PATH PLANNING FOR THE HYBRID AERIAL UNDERWATER ROBOTIC SYSTEM

by

Anthony C. Davis

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PREFACE

Parts of this thesis are based on a published work, of which I am the first author.

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ABSTRACT

Author: Anthony C. Davis

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Thesis Advisor: Dr. Bing Ouyang

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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, but it requires continuous water quality data to successfully grow and harvest fish. Aerial drones have great potential to monitor large areas quickly and efficiently. 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. The routing of drones to cover each fish pond on an aquaculture farm can be reduced to the Vehicle Routing Problem (VRP). A dataset is created to simulate the distribution of ponds on a farm and is used to assess the HAUCS Path Planning Algorithm (HPP). Its performance is compared with the Google Linear Optimization Package (GLOP) and a Graph Attention Model (GAM) for routing around the simulated farms. The three methods are then implemented on a team of waterproof drones and experimentally verified at Southern Illinois University's (SIU) Aquaculture Research Center. GLOP and GAM are demonstrated to be efficient path planning methods for small farms, while HPP is likely to be more suited to large farms. HAUCS shows

great value as a future direction for intelligent aquaculture, but issues with obstacle avoidance and robust waterproofing need to be addressed before commercialization. The future of aquaculture promises more integrated and sustainable operations by mimicking natural systems and leveraging deeper understandings of biology.

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CHAPTER 1
BACKGROUND

Aquaculture is the ancient practice of cultivating and harvesting food from aquatic environments. While it is widespread in Asia, it is a relatively small industry in the rest of the world. This chapter will introduce aquaculture and explain the rationale and concept of the Hybrid Aerial Underwater Robotic System (HAUCS).

1.1 AQUACULTURE

Global fish stocks in every ocean have been declining for decades, primarily due to overfishing [11, 12]. 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 [13, 14]. Since 1990, fish consumption has risen more than 400%, while capture fishery production has remained constant, see figure 1.1. The rising demand has been met by the explosive growth of aquaculture, which has increased production 25-fold in the past 5 decades [15], producing more fish than capture fisheries for the first time in 2012 [16], see figure 1.1. About half of the world's aquaculture production is in China, where it has been practiced for thousands of years [17].

Aquaculture is a varied and ancient practice. Hundreds of different marine creatures from every trophic level are grown and harvested around the world, from mollusks to tuna. The most common technique uses man-made ponds as a habitat to grow the fish, which can take many months or a few years to reach maturity. The fish are then harvested by pulling a net through the pond with a set of tractors or man-

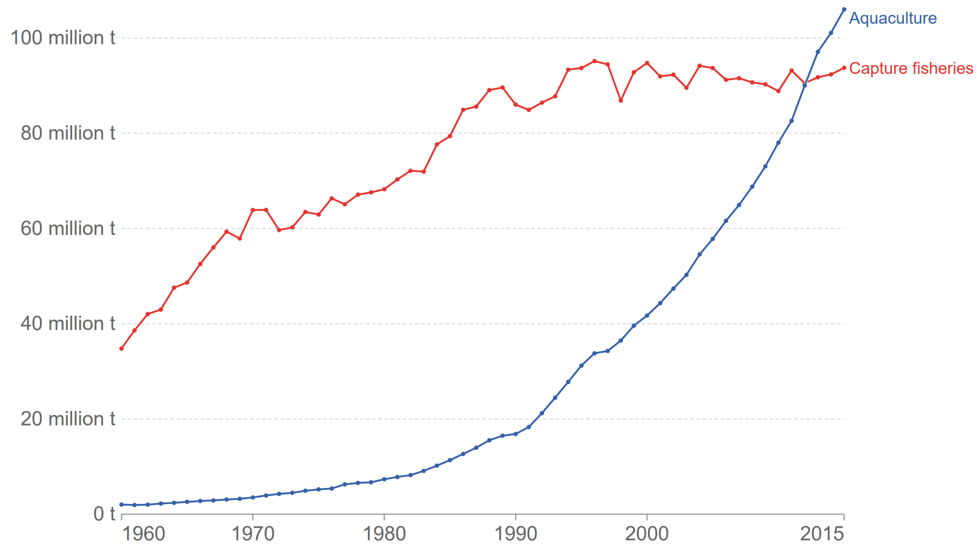

Figure 1.1: Global wild capture vs. aquaculture production, 1960-2018. Adapted from [1].

ually. Marine livestock have diverse dietary requirements, some being carnivorous, such as salmon, while others are omnivorous or herbivorous. Fish have the lowest feed conversion ratio (FCR) of any livestock [2], meaning they require the least feed input out of all animal protein sources, see figure 1.2. However, carnivorous fish require wild caught fish for feed, which can put additional pressure on those fish stocks and are an additional expense [18].

One of the most critical and laborious aspects of the fish aquaculture is maintaining proper dissolved oxygen (DO) levels. Fish breathe DO through their gills, so if levels drop too low, the fish pond will collapse. Traditionally, DO monitoring relies on human operators driving trucks around the farm to manually measure the DO concentration in 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 dominance of plant respiration. When low DO is detected, aerators can be positioned at the pond to mix air with the water to increase the DO level. This process is both labor-intensive and costly.

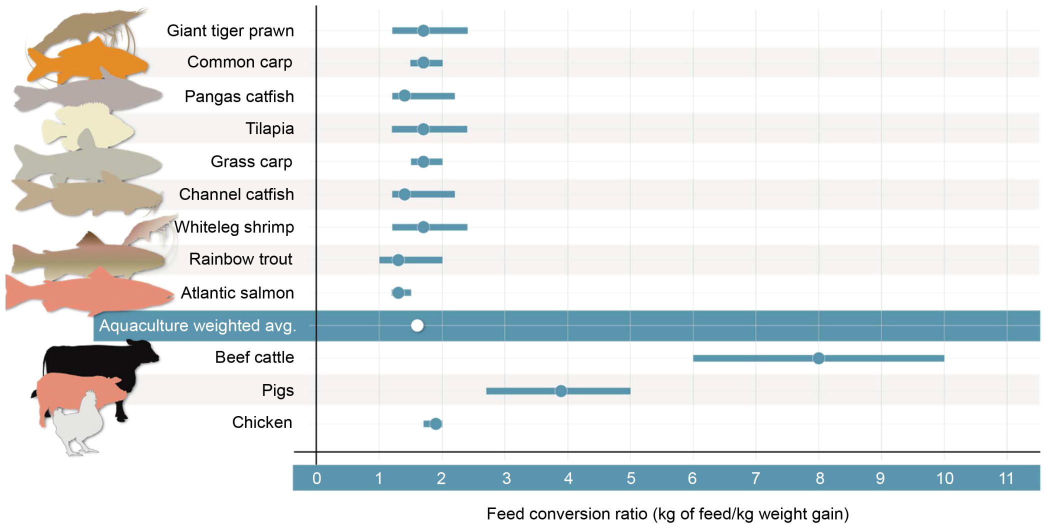

Figure 1.2: Feed conversion ratio comparisons. Adapted from [2].

To meet rising consumer demand for fish and maintain affordable prices, the aquaculture industry must improve its labor efficiency through automation. Because DO measurement is a repetitive and relatively simple task, it is a prime target for automation.

1.2 INTERNET OF THINGS

The Internet of Things (IoT) is a concept which has risen to prominence because of the ubiquity of computing and the affordability of sensors. The combination of sensors and computing connected through wireless networks has applications in the consumer, industrial, infrastructure, and military sectors. IoT promises to remove barriers to information propagation by interconnecting all devices, so tasks can be automated and resources can be used efficiently [19].

Much advancement has been made toward the use of IoT 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 [20, 21]. Integrating information from all aspects

Figure 1.3: Aquaculture pond buoy from In-Situ, Inc.

of a farm can enable better decision-making and reduce costs. The future directions of IoT will be further discussed in chapter 4.

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 to continuously monitor water quality levels [22, 23, 24], see figure 1.3. 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. Furthermore, these stations may hinder other operations in the pond, such as fish harvesting. 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 [25, 26] and vehicles [27, 28] which travel between ponds regularly to collect water quality data. This reduces the maintenance burden and eliminates the need to install sensors for each pond. Research into this approach has demonstrated that while DO measurement by autonomous vehicles is feasible, it has not yet been implemented in an operational system.

Remote sensing techniques have also been proposed to predict DO levels using multispectral images of the pond surface [29]. Remote sensing would greatly increase the scalability of DO monitoring, but it introduces the risk of poor DO prediction due to the unknown level of oxygenation beneath the surface. It is also challenging to monitor the pond conditions during the evening using multispectral images.

