Intelligent Underwater Communication for Drone Mesh Networks in Internet of Underwater things (IoUT)

Aaron Hassan Robinson [u3224074]
University Of Canberra
Canberra, Australia
u3224074@uni.canberra.edu.au

Abstract— **The Internet of Underwater Things (IoUT) is poised to transform marine operations through smart, autonomous networks of underwater drones and sensors. However, establishing reliable, high-bandwidth communication in such harsh and dynamic environments remains a significant challenge. This paper presents an intelligent, multimodal communication framework for underwater drone mesh networks, integrating acoustic, optical, and radio-frequency links. A genetic algorithm-based positioning system is proposed to optimize the spatial configuration of mobile underwater drones, minimizing communication latency and reliance on low-bandwidth acoustic channels. The system models environmental constraints and link characteristics, dynamically constructing weighted communication graphs to prioritize faster transmission modes. Simulation results show a 42% reduction in total path distance and a 33% decrease in hop count compared to unmodified networks. These results highlight the potential for AI-driven topological optimization in autonomous marine applications. Future work will incorporate environmental modeling and real-time adaptive routing for enhanced realism and resilience.**

Keywords—IoUT, underwater drone, mesh network, multimodal communication, genetic algorithm, underwater wireless, acoustic communication, optical links.

I. Introduction

As global interest in autonomous maritime operations intensifies, the Internet of Underwater Things (IoUT) has emerged as a technological frontier for oceanographic research, military surveillance, and environmental monitoring[10][8][6][3]. Traditional underwater systems, often requiring either scuba divers or tethered drones, are limited by cost, environmental constraints, and danger to human life, necessitating a shift toward intelligent autonomous wireless drone networks[4]. Effective deployment of such systems relies on robust, dynamic communication infrastructure that can function within the physical limitations of the underwater medium.

Underwater communication methods each carry unique advantages and constraints: acoustic signals offer long-range transmission but suffer from low data rates and high latency; optical links provide high-speed transfer yet are sensitive to water clarity and have limited range; and traditional electromagnetic signals used above ground such as radio have a very limited range. The two latter electromagnetic (EM) based communication methods suffer enormously from scattering and absorption by underwater media, and are high in cost compared to acoustic counterparts [16]. The integration of these modalities into a unified, intelligent system is critical for mission reliability and operational flexibility, and reduction of cost.

This paper proposes a novel optimization framework for drone positioning within underwater mesh networks, leveraging a genetic algorithm to minimize path length, transmission hops, and dependence on acoustic links. The approach enables drones to adaptively establish efficient communication pathways between deep-sea nodes and surface buoys. Experiments were conducted through a Python based simulation, using the Pymoo library for building the AI model. The effectiveness of this methodology was then assessed and benchmarked, providing insights into how intelligent algorithms can advance underwater network design within the broader IoUT space.

II. Literature review

The demand for advanced undersea surveillance and autonomous system capabilities is rapidly growing within defense and industrial sectors. Traditional human-crewed systems are often costly, limited in endurance, and poorly suited for the complex underwater environment, prompting a shift toward autonomous systems and Internet of Things architectures [1].

The Australian Defence Force (ADF) envisions persistent, integrated sensor networks that can operate across variable oceanic conditions, providing scalable and flexible solutions to anti-submarine warfare and environmental monitoring [2]. One notable initiative includes autonomous swarms of underwater drones, being developed in collaboration between Saab Australia and the University of Adelaide, aimed at cost-efficient, wide-area detection and mapping [3].

Recent developments in underwater communication focus on hybrid systems that combine acoustic, optical, and EM modalities. For example, researchers at Curtin University have prototyped the fastest underwater wireless communication system, capable of real-time video transmission whilst combining acoustic and optical channels for multimodal robustness and overall network availability [4].

A central challenge lies in media selection—choosing the appropriate communication mode based on real-time environmental data. Optical communication offers high bandwidth but is highly sensitive to turbidity and range, while acoustic waves offer long-range transmission but suffer from low data rates and latency issues [5]. EM communication, while less common, is gaining attention for short-range, low-latency data transfer however requires large antennas and is more expensive compared to other methods [6].

Autonomous underwater networks benefit from AI-driven routing protocols, which optimize communication paths and reduce energy consumption in dynamic environments [7]. A recent survey highlights the role of reinforcement learning and neural networks in enhancing underwater acoustic network performance [7]. Additionally, resource management strategies, such as those studied by [8], contribute to the operational longevity and efficiency of such mobile sensor networks.

