Cluster Computing (2026) 29:79
https://doi.org/10.1007/s10586-025-05736-9

Developing an autonomous fleet of unmanned underwater vehicles and aerial platforms for marine missions

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Received: 24 April 2025 / Revised: 21 August 2025 / Accepted: 24 August 2025
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Abstract

A new generation of Internet of Underwater Things (IoUT) has been facilitating the development of a new class of IoT apps, i.e. marine apps. Of interest in this research are Unmanned Underwater Vehicles (UUVs). Our experience with Unmanned Aerial Vehicles (UAVs) thus far suggests that UUVs have the potential to become effective and efficient when supported with optimisation algorithms. To explore this, this work first puts together a school of UUVs by using acoustic communications, and Deep Learning (DL). It then introduces an aerial platform as a source of renewable energy for the school. The resulting fleet is then empowered to operate autonomously for the purpose of carrying out marine missions and detecting underwater objects using a dual cognitive brain developed using a Dolphin Optimization Algorithm (DOA) and a Support Vector Machine (SVM). The results obtained indicate that the communication link budget parameters, reliability and localization, as well as the accuracy of coordination among the school of UUVs and the aerial platform as well as initial management of underwater missions and object detection is reasonable. Key findings at 50 kHz frequency and depths ranging between 4 and 7 meters reveal: the optimal number of acoustic Multiple Input Multiple Output (MIMO) users is 18; an acceptable Received Signal Strength (RSS) average of -61.8dB with the lowest Bit Error Ratio (BER) of $1x10^{-6}$ which indicates reasonable performance for MIMO antennas; confidence scores on the health of underwater plants ranging between 91% and 96%; a synchronous autonomy accuracy ranging between 0.91 and 0.99; an object detection accuracy ranging between 0.85 and 0.93; the supply of energy exceeds demand. Finally, a sensitivity analysis experiment on several missions does not reveal any variable outliers since changes in all input variables appear to be directly proportional to model outputs, therefore, indicating an otherwise robust model.

Keywords Autonomous school of UUVs · Acoustic communications · Wireless communications · DL · IoUT

1 Introduction

Fourth Industrial Revolution (4IR) technologies are playing a crucial role in advancing underwater communication capabilities, enabling new applications. Figure 1 shows the main 4IR technologies that are associated with UUVs. As technology continues to evolve, we should expect to see a more diverse and innovative range of solutions for more reliable and efficient underwater communications, whilst avoiding known exclusion zones like Nan Madol which exhibit significant levels of radiation and affect UUVs communications and functionality.

Since the 4IR is a fusion of technologies, this blurs the lines between the physical, digital, and biological spheres. This raises both immense opportunities and challenges when it comes to the autonomous fleet of UUVs [1–3]. The main 4IR challenges this work addresses includes:

- Accurate and reliable localization and navigation for UUVs which is hindered by poor hydroacoustic sensor capabilities and signal attenuation.

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Published online: 06 January 2026