1.3 HAUCS

The Hybrid Aerial Underwater Robotic System (HAUCS) is an aquaculture IoT framework designed to integrate farm data and prediction models with mobile controls to allow farmers to manage their farm autonomously [8, 30]. By integrating these data and controls into a single platform, the goal is to reduce the labor costs of one of the most burdensome and critical aquaculture tasks. It hopes to provide a scalable means of operation and timely, accurate data to operators.

Data is collected from the ponds via sensors on the underside of drones, which travel from pond to pond on a regular basis. This data is combined with weather data to inform a prediction model, which determines where and when to send mobile aerators to deliver oxygen to the ponds and how frequently to send the drones. All data is uploaded to a cloud service for easy monitoring via a mobile application. A concept sketch of HAUCS is seen in figure 1.4.

The system will be able to handle farms of any size by simply increasing the number of drones used. This eliminates the need to install sensors into each pond, and instead simply adding additional drones to meet the range and measurement frequency required.

Affordability is top priority for the HAUCS hardware specifications. No high-

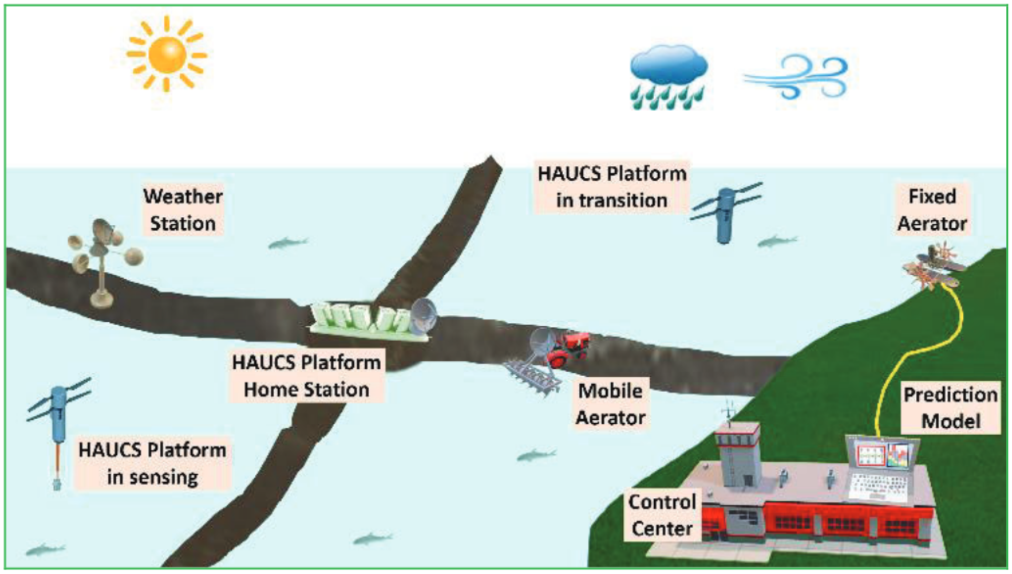

Figure 1.4: Basic HAUCS concept of operations. Adapted from [3].

performance components are required. Commercial off-the-shelf (COTS) drones are becoming increasingly affordable and capable, and can be easily modified to accommodate additional sensors and actuators. LoRa transceivers can be used for cheap, long-range communication. 3D-printed components are used to build the necessary mechanisms for the sensors.

This initial concept involves managing only fish, but future work will combine multiple species in an integrated manner to improve sustainability and profitability by taking advantage of fish waste products [31], to be discussed further in chapter 4.

CHAPTER 2

DESIGN AND SIMULATION

The routing of the drones around the aquaculture farm in a safe and efficient manner is a complicated problem. This chapter will discuss the approach taken to test several path planning algorithms in a simulated aquaculture environment.

2.1 THE VEHICLE ROUTING PROBLEM

Multi-robot navigation is a well-studied topic of research, with many constraints and requirements for different environments [32, 33]. By representing pond locations as nodes on a graph, this HAUCS navigation problem can be described as the Vehicle Routing Problem (VRP), a well-studied generalization of the Traveling Salesman Problem (TSP).

Consider a set of ponds $P = \{1, ..., n\}$ and a set of D drones. Each pond must be visited once, and each drone must take off from the depot. A graph $G(N, E)$ can then be constructed where $N = P \cup \{0, n+1\}$ with the depot nodes as 0 and $n+1$. E is the set of arcs for each pair of nodes $i, j \in N$. An arc i, j has a distance denoted by c_{ij}, and x_{ij} represents a binary decision variable that is 1 if and only if there is a route from pond i to j. With these parameters, you can formulate the VRP as:

$$\min \sum_{i=0}^{n+1} \sum_{j=0}^{n+1} c_{ij} x_{ij} \tag{2.1}$$

$$\text{s. t.} \sum_{\substack{j=1 \\ j \neq i}}^{n+1} x_{ij} = 1 \qquad i = 1, ..., n \tag{2.2}$$

$$\sum_{\substack{i=0\\i\neq h}}^{n} x_{ih} - \sum_{\substack{j=0\\j\neq h}}^{n+1} x_{ih} = 0 \qquad h = 1, ..., n \tag{2.3}$$

$$\sum_{j=1}^{n} x_{0j} \leq D \tag{2.4}$$

$$x_{ij} \in \{0, 1\} \qquad i, j = 0, ..., n + 1 \tag{2.5}$$

Constraint 2.1 is the objective function to minimize the sum of the route lengths. Constraint 2.2 allows a pond to be visited only once. Constraint 2.3 references the fact that a drone which arrives at a pond must leave the pond. Constraint 2.4 limits the number of drones to the number of ponds. Constraint 2.5 is the integrality constraint, meaning a movement between two ponds must either occur or not [34].

TSP is perhaps the most well-studied combinatorial optimization problem in computer science. However, VRP is more realistic for practical applications and has attracted significant research. There are numerous variations of VRP, such as the Capacitated VRP (CVRP), where vehicles have a limited capacity and customers have a certain demand, VRP with Time Windows, where locations must be visited within specific times, and Distance Constrained VRP (DVRP), where vehicles have a limited range before returning to the depot. VRP with no additional constraints is sometimes referred to as the Multiple Traveling Salesman Problem (MTSP). Several surveys specifically addressing MTSP and VRP go into further detail about the current literature's approaches and applications [35, 36, 37]. The HAUCS environment is an example of DVRP due to the limiting factor being the range of the drones. However, to simplify the implementation and due to the relatively limited literature on DVRP, this problem was modeled as a traditional VRP and the routing distance was used as a performance metric instead of a constraint.

Unlike TSP, VRP algorithms have the added complexity of finding the most optimal collection of sub-routes such that the longest route is minimized, rather than

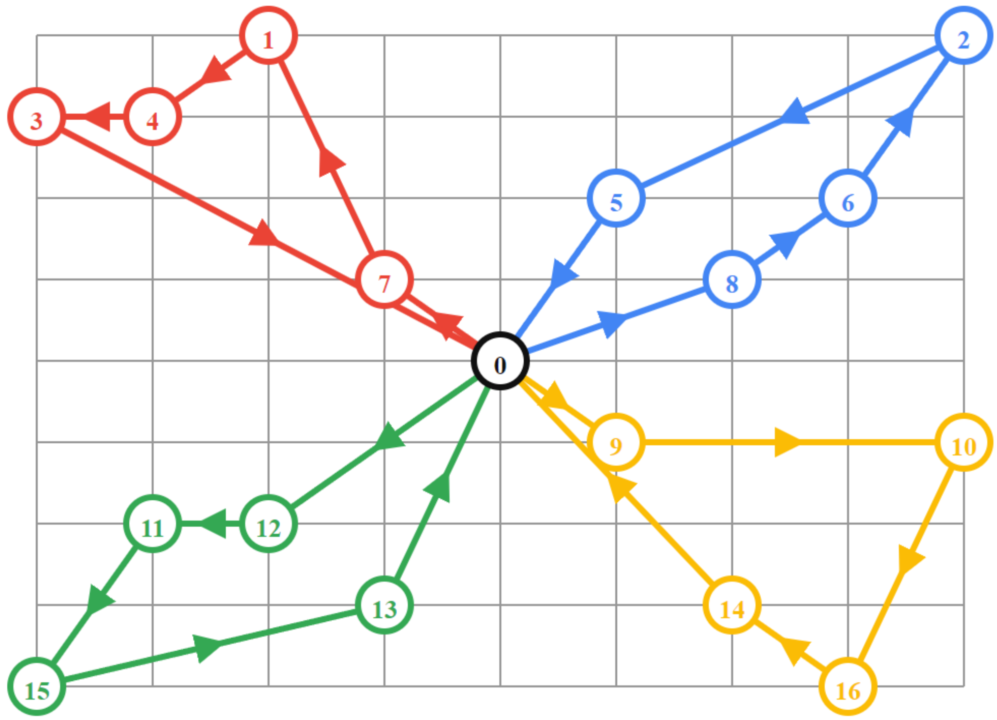

Figure 2.1: Example diagram of a VRP solution. Adapted from [4].

simply finding the shortest single route to visit all nodes. This constraint ensures the most equal distribution of distance required to be traveled by each vehicle, which allows the fewest possible number of vehicles needed to traverse the graph. Considerable research has been invested in TSP, VRP, and their numerous variants, and, as a result, many solutions to this routing problem are available [35, 37, 36].