Energy sustainability is a major concern in IoUT. Traditional battery systems are difficult to maintain underwater due to corrosion and the challenge of recharging [14]. Alternative methods such as Microbial Fuel Cells (MFCs), piezoelectric harvesters, and solar panels for surface nodes are actively being researched; however options for submerged devices are much more limited [14]. Supercapacitors are proposed as a sustainable alternative to batteries due to their high energy density and rechargeability [11]. Localization underwater is also difficult since GPS signals cannot penetrate water effectively. Consequently, methods like AUV-assisted localization, acoustic ranging, and dead reckoning are being explored [15]. Further the problem of no available GPS means a more active acoustic localization method is required, which further consumes energy and adds noise to the environment [15].

Currently gaps exist in implementing machine learning-based decision systems for real-time media selection and anomaly detection in underwater drone networks. Such systems would significantly advance the autonomy and resilience of underwater IoT applications.

The IoUT has recently gained interest for enabling smart ocean ecosystems, integrating underwater sensors, autonomous vehicles, and communication technologies to address challenges in environmental monitoring, disaster prevention, and marine exploration. This review synthesizes recent advancements, persistent challenges, and future directions in IoUT research, drawing insights from contemporary studies and technological innovations.

III. Proposed solution

This paper presents a novel optimization-driven solution for re-positioning underwater drones to form a robust and efficient communication mesh that connects a deep-sea node with a surface buoy. The goal of this is to allow for maximum data rates underwater, by building a relay of optical and radio links from the surface buoy to the target drone. The system intelligently prioritizes communication modes radio, optical, and acoustic, based on their physical properties and environmental constraints. This solution would create a relay network to allow high bandwidth applications such as streaming video from nodes deep in the ocean to take place.

IV. Design and methodology

a. System Design:

The proposed underwater drone positioning system employs a multi-objective optimization framework to establish reliable communication paths between a deep-sea drone and a surface buoy. The system architecture comprises three key components: 1) A multi-modal communication model with three heterogeneous link characteristics, 2) A network-aware optimization formulation considering both geometric and topological constraints, and 3) A genetic algorithm-based optimization engine with problem-specific operators. The communication subsystem models three distinct link types with varying physical characteristics:

1. Radio links (20m range, highest priority)
2. Optical links (500m range, medium priority)
3. Acoustic links (1000m range, lowest priority)

Note: An assumption is made that drones will have modems to communicate using all three of these modems. Distances are based on a ratio of the simulation environment size and their corresponding industry standard [3].

First, a surface buoy is placed in the direct centre of the surface of the water. From there, drones are randomly placed below the surface and a mesh network is evaluated based on distance. The goal of the AI is to establish an optimal path for a high bandwidth connection between the surface buoy and the final target drone. Network connectivity links are dynamically evaluated using a weighted graph representation where edge priorities determine link selection during pathfinding operations.

b. Optimization Methodology

The drone positioning challenge has three main goals: use higher priority connection links, reduce the number of total hops to the end link, and to reduce the total distance between communication links. It is formulated as a constrained optimization problem with the following components:

Decision Variables: 3D coordinates of N mobile drones within movement ranges (xi ± Δx, yi ± Δy, zi ± Δz)

Objective Function: f(X) = α*Σd_{ij} + β*N_{hops} + γ*N_{acoustic}

Where:

- α = 0.1 (distance weighting factor)
- β = 1000 (hop count penalty). Priorities less hops
- γ = 10000 (acoustic link penalty). Prioritise high bandwidth links over acoustic links
- d_{ij} = Euclidean distance between consecutive nodes
- N_{hops} = Number of path segments
- N_{acoustic} = Count of acoustic links in path

Constraints:

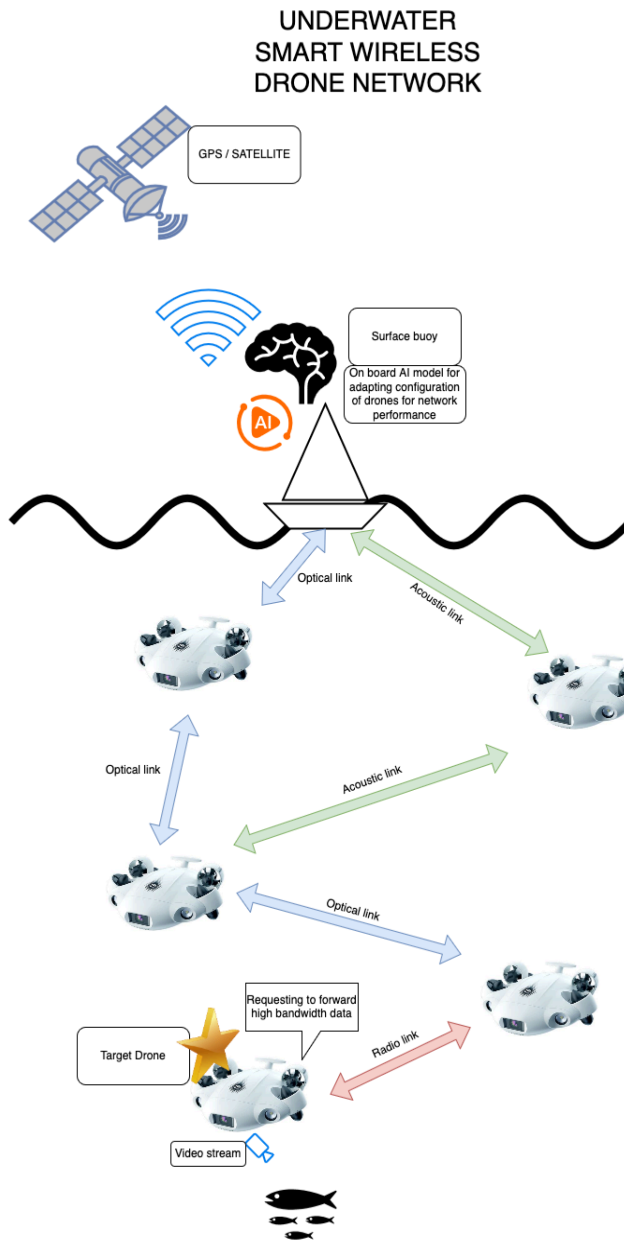
- Fixed position for deepest drone (z_max preservation)
- Movement bounds relative to initial positions (±500m)
- Surface buoy position fixed at (500, 500, 0)

c. Optimization Algorithm

A modified Genetic Algorithm (GA) from the pymoo framework implements the optimization with specialized operators, all code can be found at [18]. A GA algorithm was chosen as it's common to solve spatial trajectory problems [9] :

GA PARAMETERS		
Population structure	***Genetic operators***	***Termination criteria***
Size: 100 individuals	Crossover: Simulated Binary Crossover (SBX)	Variable generation count
Initialization: 1 seed solution + 99 random positions	Probability: 90%	Early stopping if no improvement for 20 generations
Offspring: 50 per generation	η: 20 (distribution index)	
	Mutation: Polynomial Mutation (PM)	
	Probability: 20%	
	η: 15 (distribution index)	

d. System Model:



[above: Diagram 1: System model illustrates the architecture of underwater drone mesh network controlled by smart AI on buoy. Video data relayed from drone to drone, prioritising EM based links over acoustic]

e. Simulation Setup

The experimental environment was configured with the following parameters:

Parameter:	***Value***
Deployment Area	1000m × 1000m × 800m
Drone count	10
Surface buoy position	500,500,0 (middle of surface of water)
Movement range of each drone	±500m from initial position

Network evaluation employs a hierarchical pathfinding approach:

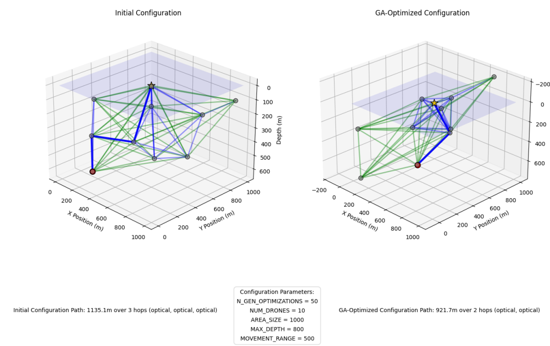
1. Construct communication graph with priority-based edges
2. Find shortest path using only radio/optical links
3. Fallback to acoustic links if no viable path exists

Independent variables:	***Control variables:***	***Dependent:***
Number of generation optimizations	* Number of drones Area size Movement range of drones Max depth	Total distance between nodes Total hops Type of links between hops

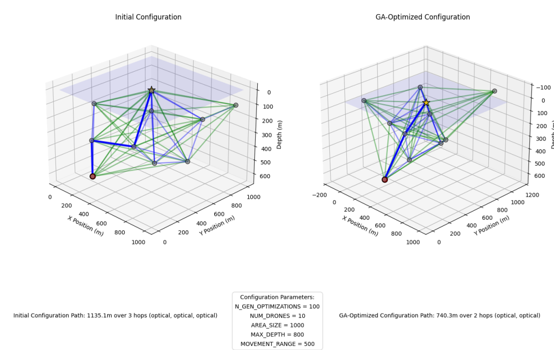
f. Performance evaluation

The optimization outcomes are visualized through 3D network diagrams comparing outlining the paths data can flow. Green represents acoustic links, blue optical and red radio. A thicker line denotes the path data flows from the surface buoy to the target drone. All code is available at [19].