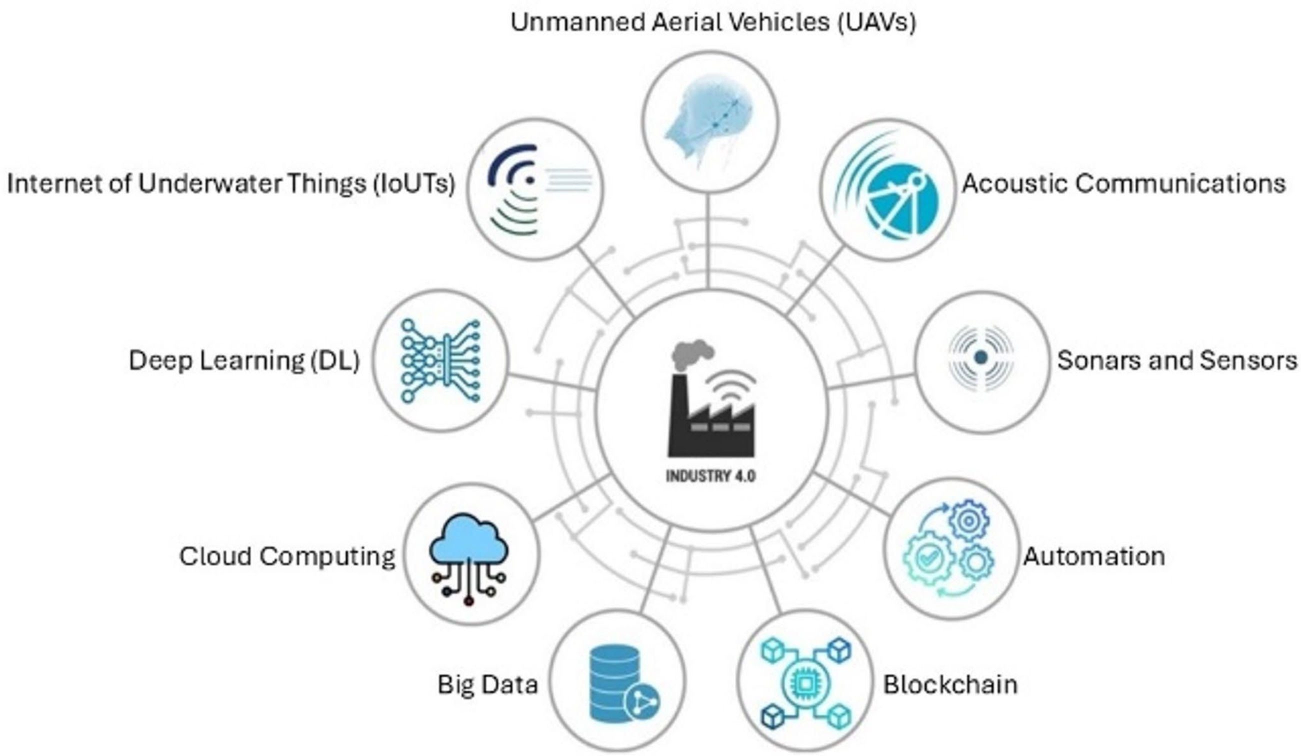


Fig. 1 4IR technologies associated with UUVs

- Wireless communication, underwater, which is severely limited by signal attenuation. This restricts real-time data transmission and remote control, often requiring UUVs to operate with more autonomy and pre-programmed missions, making dynamic adjustments difficult.
- Energy supply to UUVs for extended missions which is disrupted by battery depletion and will require frequent recharging or replacement. This interrupts continuous monitoring and operations.
- Effectiveness of UUV sensor technology, both acoustic and optical, which is hampered by water turbidity, light conditions, and the presence of marine life, leading to inaccurate data or missed detections.

In this work we propose to resolve some of the above challenges by endowing UUVs with IoUT and DL which enables:

- Autonomy that allows UUVs to make dynamic adjustments to their mission plan without any human intervention if, for example, they are affected by signal attenuation. In turn, this allows them to operate for longer periods of time, expands their range of tasks and helps with reducing their power consumption.
- Intelligent real-time decision-making that allows UUVs to pursue continuous learning using data they have collected from past missions in complex and changing environments and choose, for example, a new path that recognizes and avoids obstacles or prioritizes targets. In turn, this allows them to become more efficient and effective with their navigation and mission objectives and helps with reducing their power consumption.
- Data analytics on the large amounts of data collected, such as images, videos, and sensory data, from which to extract valuable information about the surrounding environment.

The rest of this paper is organized as follows: Sect. 2 presents a review of related studies from which we draw our motivation for a framework we propose in Sect. 3. Section 4 details a framework simulation and then discusses the initial results. Section 5 concludes.