Modern approaches to combinatorial optimization problems, such as VRP, span several computer science disciplines, most notably linear optimization, metaheuristics, and machine learning. Exact algorithm approaches are well studied but have long run times [38], and the study of simple heuristics has stalled mainly due to the development of more sophisticated algorithms.

2.1.1 Linear Optimization and Exact Solutions

Linear optimization tends to find highly optimal solutions but has at least polynomial computational complexity and therefore cannot be used on large graphs [39]. This is an attractive method when working with small enough graphs, but otherwise may be intractable. Operations research efforts have led to the release of open-source linear optimization tools for VRP, such as Google's OR-Tools [4] which enable easy implementation of VRP solvers.

Exact solutions are less practical for our purposes because of their high computational complexity, but Almoustafa et al. proposed an exact method for DVRP solutions on large graphs [9], which is highly applicable to the HAUCS use case. Others such as Pecin, Qureshi, Queiroga, and many more propose alternative exact solutions for VRP [40, 41, 42].

2.1.2 Metaheuristics

Metaheuristics are highly successful techniques that are widely applicable because of their general lack of assumptions, but can be unreliable in that they may not have stable convergence and may have unknown run times [43]. These are techniques such as ant colony optimization [44], genetic algorithms [45], simulated annealing [46], and adaptive large neighborhood search [47]. There is a great deal of literature on effective metaheuristics for VRP and other optimization problems [48]. Vidal et al. propose a unified framework for VRP metaheuristics which is highly optimal and efficient [49].

2.1.3 Machine Learning

The vast number of VRP variations makes it challenging to find rule-based methods that apply to a specific problem, but some work has been done to produce generalizable methods using machine learning algorithms. Machine learning has proven to be highly effective for a wide range of applications but suffers from specialized hardware requirements, lack of explainability, and many of the same problems as metaheuristics, including unreliable convergence and unpredictable runtimes. Graph neural networks are developing to become extremely useful in many domains of science, particularly chemistry and biology, and have shown use as a means to coordinate multi-agent systems [50], as well as path planning [51]. Kool et al. use a graph attention network to encode node locations and a reinforcement learning algorithm to train the navigation network, resulting in a method that can solve multiple types of routing problems [7]. Other machine learning approaches include Neural Large Neighborhood Search [52], Residual Graph Attention Networks [53], Reinforcement Learning for TSP [54], and more.

2.1.4 Drone specific approaches

Additionally, approaches to VRP have been investigated as they pertain specifically to aerial drones. The study of using drones to navigate a TSP scenario is motivated primarily for commercial home deliveries [55]. Rigas et al. use linear optimization to solve scheduling problems with a fleet of drones on a monitoring mission [56]. Raj and Kim et al. consider the flying sidekick problem, allowing drones to land on a truck to save battery and increase range [57, 58]. Kitjacharoenchai et al. use heuristics to model MTSP for drones [59]. Es Yurek and Ozmutlu investigate TSP with a recharging policy for drones [60]. Drone speed is considered by Tamke and Buscher as an additional VRP constraint [61]. Cavani et al. propose multiple exact methods for MTSP, specifically for drones [62].

2.1.5 Aquaculture VRP

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 up to hundreds of ponds. Aquaculture

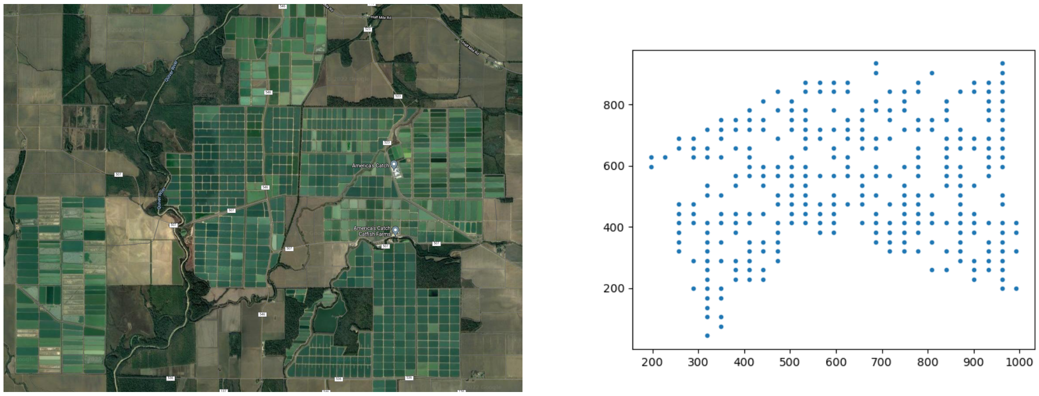

Figure 2.2: **Left:** America's Catch Catfish Farm with approximately 700 ponds. **Right:** Example of 300 pond simulated aquaculture distribution [5].

farms often dig their ponds in a regular, grid-like manner, which would facilitate repetitive, straight paths. There are relatively few VRP methods which are intended for calculating routes for more than 100 nodes [63, 64], and fewer methods for calculating paths in a grid space [65, 66]. Another factor to consider is the drones will be required to fly in inclement weather. Wind may be an important consideration in drone routing, yet there is very little research regarding its impact [67, 68]. These unique conditions require special considerations that are not sufficiently studied in the literature.

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. Then, that polygon is filled with a square grid of points of equal spacing. Finally, 20% of the points are removed 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 spatial distribution of typical fish farms, see figure 2.2 for an example. Future work will consider the impact of wind by increasing the accumulated cost of traveling in upwind directions.

2.2 METHODS

Three different VRP approaches were chosen and used to create routes around these simulated fish farms [5]. These approaches were the Google Linear Optimization Package (GLOP) [4], Graph Attention Model (GAM) by Kool et al. [7], and our proposed heuristic solution, the HAUCS Path Planning algorithm (HPP). These methods were selected because they represent high performing VRP methods using different approaches. GLOP is a linear optimization method, which computes the most optimal or nearly optimal solution for a set of node locations given certain linear relationships. GAM is a machine learning method which uses a transformer network with self attention to predict the next node to visit. Finally, HPP is a simple geometric heuristic that operates on the assumption that the nodes are evenly distributed. This assumption allows the area to be covered efficiently with a back-and-forth pattern. Links to the source code for all methods can be found in Appendix A.1.

2.2.1 HAUCS Path Planning Method

The HAUCS Path Planning (HPP) algorithm intends to take advantage of the regular distribution of ponds to quickly and effectively plan routes for a team of drones on an aquaculture farm. With the assumption that nodes are generally in a grid and given a large enough area, heuristics can be constructed that are efficient, quick to execute, and simply understood by human operators. The performance of HPP is compared with the two other approaches on three important metrics: total distance, maximum route distance, and runtime.

HPP is an area coverage path planning strategy that routes the HAUCS drones in a back-and-forth pattern. It can be described as a two-phase simple heuristic method. It first clusters, then routes. Clustering is accomplished using k-means on the entire node set to produce evenly spaced node clusters, which represent the ponds to be covered by a single drone. The convex polygons surrounding each cluster are then used in the routing phase to determine the path for an individual drone.

In the routing phase, polygons are formed by the convex hull surrounding each cluster. The antipodal pairs of each of these polygons are then calculated using the Shamos algorithm [69]. Antipodal points are vertices of a convex polygon that admit parallel lines of support such that the whole polygon lies in between, see figure 2.3. This set of antipodal pairs from each pair of vertices is then fed to the Optimal Coverage Algorithm (OCA) by Mukherjee et al. [6]. OCA calculates the shortest optimal back-and-forth path that starts and ends from one of the antipodal point pairs. The route is then assigned to follow this optimal back-and-forth pattern as closely as possible. The underlying assumption that must be met for this heuristic to work is that the distribution of nodes is generally even. This is because it essentially treats the polygon as if it were a continuous monitoring area, which is why a back-and-forth route is efficient. If nodes are placed randomly, then there may be areas of higher density, so this assumption would not hold and HPP would likely fail to produce efficient routes.