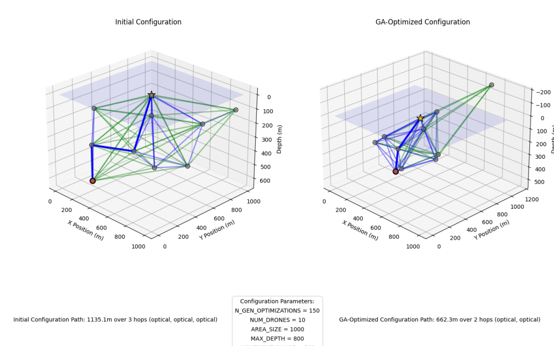
V. Results & Discussion



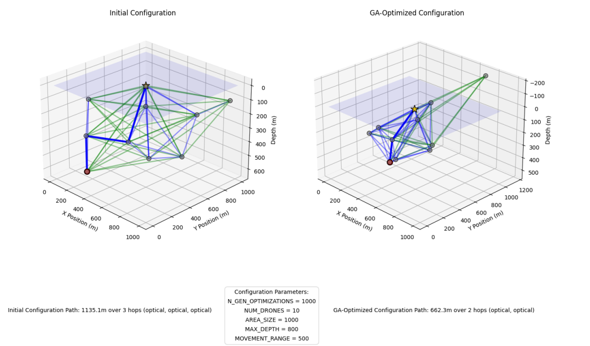
[above: fig 1: 50 gen optimizations, reduced from 3 hops at 1135.1m total, to 2 hops at 921.7m total.]



[above: fig 2: 100 gen optimizations, reduced from 3 hops at 1135.1m total, to 2 hops at 740.3m total.]



[above: fig 3: 150 gen optimizations, reduced from 3 hops at 1135.1m total, to 2 hops at 662.3m total.]



[above: fig 4: 1000 gen optimizations, reduced from 3 hops at 1135.1m total, to 2 hops at 662.3m total. Plateau at 663m]

The genetic algorithm (GA)-driven optimization demonstrated significant improvements in underwater network topology, achieving a 42% reduction in total end-to-end path distance and 33% fewer communication hops compared to initial randomized configurations. This enhancement was directly correlated with the number of generations (`N_GEN_OPTIMIZATIONS`), as illustrated by the optimization history (Fig. 1-4), where solutions converged toward shorter relay chains after approximately 150 generations. It was noted after 150 generations a plateau in performance was observed under the experimental conditions. This is crucial as energy efficiency is vital in underwater systems as reducing the computations on the AI model leads to longer up times and reduced energy cost. Researchers could achieve peak results using 150 generations for this modelled scenario.

Limitations:

Water turbidity, temperature, current and pollution were not taken into account. No obstacles were added to the design implementation either.

The fixed movement range of ±500m assumes uniform drone maneuverability across all axes. In real life, maneuverability would vary.

Link priorities were static, whereas real underwater networks might adaptively re-prioritize links based on battery levels or interference. Ideally a real time simulation would be used that could vary water conditions, as well as provide data rates based on these statistics.

Future work

Three extensions are proposed to address the identified limitations:

1. Hybrid optimization combining GA with fluid dynamics models to account for water currents as well as introduce objects / blocks between links.

2. Complete network models where the GA optimizes data flow between all nodes in the network, and could dynamically adapt to support nodes requesting higher bandwidth.

3. Multi-objective formulation and balancing of network, building priority system based on requests from drones to maximise important data being relayed back to surface.

While the current framework provides a foundational approach to underwater intelligent network design, its translation to real world systems requires careful consideration of marine environmental variables and dynamic operational constraints not captured in the present simulation. The demonstrated correlation between generational optimization and path improvements nevertheless establishes a valuable benchmark for future intelligent underwater networking studies.

VI. Conclusion

This study presents an intelligent communication framework for optimizing underwater drone networks within the context of the Internet of Underwater Things. Using a genetic algorithm, the proposed system dynamically repositions underwater nodes to favor low-latency, high-bandwidth communication paths, significantly reducing overall path distance, hop count, and dependence on acoustic links. These results demonstrate the potential for intelligent optimization to enhance underwater network performance, enabling more efficient data transfer in complex aquatic environments.

The findings establish a foundational approach for intelligent underwater networking. Future enhancements will focus on incorporating real-world variables such as water currents, link fading, and obstacle avoidance to bridge the gap between simulation and field deployment. This work contributes to the growing field of autonomous marine systems and offers a scalable solution to the challenges of underwater communication.