2 Related studies review

This section reviews studies that relate to the advancements of UUVs. To guarantee consistency within the scope, a set of criteria have been considered during review of the literature. The criteria include type of: UUV, network configuration, communication, cognitive approach, mission, and limitations. We present our findings from the various perspectives that have emerged, namely, underwater communications, autonomous motion, object detection and computer vision, and underwater missions. We conclude with highlights of our findings that bring to the fore research gaps and, in turn, motivate our own work.

2.1 Underwater communications

The works that have been included under this heading investigate various aspects of underwater communications and make some proposals for solution [4]. introduces a triangulation multipath propagation of the acoustic wave for detecting water surface activities, e.g. oil spills, or adverse weather conditions [5]. considers low complexity detection for IoUT underwater acoustic communications using a Single Carrier Frequency Domain Equalizer (SC-FDE) and Amplify-and-Forward (AF) protocols [6]. estimates the direction of arrival of underwater signal using Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) [7]. integrates Passive Acoustic Monitoring (PAM) sensors in UUVs to estimate the DOA of the source [8]. promotes vertical multilayer cooperation between UUVs and UAVs for monitoring ocean and seafloor properties with the UAVs serving either as an aerial or sea-surface acoustic station [9]. uses differential binary phase-shift keying (DBPSK) system for acoustic underwater communication to solve doppler and multipath issues [10]. proposes vertical multilayer cooperation between a seabed observation system, a sea-surface relay transmission buoy, and a remote monitoring system through a satellite. It features underwater acoustic communications and RF satellite communications [11]. evaluates air to water cross-boundary communications using optical and non-optical direct communications, and relay-based communications. It tests the communication between underwater vehicles against those on the sea-surface and above water platforms. This work suggests using Convolutional Neural Networks (CNN) or Multi-agent Reinforcement Learning (MRL) to enhance underwater channel characteristics and using beam tracking and an array structure like Multiple Input Multiple Output-Long (MIMO) antenna, with due consideration for green energy for self-sustainable networks.

2.2 Autonomous motion

The works that have been included under this heading investigate various aspects of underwater autonomic motion and make proposals for solution [12]. proposes a formation control structure of UUVs using a leader–follower approach whereas [13] proposes a visual navigation and control between an unmanned surface vehicle (USV) and a UAV in a cooperative fashion for search and rescue using a reinforcement learning approach [14]. considers task assignment and path planning using various AI approaches whilst [15] proposes formation control and investigates underwater acoustic communication [16]. experiments with autonomous path planning in riverbanks using a 2D LiDAR and PID controller [17]. presents an adaptive variable threshold event-triggered control for trajectory tracking of autonomous UUVs with actuator saturation [18]. proposes a predefined path for UUVs for data collection whereas [19] uses Cooperative coverage Path Planning (CPP) alongside a Pac-Men mechanism for UUVs to explore deep oceans [20]. proposes a fish-inspired robotic flocking algorithm that imitates behaviour and communication of schooling fish [21]. considers dynamic trajectory planning for UUVs to remain close to moving sensor nodes and exploit both short and long-range communications [22, 23] investigate vertical and multilayer cooperation between UUVs and a UAV for carrying out underwater missions such as fishery inspections [24]. use a Double Deep Q Network (DDQN) algorithm to reduce power consumption during path planning for UUVs [25]. deploy self-localized underwater fixed sensors and use a compressive node localization algorithm with corrected hop count to achieve that [10]. consider an A3C collision avoidance path planning algorithm for a school of UUVs.