If a cluster happens to be too small to form a polygon, for example, if a cluster is located on a peninsula and only contains 1 or 2 points, then the subsequent closest nodes are taken into that cluster from its neighboring cluster until all clusters have a valid size and shape. Figure 2.4 demonstrates the evenly spaced clusters of approximately equal size despite the irregular outline shape of the node locations. The performance of HPP is compared with the two other approaches to establish a performance baseline and highlight the advantages and disadvantages of each approach. Further details of the HPP implementation can be found in previous related works [5, 6].

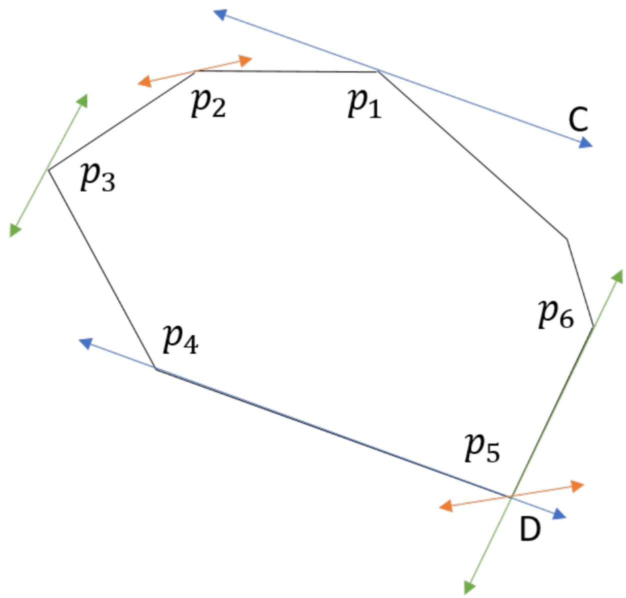

Figure 2.3: Antipodal points of a convex polygon. Adapted from [6].

2.2.2 Google Linear Optimization Package

HPP is compared with the Google Linear Optimization Package (GLOP) [4]. This method uses a primal-dual simplex algorithm to minimize the maximum route length to give a distance matrix of $(n \times n)$ values, with n as the number of nodes in the graph. Because of this exponential blow-up in complexity with the graph size, solutions for more than 200 nodes cannot be found in a reasonable amount of time, limiting its usefulness for real-time path planning.

2.2.3 Graph Attention Model

Kool et al. use a Graph Attention Model (GAM) to encode a learned representation of node locations with an attention layer to identify the most important nodes. With this representation, reinforcement learning is used to train an agent to identify the most optimal routes. Because GAM is a learning model, it requires training data. GAM was trained on multiple sizes of the simulated aquaculture graphs for 3200

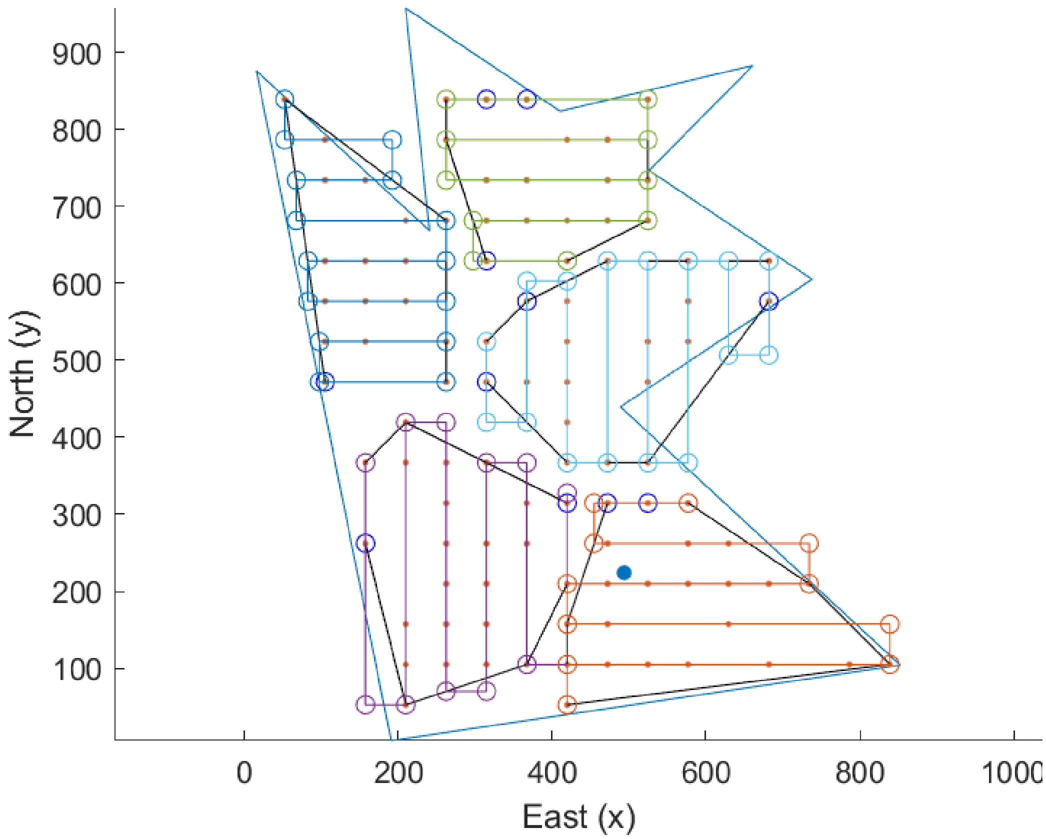

Figure 2.4: Plot of HPP clusters and optimal back and forth route plans. The blue dot signifies the depot and the blue polygon outlines the node locations.

steps with a batch size of 256 for 100 epochs, which took approximately 8 hours on an NVIDIA 3080. The training became unstable for graph sizes larger than 100, and learning did not occur, so the trained models for 50 and 100 node graphs were used and compared.

2.3 SIMULATION

The simulated dataset contains 500 graphs representing the locations of ponds in an aquaculture farm, divided into 100 instances of 100, 200, 300, 500, and 700 node graphs. Aquaculture's grid-like structure should require different heuristics than randomly placed nodes for navigation. One of the primary challenges for this application is the computational complexity required for solving VRP on large graphs. Few studies have analyzed graph data for more than 100 nodes, while this data contains up to 700 nodes. The three methods are programmed to attempt to divide the nodes between 5 routes. In practice, the number of drones to be used will be minimized depending on their maximum range.

2.4 RESULTS

The algorithms are evaluated on 3 metrics: average total distance, average maximum route distance, and runtime. The average total distance will measure the method's overall efficiency, while the average maximum route distance tests each method's ability to distribute nodes evenly. Runtime is difficult to fairly measure because of the differences in implementation, optimization, and hardware. All experiments were run in Ubuntu 21.04 with an AMD 5600x CPU, NVIDIA RTX 3080 GPU, and 16 GB of 2133 MHz DDR4 RAM. HPP and GLOP utilize only the CPU, while GAM's CUDA implementation can take advantage of parallel GPU structure. HPP is implemented in MATLAB with no multi-threading, GLOP is primarily developed using C++ and Python, and GAM is entirely developed in Python with PyTorch. Optimal VRP solutions do exist, but their long runtimes make them intractable for this application, and therefore the optimality gap cannot be used as a performance metric.

Tables 2.1-2.3 show the performance of HPP compared to GLOP and GAM trained on 50 and 100 node instances. For graphs larger than 200 nodes, HPP is the best in terms of total distance, maximum route length, and runtime. However, GLOP's performance for graphs larger than 200 nodes was not considered because its runtime was longer than 8 hours. The runtime for HPP is orders of magnitude smaller than GAM or GLOP, which is to be expected for a simple heuristic method. At only 100 nodes, GLOP takes nearly 11 minutes to solve 100 instances. This alone would disqualify GLOP as a practical solution to the HAUCS VRP. Interestingly, GAM50 (GAM trained on 50 nodes) seems to outperform GAM100 (GAM trained on 100 nodes) up to 100 nodes in terms of total distance and up to 200 nodes in terms of maximum route length, despite being trained on only 50 nodes. GAM100 does outperform GAM50 on larger graphs, especially on 700 node graphs where GAM50 becomes unstable.

