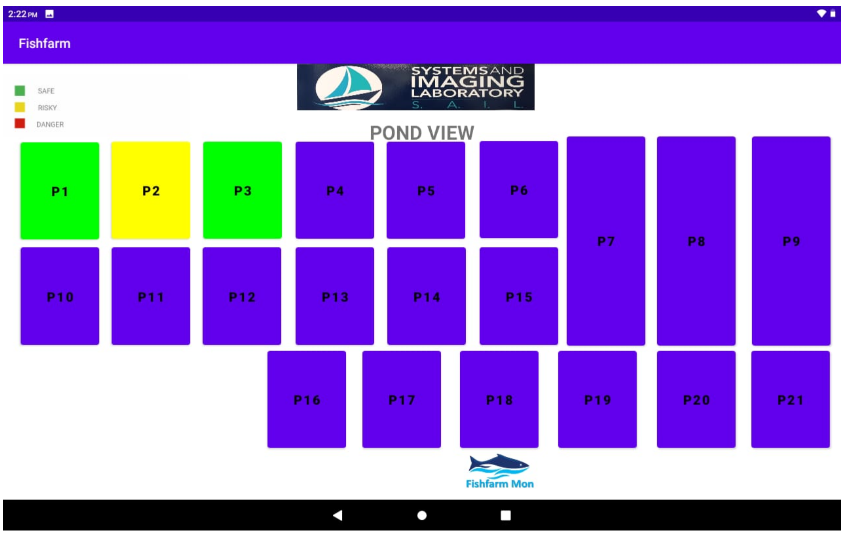


**Figure 4.** Android app displaying water quality readings sent by the drone


**Figure 5.** Southern Illinois University Aquaculture Research Center. The takeoff location is marked with a green dot, all available ponds are marked with a blue dot.

To produce the mission plan, the custom flight control software takes in the list of pond coordinates from the three routing techniques and generates a set of waypoints with appropriate landing, take-off, and payload activation commands to successfully and reliably land in the water, activate the sensor payload to lower and return, take off and report the data to the base station. The payload was activated through the camera activation pin in the Splashdrone momentarily before it lands in the water, whereupon receiving the signal would lower the winch and begin sensing, then after a set time would retract the winch and end sensing. The payload was then activated again once the drone reaches its maximum altitude to send the data to the base station. The software used to transmit missions to the Splashdrones, along with the GLOP and HPP methods, are available at https://github.com/tonydavis629/HAUCS.

A satellite image of the Southern Illinois University Aquaculture Research Center is seen in figure 5. This facility has the capacity for 90 ponds, however at the time of testing only 26 ponds were safe to land in. Issues such as lack of water, excessive overgrowth, and power line obstacles prevented the use of 64 ponds. These 26 available ponds were loaded into the three path planning methods: GLOP, GAM and HPP.

## 3. Results

The GPS coordinates of each of the ponds were recorded and normalized between 0 and 1 in order to facilitate the computation of the routes. These normalized list of coordinates were input into each of the three path planning methods, the output of each being three lists of the GPS coordinates of each pond to be visited by each drone. These three routes were then loaded into the drones using our mission control software for flight testing. During the flight, GPS, compass, battery, and temperature data were recorded. The routes for each method are simulated and visualized in figure 6.

### *3.1. Simulation Data*

For each path planning method, the simulated distance is calculated as a means to estimate the relative energy draw and time required from each drone, see table 7. As expected by the results of our previous study, GLOP and GAM are comparatively efficient and HPP produces significantly longer routes. HPP works on the assumption that the ponds are evenly distributed, which was not valid for our tests because only a small number of ponds were used. As a result, HPP is not effective for this situation. If all 90 ponds were available, it would be expected to be comparatively optimal to the others, while also allowing for better airspace deconfliction and requiring minimal computation.