2.3 Object detection and Computer vision

The works that have been included under this heading investigate various aspects of visual object detection and make proposals for their solution [26]. investigates underwater recording of sonar images taken by UUVs and their processing whereas [27] pursues a CNN approach for the processing of underwater images [28]. proposes an underwater robot for target tracking alongside a bionic Closed-loop central Pattern Generator (CPG) that integrates fuzzy logic control [29]. proposes two acoustic sensors for automatic target recognition and geolocation of underwater gas leakages, a Doppler Velocity Log (DVL) sensor, and an Ultra-Short BaseLine (USBL) sensor. For improved detection, they propose a fusion of computer vision and CNN [30]. uses swarm robotics for underwater monitoring in a virtual reality testbed for resolving of navigation and objectives in-dive [31]. equips UUVs with an underwater hyperspectral imager (UHI) and stereo-camera for detecting and mapping marine debris. Through their work they highlight the challenges faced with degraded plastic and material diversity [32]. proposes the use of the CUREE platform to carry out an audio-visual benthic survey for underwater exploration and monitoring of habitats and coral reefs [33]. attempts to improve underwater object detection accuracy where blurring has occurred, using a dual-branch feature extraction [34]. models shoal of fish robots for underwater exploration using a max-plus algebra and Points of Interest (POIs) approach [35]. propose a turbidity-adaptive underwater image enhancement method using image fusion. Through their work, they highlight the challenges posed by colour deviation, image textures, and overall image quality in harsh underwater environments whereas [36] uses binary sensory information, i.e. see or not see, to control the motion of a swarm of underwater robots and highlighting the challenge posed by physical obstacles and constrained environments [37]. proposes the use of a robotic swarm of fish equipped with camera infrared (IR) sensors and CNN for swarm pattern recognition.

2.4 Underwater missions

Unmanned (sea) surface vehicles offer many advantages in patrolling coastal areas and collecting data from the surface of the sea or in very shallow waters. Yet, underwater deployment using remote sensory and underwater antennas offers more; the smaller size of UUVs, speed, and higher maneuverability, enables participation in coordinated behavior like in a school of fish or pod of sea mammals, which in turn can yield various benefits such as task allocation and coordination, data sharing and fusion, and overall enhanced efficiency from working as a team. Working as a school or pod, UUVs can pursue discovery exploration and monitoring tasks ranging from scientific research to military surveillance [38, 39]. Indeed, multipath propagation of acoustic wave that support multiple IoUT sensors can enhance the heterogenous topology and connectivity.

A wide range of IoUT applications with UUVs have evolved and Fig. 2 shows their primary tasks.

The application area of interest to this work is the aquaculture industry which Technology has revolutionized in the past few years by enabling sea farmers to optimize operations, improve efficiency, ensure sustainable practices and help them meet the growing demand for sustainable seafood while protecting the environment [40–42]. Sea vegetables on demand are not limited to seaweed, they include green, red and brown sea vegetables, e.g., sea lettuce, nori, dulse, arame, hijiki, kombu, wakame.