The results for these three methods differed depending on the scale of the simulated farm. 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 not able 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 2.1: 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 2.2: 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 2.3: 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	—

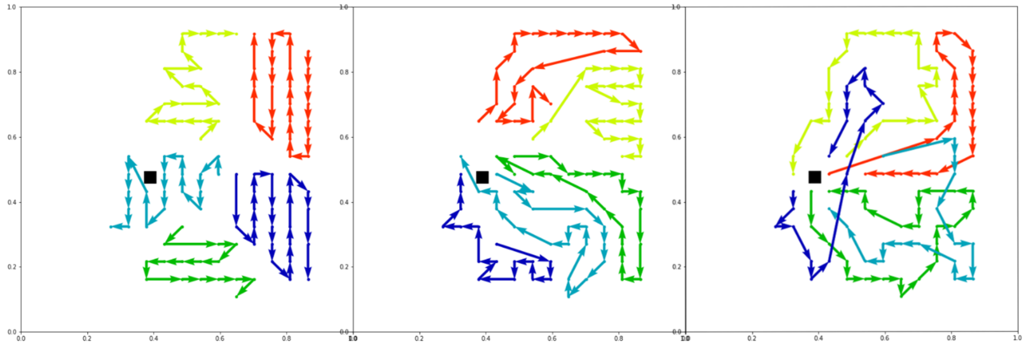

Figure 2.5: Route comparisons between (a) HPP, (b) GAM and (c) GLOP. Depot is signified by the black box. Plotted using tools from [7].

2.5 DISCUSSION

Figure 2.5 illustrates the different style that HPP takes when producing a route solution. HPP uses the grid-like layout of the nodes by moving in straight lines wherever possible. Based on inspection of GAM routes, it seems that GAM did not learn this heuristic despite being trained on the HAUCS dataset. Pretrained GAM models, which used randomly placed nodes for training, had a slightly worse performance than GAM100. It is certainly possible that a learning algorithm could learn such a heuristic and outperform HPP. GLOP's strategy appears to start all routes near the depot then circle the graph to return to the depot at the end of the route, resulting in significantly shorter routes than either HPP or GAM.

An additional benefit to HPP for aerial drones is the natural airspace deconfliction that results from assigning routes based on area. While GAM and GLOP may produce shorter routes in small graphs, they tend to cross each other's airspace, potentially resulting in mid-air collisions. HPP routes are also more maintainable and interpretable for human operators. Should a problem occur during operation, it is easier to identify which drone failed based solely on its location, without needing to investigate the software.

It may be argued that for stationary locations, such as the ponds in an aquaculture farm, that the runtime is not critical because the routing will never change once an optimal solution is found. While this is true, the reality of operating aerial drones in windy conditions and changes in pond conditions (i.e., certain ponds in stress may need to be sampled at a higher frequency) may require the routing to be readjusted frequently to ensure successful operation. Should a drone be disabled or not reach a certain pond, the pathing algorithm must be able to run in real-time to correct any deficiencies by rerouting drones mid flight or activating additional drones. It is also vital to consider scaling the algorithm for commercial use, where a central server may simultaneously plan routes for several farms. Therefore, it is important that the routing solution be efficiently computed.

The ability for machine learning algorithms to develop heuristics for navigating routing problems has been proven to be successful. However, most if not all investigations into machine learning for routing problems have used randomly distributed node locations. In reality, problems typically have some kind of structure that can be exploited to develop simple and effective heuristics whose performances are comparable to the most sophisticated learning algorithms. In this case, the grid-like distribution of nodes allows HPP to have comparable performance to GAM because HPP is designed to move in straight lines down the rows and columns when possible, instead of diagonally. For unique settings such as aquaculture farms, hand-crafted heuristics like HPP may be more appropriate than learning algorithms because this regular structure can be exploited and doesn't necessarily need to be learned. For more complex tasks where human intuition is insufficient, such as predicting protein structure or controlling hot plasma, recent machine learning progress has shown that it is a more capable solution [70, 71].

Additionally, it is important to remember that GAM performs well in various routing problems and is not explicitly designed for this problem like HPP. So, while machine learning algorithms may not always be the most optimal, they may be the most generalizable solutions. This implies that machine learning algorithms are useful for navigating complex, unstructured data and can be used in various environments, but purpose-built classical algorithms are simpler to implement and can perform better depending on expert knowledge and the specific environment. However, the importance of flexible solutions cannot be understated, and it is plausible that machine learning algorithms could surpass all human written heuristics in the future.

Table 2.4: Summary of algorithm characteristics

	Optimality	Scalability	Practicality
HPP	Medium	High	High
AM	Medium	Medium	Medium
GLOP	High	Low	Medium

On the other hand, numerical solutions such as GLOP can produce highly optimal routes at the expense of long runtimes. For all graph sizes that GLOP was able to compute, it produced the most optimal paths. As long as the runtimes do not interfere with reliable operations, this makes GLOP the more attractive solution for solving routes smaller than 200 nodes. However, airspace will have to be more closely managed to prevent in-air collisions between the drones.

For larger graphs, HPP was the most practical solution because of its scalability. It achieved more optimal routes than GAM in large graphs, despite both solving in linear time. The benefit of the cluster-then-route heuristic only becomes apparent when enough nodes are included in a cluster. With too few nodes for each cluster, the back-and-forth routing cannot occur, and the route is suboptimal. Table 2.4 summarizes the advantages and disadvantages of each method discussed.

Metaheuristic algorithms that focus on large graphs were also investigated, such as large neighborhood search, but their runtimes were significantly longer than GLOP, making them unsuited for our application. Additional research is necessary to thoroughly investigate the wide variety of VRP solutions available, especially those meant to solve large graphs.

2.6 CONCLUSION

One of the core components in the HAUCS framework is a team of cooperative robotic sensing platforms to support automated DO measurement. In this regard, an effective path planning algorithm to coordinate their operations is essential. This research presented the HAUCS Path Planning algorithm to plan routes for a team of aerial drones to measure dissolved oxygen levels in an aquaculture farm. The grid-like layout of an aquaculture farm allows a simple cluster-then-route heuristic to outperform some of the most sophisticated VRP solvers available on large graphs. Linear optimization solver GLOP produced the most optimal routes on smaller graphs. Modern operations research has focused on using metaheuristics and machine learning to solve a wide variety of problems, but it may be at the expense of creating simpler, specialized solutions that are faster and more optimal for their specific application. HPP is also more amenable to hardware implementation because of its clear separation of airspace. The differences between the algorithms' performance on different sized graphs is critical. There are various scales of aquaculture farms, ranging from dozens to hundreds of ponds. Therefore, instead of assessing a single algorithm for all farm sizes, it may be more important to consider a family of path planning algorithms.

CHAPTER 3
IMPLEMENTATION AND FIELD TESTING

This chapter is intended to validate the conclusions derived from the simulations. Three VRP methods are applied to a physical aquaculture farm at the Southern Illinois University (SIU) Aquaculture Research Center to record power and sensor measurements from the drones.

3.1 HARDWARE DESIGN

3.1.1 Drone and Sensors

The drones used to facilitate this study are 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 conduct the experiment.

Attached to the underside of the drone is the sensing system. The topside of the sensing system, directly mounted on the drone, relays information between payload and base station and controls a winch release mechanism, see figure 3.1. 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. It is connected to the camera control pins activated by the drone.

The payload consists of a XIAO nRF52840 Sense board which is used to send the sensor data wirelessly over Bluetooth Low Energy (BLE) to an ESP32 Wi-Fi LoRa V2 board contained in the topside, where it is then forwarded to the base station. The payload board is connected to a YSI 2002 Galvanic DO sensor and a LPS28DFWTR

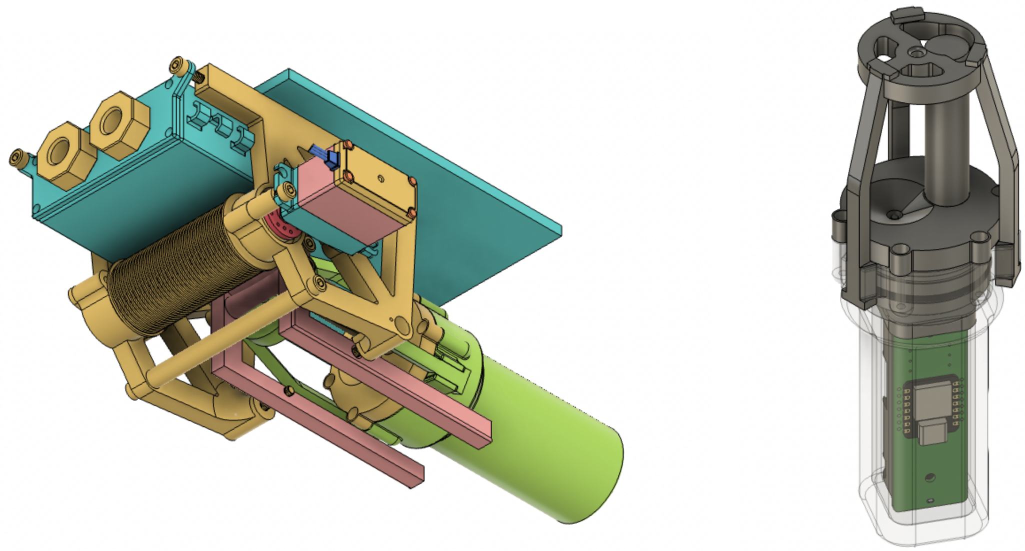

Figure 3.1: **Left**: 3D model of topside structure (blue), winch mechanism (yellow) and payload (green). **Right**: 3D model of the sensor payload.

barometer/thermometer, and powered by a standard 18650 battery. See figure 3.2 with the assembled topside and sensor package casing. The topside and payload systems were designed and assembled for the HAUCS project by another student, Will Fairman.