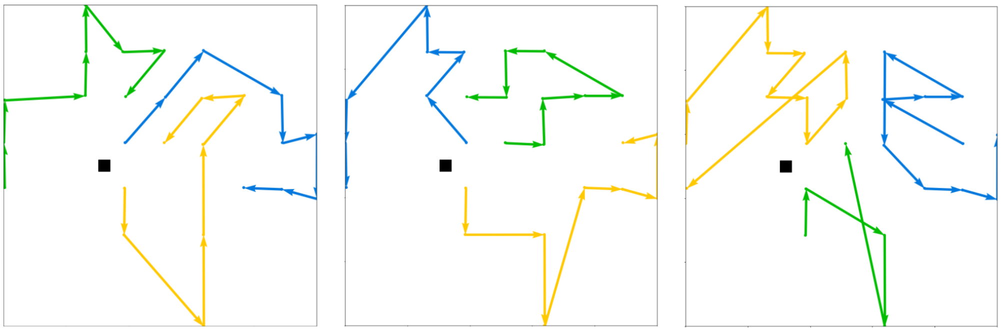

**Figure 6.** Routes for each path planning method, from left to right: GLOP, GAM, HPP. The black square signifies the launch point. Plotted with tools from [34].

**Table 7.** Simulated Distance

| Method | Drone 1 | Drone 2 | Drone 3 | Total | Average |
|---|---|---|---|---|---|
| **GLOP** | 1.91 | 1.87 | 1.91 | 5.70 | 1.90 |
| **GAM** | 2.35 | 1.64 | 1.73 | 5.72 | 1.91 |
| **HPP** | 2.9 | 1.73 | 3.01 | 7.64 | 2.55 |

### 3.2. Flight Data

Power data from the flights were recorded using the Splashdrone's flight recorder in order to validate the simulated power draw of each method. DO, temperature, and pressure data were not recorded as they were not the focus of this experiment. Tables 8, 9 and 10 shows similar results to the simulated data. GLOP is slightly more optimal than GAM, which are both significantly more efficient than HPP. In terms of power draw, GLOP and GAM were not significantly different. These results give validation to the assumption that using calculated horizontal distance is a good proxy for power consumption, and our simulations can give a good approximation of the range requirements for drones in HAUCS. This assumption may not hold for situations such as high winds or farms with significant changes in elevation.

**Table 8.** Flight Time (seconds)

| Method | Drone 1 | Drone 2 | Drone 3 | Total | Average |
|---|---|---|---|---|---|
| **GLOP** | 586 | 621 | 448 | 1655 | 552 |
| **GAM** | 689 | 517 | 586 | 1792 | 597 |
| **HPP** | 863 | 426 | 862 | 2151 | 717 |

**Table 9.** Battery Drain (mAh)

| Method | Drone 1 | Drone 2 | Drone 3 | Total | Average |
|---|---|---|---|---|---|
| **GLOP** | 1518 | 1716 | 1848 | 5082 | 1694 |
| **GAM** | 1914 | 1584 | 1650 | 5148 | 1716 |
| **HPP** | 2442 | 1254 | 2442 | 6138 | 2046 |

**Table 10.** Battery Drain (%)

| Method | Drone 1 | Drone 2 | Drone 3 | Total | Average |
|---|---|---|---|---|---|
| **GLOP** | 23 | 26 | 28 | 77 | 26 |
| **GAM** | 29 | 24 | 25 | 78 | 26 |
| **HPP** | 37 | 19 | 37 | 93 | 31 |

Wind conditions on the day of our testing were 0-5 mph in variable directions, so we did not have the opportunity to validate our simulation of steady wind conditions on path planning efficiency.

### *3.3. Issues*

A number of hardware and software failures were experienced during the automated flight tests. The Splashdrone is designed to reach a desired altitude relative to the take-off location, not an absolute above sea level altitude. This causes issues when the elevation of the ponds are significantly different because the drone will reach inconsistent altitudes when traveling between the ponds. This is not only a problem for airspace deconfliction, but it requires that the drone's altitude be set according to the maximum difference in elevation of its ponds. This is not ideal from a battery or safety perspective, and supports the use of a flight controller which can be programmed to take off to a specified sea level altitude. This way, the drones can be assigned to certain altitudes to avoid the possibility of in-air collisions. Using an above ground level altitude assigned may also work and reduce the amount of altitude required to keep airspace deconflicted, but introduces greater complexity as the drones would be changing altitude between ponds.