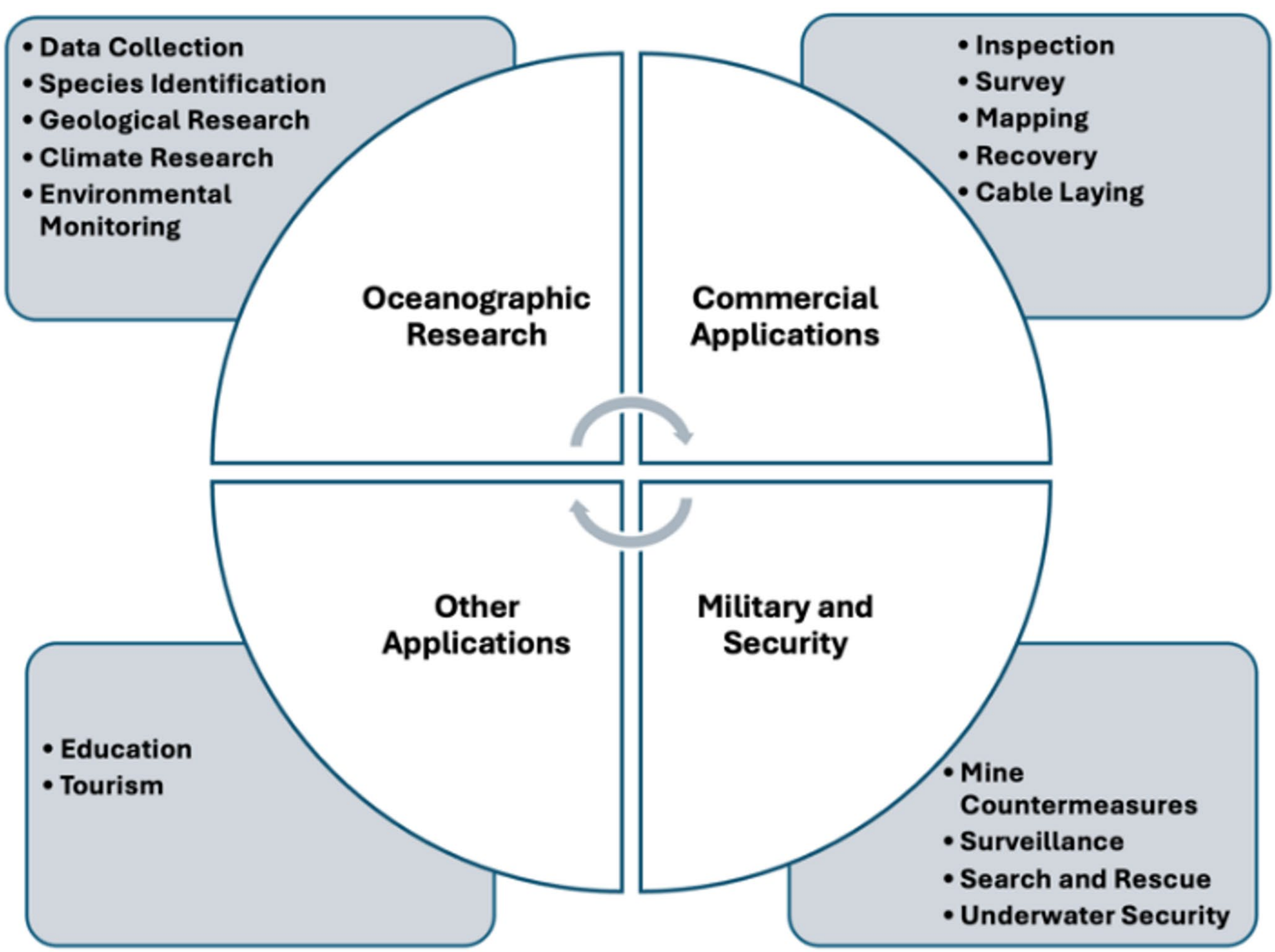


Fig. 2 UUV applications across various fields

Table 1 Our approach against approaches reviewed

Perspective	Advantages	Limitations
Underwater comms [4–11]	Leader–follower, Navigation/path planning, Acoustic comms/LiDAR, Cooperative coverage, AI to enhance predictions	Predefined path, Limited control over energy use, Fixed sensors, Limited collision avoidance
Autonomy [10, 12–25]	Long distance sonar imaging, Visual and sensor integration, Stereo camera, AI to enhance detection	Limited object detection accuracy due to blurring, School of UUVs coordination
Object detection, Computer Vision [10, 26–37]	Supports 17 UN SDGs, Seaweed aquaculture, Underwater farm inspection, AI to enhance inspection	Single ROV, Limited sea farming functions
Sea farming [38–46]	Multipath propagation of acoustic wave, Multiple IoUT sensors, Heterogenous underwater and sea surface schemes, Smart antennas and AI to enhance connectivity	Last-mile environmental complexity, Little thought for energy use
Own	Underwater comms link using adaptive acoustic MIMO antennas and Neural Networks (NN), Dual cognitive brain for synchronous autonomy, object detection, and underwater monitoring, Green energy via tethered aerostat for UUV recharging	Cost and complexity of multilayer framework