3.1.2 Base Station

The base station uses a high-power antenna connected via coaxial cable to another ESP32 board, identical to that in the topside, to receive the sensor data from the drone-sensor system. The board then connects to a laptop via USB, where it uploads the received sensor data to a Google Cloud hosted Firebase server, automatically updating an Android application with the water quality status of each pond, see figure 3.5.

Figure 3.2: **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.

3.2 SOFTWARE DESIGN

The SwellPro Software Development Kit (SDK) was used as the interface between the path planning methods and the flight controllers. To send mission data to the drones, a laptop is connected via Wi-Fi to the Splashdrone controller, which forwards the data to the drone via a proprietary radio link. The GPS coordinates of each of the ponds were recorded and normalized between 0 and 1 to facilitate the computation of the routes. Given the routes from each path planning method as an ordered list of coordinates, a Python script converts that route to a list of Splashdrone commands, which are all sent all at once to the drone before its takeoff. No communication between the controller and drone is necessary during flight, so it is capable of autonomously flying out of controller range.

The script defines a sampling routine to coordinate the process of dropping the payload, collecting the data, and sending the data to the base station. Waypoints are created at a specified altitude above each pond in the route, with short pauses at each waypoint to ensure stability. When the drone arrives at a waypoint, it lands on the pond and simultaneously activates the topside to drop the payload. The topside activates the sensor payload before being submerged to maintain communication, as the Bluetooth Low Energy (BLE) cannot transmit through water. The topside retracts the payload on a timer and sends the data to the base station once it reaches altitude above the pond. It then navigates to the following pond waypoint. The custom mission control software used to transmit missions to the Splashdrones is available in Appendix A.2.

3.3 FIELD AND SIMULATION DATA

A satellite image of the Southern Illinois University (SIU) Aquaculture Research Center is seen in figure 3.3. This facility has the capacity for 90 ponds, however at

Figure 3.3: Southern Illinois University's (SIU) Aquaculture Research Center. The takeoff location is marked with a green dot, all available ponds are marked with a blue dot.

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 path planning methods to produce a set of three different routes for each of the three drones, totaling in nine routes to be flown. The routes for each method are simulated and visualized in figure 3.4.

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 3.1. As

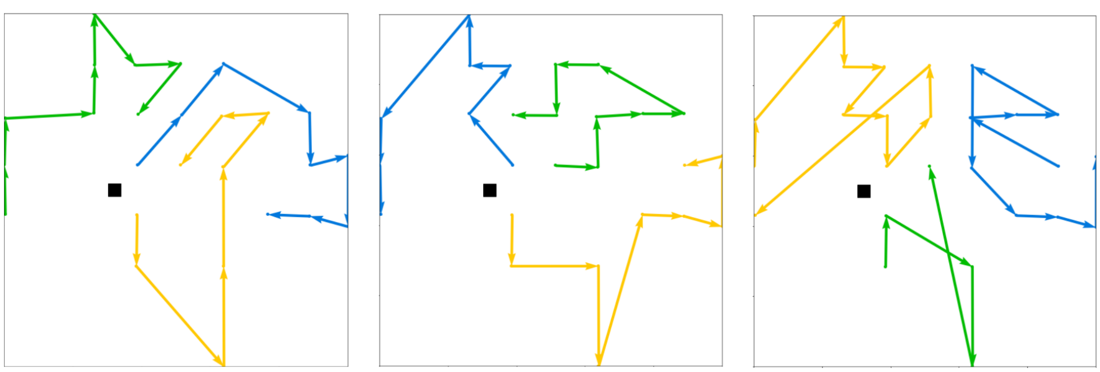

Figure 3.4: Routes for each path planning method, from left to right: GLOP, GAM, HPP. The black square signifies the launch point. Plotted with tools from [7].

Table 3.1: 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

expected by the results of the previous chapter, GLOP and GAM are comparatively efficient and HPP produces significantly longer routes due to the small number of ponds to visit. HPP works on the assumption that the ponds are evenly distributed, which was not valid for this test. As a result, HPP is not effective for this situation. If all 90 ponds were available, it would be expected to be comparatively more optimal, while also allowing for better airspace deconfliction and requiring minimal computation.

Power data from the flights were recorded using the Splashdrone's smart battery 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 3.2, 3.3 and 3.4 show the collected data with similar results to the simulated data shown in table 3.1. 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 3.2: 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 3.3: 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 3.4: 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

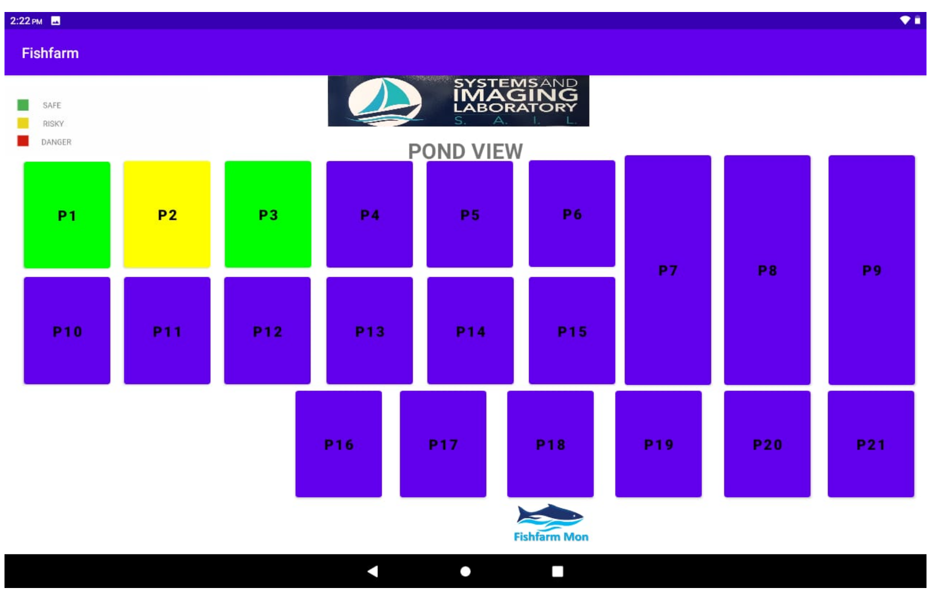

Figure 3.5: Android application displaying water quality readings sent by the drone. Implemented by Md Arshadul Karim.

3.4 FAILURES

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 takeoff location, not an absolute above sea level altitude. This causes issues when the elevations of the ponds are significantly different because the drone will reach inconsistent altitudes when traveling between the ponds. This does not only result in potential airspace confliction, but it also requires that the drone's altitude be set to at least the maximum difference in elevation of its ponds. This is not ideal from an energy 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 dedicated altitudes to avoid the possibility of in-air collisions. Using a consistent, dedicated above ground level altitude for each drone 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 according to the sensed land elevation.

Towards the end of testing, one of the drones developed a water leak during a pond landing and was subsequently water 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 an undetectable 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 determined to be due to a compass calibration error. Redundant measures must be taken to prevent crashes, particularly due to the sensitivity of water seals. GPS direction can be used as a means to check compass calibration, which is not a feature on the Splashdrone. Object avoidance measures such as radar or vision would also be a possible solution, however they will increase expense, weight, power, and complexity.

3.5 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 labor shortages in the agriculture industry [72].

Significant work is still required before HAUCS is ready for commercialization. Reliability and robustness of the automated flights is of utmost importance, and as demonstrated by our system failures, it is still a work in progress. Lightweight object avoidance systems for UAVs do exists [73, 74], and may need to be implemented for safety and reliability. However, additional testing is required to verify if GPS-only 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 farms of larger size. Considering that measuring nine ponds took approximately 26% battery capacity, all 90 ponds of the SIU Aquaculture Research Center could reliably be measured by three to five 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 larger sized ponds with greater distances and elevations 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

Figure 3.6: Splashdrone collecting data in a pond

planning algorithm 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 due to the unpredictable effect of harsh weather on DO and the fact that flights may be inhibited or grounded. High winds may make certain routes more inefficient if they involve traveling upwind unnecessarily. Factoring in the wind by increasing the simulated cost or distance in the upwind direction may be needed to fly efficiently in windy regions. Routes may also need to be reconstructed in real-time 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 if flights cannot be conducted for any reason. Programming a type of automatic emergency response system will be necessary in the event of sudden and unexpected weather. Such a response may consist of the use of protective waypoints for drones to take shelter temporarily without the need to return to the home station.