Towards the end of our testing, one of the drones experienced a water leak during a pond landing and was subsequently damaged. This is a critical concern for HAUCS, as the drones will be expected to work robustly without leaks on a regular basis. This particular drone had crashed earlier during testing, so it is likely the damage from that crash caused a fault in a seal or a crack in the body. Future iterations of HAUCS will require great care in the design of the drone body to ensure the testability of a water tight seal in the event of a crash and as a matter of regular maintenance.

Another failure occurred which resulted in the drone directing itself off course and into the tree line, which was likely caused by a failure of the onboard GPS. High accuracy GPS is not required, but high reliability is, especially due to the risk of crashing during automated flights. A potential solution to this would be redundant onboard GPS modules, which would likely be worth the added expense due to the importance of the GPS modules in this system. Object avoidance measures such as radar or vision would also be a possible solution, however they may also significantly increase expense, weight, and complexity.

## 4. Discussion

These initial results validate the use of drones as a means to monitor water quality levels in an aquaculture environment. With simple software and off the shelf hardware, precalculated missions can be sent to drones, which dutifully execute and send data to a cloud service for real-time monitoring. This system has the potential to reduce prices of farmed fish and address the shortage of labor in the North American aquaculture industry.

Significant work is still required before HAUCS is ready for commercialization. Reliability and robustness of the automated flights is of the utmost importance, and as demonstrated by our system failures, it is still a work in progress. Lightweight object avoidance systems for UAVs do exists [43,44], and may need to be implemented for safety and reliability. However, additional testing is required to verify if GPS guided flight can function reliably for aquaculture monitoring.

Extrapolating from the data collected for these 26 ponds, estimations for drone range capacity requirements can now be made for other farms. Considering that measuring 9 ponds took approximately 26% battery capacity, all 90 ponds of the SIU Aquaculture Research Center could reliably be measured by 3-5 Splashdrones. Additional data will need to be collected from other facilities to give a better picture of the range requirements in general, as different farms will have different sized ponds with different distances between them.

Additional testing will also be necessary to further validate the three path planning methods. As was expected, GLOP and GAM perform nearly identically for small farms. Testing HPP on a large farm could validate its use as a large-scale path planning algorithm

**Figure 7.** Splashdrone landing in a pond

for aquaculture monitoring. Most commercial farms are indeed much larger than the SIU facilities, so its validation would be highly valuable.

Inclement conditions such as wind and rain provide an additional complication for HAUCS, as fish ponds need to be monitored particularly closely in these conditions. High winds and precipitation can have unpredictable effects on DO levels because of the stratification of oxygen in the ponds. Combined with the fact that flights may be inhibited or grounded, inclement weather is an important factor to consider in the design of HAUCS. High winds may make certain routes more inefficient if they involved traveling upwind unnecessarily. Path plans may also need to be reconstructed on the fly due to changes in conditions or hardware failures. Real-time monitoring and flight adjustment will be required of HAUCS to operate in all conditions, as will proper user notification in the event that flights cannot be conducted. An inclement weather protocol may also involve the use of protective waypoints for drones to take shelter temporarily without the need to return to the home station.

## 5. Conclusions

The Hybrid Aerial and Underwater Robotic System is a promising direction for reducing labor costs in aquaculture farms. The concept has been experimentally validated for its potential, but requires significant improvement before commercialization. Additional testing must be completed on larger farms to confirm the expected performance of the HPP method, as well as to collect data on varied aquaculture environments. Drones which are equipped with accurate altitude instruments, robust waterproofing, and some means of object avoidance should be used in future tests in order to address problems which were identified in this study. Flights in windy and rainy conditions pose an especially difficult problem due to the elevated need for water measurements and the danger of flying in inclement weather.

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**Data Availability Statement:** Collected data can be found at https://github.com/tonydavis629/HAUCS

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