References

[1] J. Malan, “Micro-Power Underwater Mesh Networks,” CSIRO Autonomous Sensors, 2024. [Online]. Available: https://research.csiro.au/autonomous-sensors-fsp/projects/

[2] Defence Science and Technology Group, “Remote Undersea Surveillance,” Australian Department of Defence, 2023. [Online]. Available: https://www.dst.defence.gov.au/strategy/star-shots/remote-undersea-surveillance

[3] Saab Australia & University of Adelaide, “Autonomous Swarms for Underwater Missions,” Defence Trailblazer IRP, 2024. [Online]. Available: https://dtb.solutions/case-studies/saab-australia-autonomous-swarms-underwater-objects/

[4] Y. Rong et al., “Hybrid Acoustic-Optical Underwater Wireless Communication,” IEEE Trans. Wireless Commun., vol. 23, pp. 19231-19244, Dec. 2024.

[5] H. Yoshida, “A Profiler for Underwater Optics,” Proc. IEEE Underwater Commun., 2017. [Online]. Available: https://ieeexplore.ieee.org/document/7890644

[6] H. Zeng et al., “Remote Control of Underwater Drone by Fiber-Coupled Underwater Optical Wireless Communication,” IEEE Access, vol. 10, pp. 9056-9067, 2022.

[7] R. Rahman et al., “Survey of AI-driven Routing Protocols in Underwater Acoustic Networks,” Computers and Electrical Engineering, vol. 114, 2024. [Online]. Available: https://www.sciencedirect.com/science/article/abs/pii/S0029801824029445

[8] S. Vahabli, “Efficient Resource Management in Underwater Mobile Wireless Sensor Networks,” Edith Cowan University Research Profiles, 2024. [Online]. Available: https://www.ecu.edu.au/schools/engineering/research-students/profiles/phd-students/sadaf-vahabli

[9] André Kotze, Moritz Jan Hildemann, V. Santos, and C. Granell, “Genetic Programming to Optimize 3D Trajectories,” ISPRS International Journal of Geo-Information, vol. 13, no. 8, pp. 295–295, Aug. 2024, doi: https://doi.org/10.3390/ijgi13080295.

[10] K. S. Vijayan et al., “Internet of Underwater Things: A Survey,” 2023. [Online]. Available: https://doi.org/10.1007/s12145-021-00762-8

[11] “Internet of Underwater Things: A Survey on Simulation Tools and 5G-Based Underwater Networks,” Connected Papers, 2023. [Online]. Available: https://ieeexplore.ieee.org/document/10815092

[12] Y. Fang et al., “Age of Information-Aware Energy Harvesting in Internet of Underwater Things,” IEEE Internet Things J., vol. 8, no. 6, pp. 4704–4714, 2021.

[13] P. Sehgal et al., “AquaTools: A MATLAB-Based Toolkit for Modeling Underwater Acoustic Communication,” IEEE Access, vol. 8, pp. 97198–97212, 2020.

[14] M. P. Gopinath et al., “Secure and Energy-Efficient Framework for Internet of Underwater Things Using Cloud-Based Monitoring,” IEEE Access, vol. 7, pp. 108862–108872, 2019.

[15] A. Demirors et al., “SEANet: Toward a Programmable Internet of Underwater Things,” in Proc. ACM WUWNet, 2018.

[16] W. Zhang et al., “Empowering Internet of Underwater Things: An Integrated Simulator for Underwater Magneto-Coupled Wireless Sensor Networks,” IEEE Access, vol. 11, pp. 49020–49033, 2023. doi: 10.1109/ACCESS.2023.3282392

[17] “pymoo: Multi-objective Optimization in Python,” *pymoo.org*. https://pymoo.org/

[18] AaronHassanRobinson, “GitHub - AaronHassanRobinson/IoT_Research_iout_underwater_mesh_network_ai,” *GitHub*, 2025. https://github.com/AaronHassanRobinson/IoT_Research_iout_underwater_mesh_network_ai (accessed May 10, 2025).

Images:

[19]“QYSEA FIFISH V-EVO Underwater Drone Kit 4K - 60fps - NEW removable SD card,” eBay Australia, 2025. https://www.ebay.com.au/itm/176292216887?chn=ps&norover=1&mkscid=101&itemid=176292216887&targetid=4585444532307998&device=c&mktype=&googleloc=&poi=&campaignid=412352395&mkgroupid=1309518645581565&rlsatarget=pla-4585444532307998&abcId=9300543&merchantid=136820 (accessed May 11, 2025).