3.6 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 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 equipped with accurate above sea level altitude instruments and some means of object avoidance should be used in future tests 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.

CHAPTER 4
FUTURE DIRECTIONS

The HAUCS project continues to develop the hardware and software integration necessary to realize the goal of automating aquaculture. Additional research is currently underway to establish the networks, sensors, and charging stations required to make HAUCS a commercial reality. This final chapter will discuss the future direction of the HAUCS project and of aquaculture in general.

4.1 IMPROVING HAUCS

4.1.1 VRP

As it is currently implemented, HPP is a method for the standard VRP, but due to the range limitations of drones and varying fish pond conditions throughout the day and seasons, the actual application of HAUCS will require a solution to the Distance Constrained VRP with Time Windows. This specific variation of the VRP has not been implemented and should be the subject of future research. The closest example identified is by Semiz and Polat who propose a Distance Constrained and Capacitated VRP with Time Windows [75]. Capacitated VRP stipulates that the vehicles are carrying some kind of limited cargo which is being delivered, unlike a monitoring problem which doesn't have such a requirement.

4.1.2 Improving HPP

The position of the cluster centroids is essential to the optimality of HPP and is currently solved with k-means. K-means has the potential to produce disproportionate cluster sizes if the geography of the farm is particularly irregular because the cluster locations are chosen based on their equivalent centroid distances. If these clusters could be optimized such that each cluster's route is minimized, such as by requiring all clusters to contain equal area, it would improve HPP's efficiency. Choosing optimal clusters is an example of an assignment problem, which would also requires optimization.

Another potential improvement for HPP is to compare the back-and-forth routing against a more general heuristic or exact TSP solution for its routing phase. This would essentially be a divide and conquer strategy, similar to that proposed by Mariescu-Istodor et al. [76]. Clearly more work can be done to improve the efficiency of HPP, but adequately testing HPP requires a large farm to deploy on, and further testing should be a higher priority than continued optimization.

4.1.3 Decentralized Vs Centralized Decision-Making

The idea of decentralized communication and decision-making is popular in the literature of IoT and multi-agent robotics. HAUCS is currently designed as a centralized platform, that is, with a central hub through which all communication flows. Decentralized networks involve drone-to-drone communication. This is valuable because it is a much more robust network topology. These decentralized networks are generally valuable in environments involving long-range and inconsistent communication links, such as battlefields. Such a system may be valuable for HAUCS to enable communication for large aquaculture facilities that would suffer from connection issues. However, cheap LoRa transceivers can easily communicate over several kilometers, which is farther than the range of the actual drones. Therefore, it is likely a rare scenario in which a drone in HAUCS could not maintain communication with the base station. There may be situations in which significant changes in elevation, trees, buildings, or weather interrupt radio links and the system would benefit from the

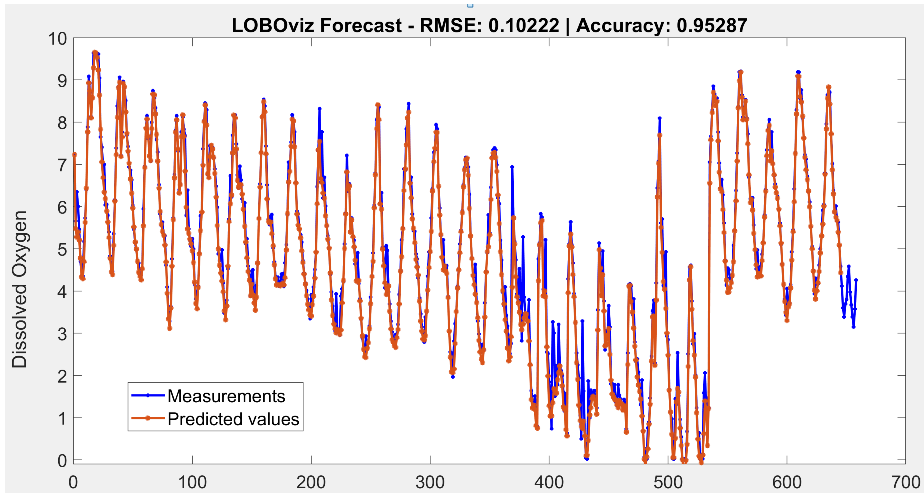

Figure 4.1: Performance of the DO prediction model for the LOBO dataset. Adapted from [8].

redundant capabilities of a decentralized architecture with drone-to-drone message passing.

4.1.4 Predicting DO Levels

In order to know when the HAUCS drones need to take measurements, it is important to accurately predict DO levels several hours in advance. To do so, a machine learning model can be trained on collected data of the pond environment and its resulting DO levels. Ouyang et al. have demonstrated that this is a possibility using a Long Short Term Memory (LSTM) model trained using temperature, sunlight, color, precipitation, and previous DO levels collected from the Harbor Branch Oceanographic Institute Indian River Lagoon Land/Ocean Biogeochemical Observatory (LOBO) [8], see figure 4.1. Most of the DO in a pond is a result of photosynthesis, so DO levels are closely correlated to the amount of sunlight the pond is receiving and its algae content. Knowing when DO levels are expected to drop will be important to ensuring that ponds are aerated before DO levels become dangerously low, and that drone flights are planned as efficiently as possible.

4.2 MULTISPECIES SYSTEMS

4.2.1 Integrated Multi-Trophic Aquaculture

Fish waste is a potentially valuable fertilizer for other organisms. By maintaining multiple species of different trophic levels and cycling nutrients between them, aquaculture can improve efficiency, produce more diversified products, and reduce environmental impact. This is known as Integrated Multi-Trophic Aquaculture (IMTA), and it is part of a much larger movement from monoculture agriculture to the more sustainable practice of polyculture. A common type of IMTA system may use a carnivorous fish to produce ammonia and phosphorus, which are used to fertilize seaweed and algae. Both can then be harvested and used for a variety of products, increasing profitability. Economic research has shown that IMTA systems are more operationally robust and profitable than monoculture systems [77] due to their diversity of products.

Open water aquaculture is the practice of growing and harvest products in the open ocean, rather than a land-based fish farm. Without the need to dig ponds and manually maintaining water quality, open water aquaculture shows promise as a more scalable solution. However, one of the main concerns with open water aquaculture is the accumulation of nutrients and feeds in the marine environment. IMTA is well suited to address this problem. By using aquatic plants or filter feeders such as oysters to clean the waste from fish, IMTA can reduce this risk of runoff nutrients and be a more sustainable and affordable source of food for coastal communities. Experimental and commercial open ocean IMTA systems have shown viability [78], especially when built off already developed offshore structures such as oil rigs or wind farms.

It is still not clear at what rate coastal and open water environments can handle increased nutrient production without destructive effects [79], so more research is needed before widespread commercialization will be accepted. Just as with land-based aquaculture, automated monitoring can reduce the burden on farmers and allow them to make more informed decisions, but for open water systems it may also be essential because the excess nutrients will need to be accounted for. The characteristics of such a monitoring system would surely be different from HAUCS, a fully submersible system may be more appropriate since there is no need to traverse over land.

4.2.2 Aquaponics

In contrast with IMTA, which grows multiple aquatic species, aquaponics is the practice of using nutrient rich fish waste to fertilize land plants in a hydroponic system. The water is recirculated between the plants and the fish to mimic the natural nutrient cycles. The advantage is of course similar to that of IMTA systems, a more efficient use of resources and diversity of products.

Aquaponics provides a means of agriculture in areas suffering from water scarcity and a lack of arable land. However, because of the bespoke nature of hydroponic systems and their tendency to be indoors, aquaponics positions itself less of a large volume output approach and more suited as a small, efficient system more compatible with indoor or vertical farming. This allows food production to be closer to the consumer, cutting down on transportation costs and providing consumers with a fresher product. Indoor farming also reduces or eliminates the need to use pesticides, herbicides, or antibiotics, which can help meet the growing demand for organic food. Despite these advantages, aquaponics has not yet achieved widespread commercial success. Studies into aquaponics point to the high upfront and maintenance costs as detractors, but that higher quality product and environmental benefits can enable premium product pricing to achieve profitability [80, 81, 82].

Automated and integrated water quality monitoring is obviously critical for an aquaponic system in order to balance the needs of both plants and fish. Significant research has been conducted on improving aquaponics automation with IoT devices in order to reduce costs [83, 84, 85]. Monitoring, prediction, and control systems have the potential to reduce maintenance costs, however, the high equipment and installation costs still create a risky investment for potential aquaponics farmers. Until these upfront costs are reduced, large scale aquaponics should ideally be practiced in locations with high prices for vegetables and fish, such as islands or deserts, in order to be profitable.

4.3 BIOLOGICAL ENGINEERING

Agriculture, in a sense, is a type of biological engineering. Throughout history, that has meant tilling fields or domesticating species for more desirable traits. Today, with advanced technology that allows us to interact with life at the molecular level, biological engineering and agriculture itself are experiencing a paradigm shift which are redefining the terms.

4.3.1 Genetically Modified Fish

Domestication of animals has occurred for millennia, and fish are no different. Much of the rise in aquaculture in the past several decades can be attributed to the domestication of dozens of fish species [86]. However, there are limits to the benefits derived from domestication. Domesticated fish can only inherit those desired genes that are already in the gene pool. With gene sequencing and editing technologies, biologists can take genes from one organism and insert them into the genome of another [87].

The advantages of using genetically modified (GM) fish for aquaculture are nothing short of astounding. Mud loaches injected with a modified growth hormone gene from its own species were able to grow up to 35-fold faster, grow 4-fold larger, and increase FCR to 1.9 [88]. AquaBounty Technologies produce salmon with growth genes from a Chinook salmon and other regulatory genes from an ocean pout, which grow twice as fast as a natural salmon [89]. Tilapia spliced with a similar set of

Figure 4.2: Size comparison of an AquaBounty Salmon (background) vs. a non-transgenic Atlantic salmon sibling (foreground) of the same age [9]

genes from salmon and ocean pout grew 320% faster [90], and the list goes on. These are fundamental changes in the economics of fish farming and have the potential to radically transform the seafood industry.

GM food in general has been a controversial subject of regulation. In 2015, transgenic AquaBounty salmon achieved FDA approval, the first GM animal ever approved in the US, but was later overruled by the California courts in 2020 [91]. The primary argument against approval is the risk of GM fish escaping from a farm and crossbreeding with native fish, despite AquaBounty growing exclusively sterile fish in land-based facilities [92]. Another concern is the off-target effects of genetic modifications, but genomic analysis shows that no unintended genetic alterations are present in AquaBounty salmon [93]. To date, no GM fish or animal has been approved for consumption in the US.

Consumers and regulators must weigh the risks of eating genetically modified food with its advantages, and to do so, there must be an adequate assessment of these risks. Research into these risks have suggested there is little to no risk of GM fish escaping aquaculture facilities and successfully crossbreeding, and have also questioned how GM fish differ in this respect from domesticated fish [94, 95, 96]. However, with the expansion of more economically competitive GM fish, it is important to acknowledge this risk would grow over time and proceed with caution with appropriate regulation. Concerns of runaway GM fish are reminiscent of similar past controversies regarding GM crops, which have failed to materialize [96].

GM fish has the potential to improve the economics of aquaculture by increasing yield and FCR, which in turn would ease pressure on natural species. Additional research is necessary to more fully demonstrate what risks GM fish pose to the environment to allow regulators to make more educated decisions about regulation.

4.3.2 Cellular Agriculture

Winston Churchill wrote in a 1931 essay, "We shall escape the absurdity of growing a whole chicken in order to eat the breast or wing, by growing these parts separately under a suitable medium" [97]. Nearly 100 years later, his prediction is turning into reality [98, 99, 100, 101]. Cellular agriculture is a budding industry which hopes to replace the livestock industry by growing meat at the cellular level in bioreactors instead of pens and ponds. Growing livestock feed uses 77% of all agricultural land, which is 38% of all habitable land on the planet [10], see figure 4.3 for more details. Cellular agriculture would drastically reduce the inputs required to cultivate these proteins and would enormously reduce the environmental impact of livestock agriculture.

Animal cell cultivation is a tissue-culture system which requires cell types from the desired tissue, a growth media for the cells to reproduce, and a bioreactor to provide a supportive environment. Fish is especially suited to cellular agriculture because of its tolerance to hypoxia, high buffering capacity, and low-temperature growth conditions [102]. Furthermore, fish is commonly considered to be a more healthy source of protein than terrestrial meat [103, 104, 105]. Provided that consumers are willing to eat synthetic fish proteins and costs can be reduced with economies of scale, cellular

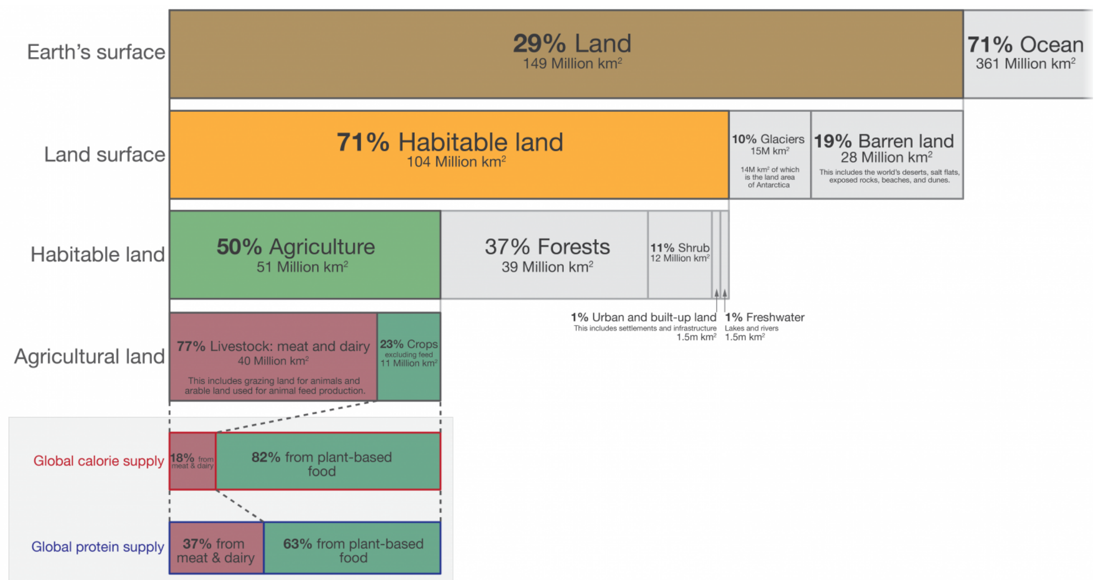

Figure 4.3: Global land use for food production. Adapted from [10].

agriculture has the potential to make aquaculture obsolete in the future. Clearly, further study is needed to make this a reality, but when it does reach commercialization, it will be a paradigm shift in the agricultural industry that will literally reshape the face of the planet.

CHAPTER 5
CONCLUSION

Human and environmental health and inexorably linked. The future of global health depends on the development of agricultural practices which produce nutritious food while minimizing resources and waste. Aquaculture is one of the most balanced avenues to feeding humanity without excessive environmental costs, but it still demands relatively high investment. The high labor costs of operating an aquaculture facility are a barrier to access for valuable aquatic products. Automating the process of data collecting by intelligently planning and implementing routes for aerial drones is a highly effective means of reducing these costs. Future research will surely continue to automate the most laborious aquaculture tasks, use multispecies integrated systems, and take advantage of newfound biological understandings. It is my hope that fish can become more affordable and accessible without becoming an excessive burden on the planet's marine ecosystems. This research and its future directions are a hopeful step toward a more harmonious coexistence between man and nature.

APPENDICES

APPENDIX A
SOURCE CODE

A.1 VRP

The HPP VRP method is available at `https://github.com/tonydavis629/HAUCS/tree/main/haucs/solvers/HPP`.

The original GLOP software is available at `https://github.com/google/or-tools`, and the HAUCS implementation with minor modifications at `https://github.com/tonydavis629/HAUCS/tree/main/haucs/solvers`.

The original GAM software is available at `https://github.com/wouterkool/attention-learn-to-route`, with the HAUCS implementation with minor modifications to support classic VRP at `https://github.com/tonydavis629/attention-learn-to-route`.

A.2 FLIGHT CONTROL AND NETWORKING SOFTWARE

The custom mission control software used to transmit mission commands to the Splashdrones is available at `https://github.com/tonydavis629/HAUCS/tree/main/haucs/mission_planner`.

The Arduino code controlling the topside, payload, and base station are available at `https://github.com/tonydavis629/HAUCS/tree/main/payload%20software`, `https://github.com/tonydavis629/HAUCS/tree/main/topside%20software` and `https://github.com/tonydavis629/HAUCS/tree/main/basestation%20software`.

The Firebase server code is available at `https://github.com/tonydavis629/HAUCS/tree/main/Android_app`.

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