Exploring the use of a single UUV for aquaculture, in general, and sea vegetable farming, in particular, is scarcely reported in the literature, let al.one the use of a school of UUVs, operating autonomously [43]. promotes the seaweed aquaculture against the 17 UN Sustainable Development Goals in aid of attaining global sustainability targets [44]. proposes a robotic Remotely Operated Vehicle (ROV) alongside a Nitrogen content spectral algorithm for monitoring outplant health and canopy macromolecular content whereas [45] presents a multipurpose underwater robotic arm mounted on a UUV for aquaculture missions [46]. proposes the use of an underwater robot alongside a window-sliding segmentation algorithm for a seaweed farm inspection. This work aims to demonstrate the novelty of our approach in arboreal underwater sea vegetable farming, from seed to harvesting with minimal intervention. Table 1 presents the advantages and limitations of all approaches reviewed by perspective group, i.e. underwater communications, autonomy, object detection and computer vision, sea farming and compares these against our own proposal.

Table 2 Research objectives and associated deliverables

Objective	Deliverable Innovation
Enhancement of UUV data rates, link reliability, localization and power consumption	Development of an underwater communications link using adaptive acoustic MIMO antennas and Neural Networks (NN)
Synchronised autonomy across the UUV school, object detection, and underwater monitoring	Development of dual cognitive brain using DOA and SVM, with the former responsible for sensory input and the latter responsible for decision making and classification
Generation of hybrid renewable energy for UUV recharging	Deployment of tethered aerostat loaded with turbines and solar panels for generating hybrid renewable energy
Validation of framework	Simulation of the framework for underwater sea vegetable farming

Our proposed framework is a noticeable shift from existing work in the literature and to achieve our aim, Table 2 sets out our research objectives that need to be fulfilled to achieve our deliverable innovation. The resulting fleet integrates multiple layers of unmanned vehicles, both aerial and underwater, with ground control.

3 The proposed framework

This section presents the proposed multilayer framework, with underwater sea vegetable farming as the application. This is shown on Fig. 3.

The methodology of choice is Model-Based Systems Engineering (MBSE) that uses models as the primary means of communication, design, and analysis throughout the system lifecycle. It has been selected because for a system as innovative and multi-disciplinary as an autonomous fleet for sustainable underwater farming, MBSE moves beyond traditional document-centric approaches to provide a powerful, integrated, and holistic method for design, development, and management.

The sky segment includes a helium-filled tethered aerostat with a payload of a transceiver, GPS sensor, HD camera, weather sensor, and microcontroller as the key components. The tethered aerostat has the advantage of generating renewable energy through turbines and solar panels which can supply all three layers with clean energy.

The ground segment includes a ground control centre (GCC) that controls wirelessly the tethered aerostat and a sea surface station, a sink. The latter acts as the link between the overground and the UUVs. The sink is anchored using a tether and powered with clean energy from the tethered aerostat via a cable. UUVs can in turn be recharged from the sink.

The underwater segment includes a school of UUVs, coupled with a DL algorithm for attaining three objectives:

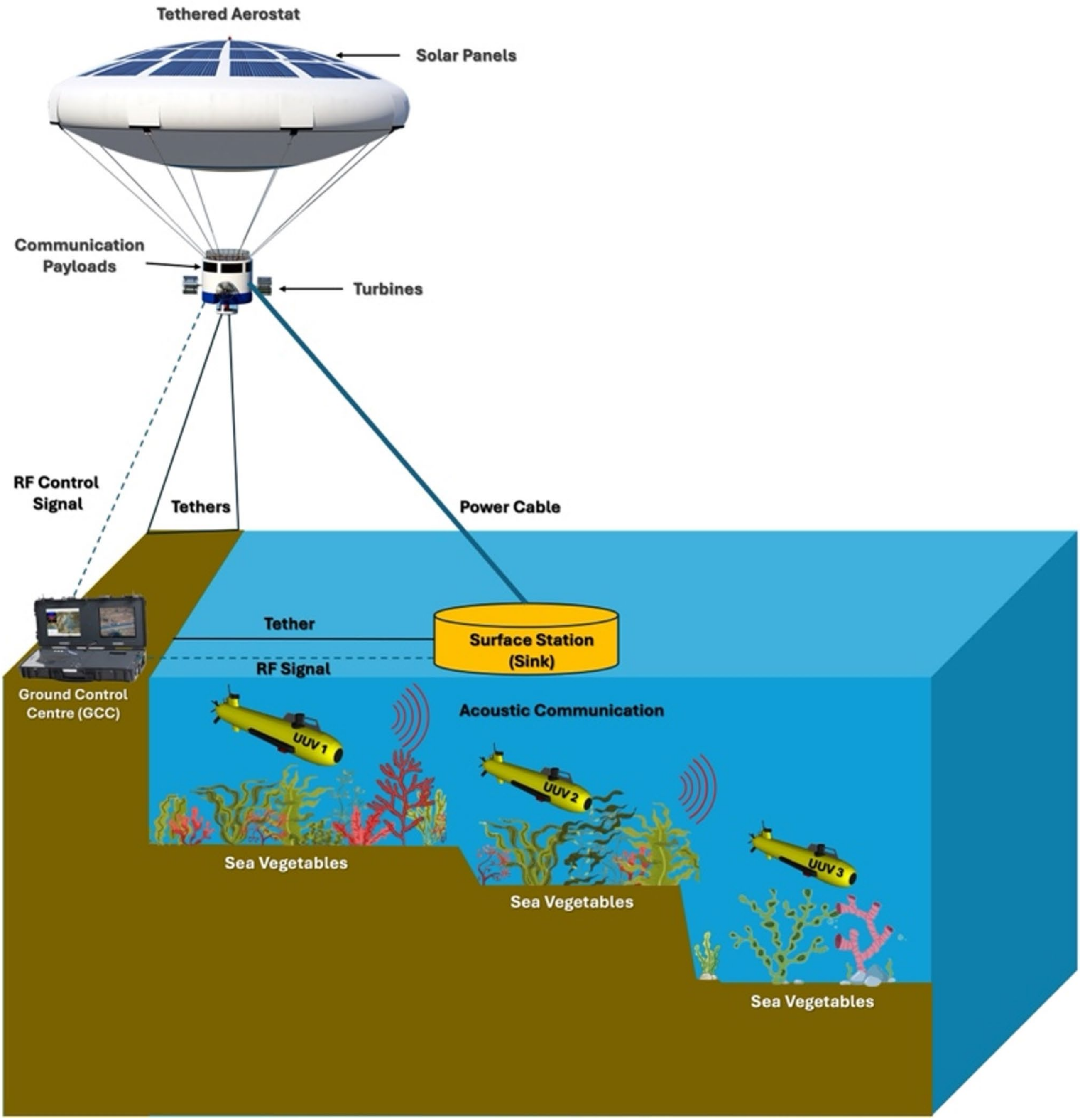


Fig. 3 The multilayer framework for underwater farming

autonomy, synchronisation and underwater detection, and monitoring of underwater vegetable farming. Acoustic communications are used to maintain communications to, from, and within the school.

Unlike swarms of UAVs up in the sky, water poses additional challenges for UUVs. Thus, attaining tight cooperation across all vehicles can help deliver greater efficiency and reliability, which would be a great contribution to the field. Therefore, what is necessary to enable this is: firstly, to develop an underwater module for communications using machine learning, such as Neural Networks (NN), and adaptive acoustic MIMO antenna, this should enhance UUV data rates, link reliability, and localization; secondly, to develop dual cognitive brains for synchronous autonomy using DOA and SVM, this should synchronise the school of UUVs, enable object detection, and underwater monitoring; thirdly, to deploy a tethered aerostat for recharging UUVs using turbines and solar panels, this should generate sufficient renewable energy to meet energy demands; and finally, develop a simulation of the framework for underwater sea vegetable farming missions for the purpose of validation. The layered framework layout that has evolved should enable recording of valuable environmental readings that will help with making decisions in aid of a safer, more sustainable, and more productive underwater environment.

Table 3 compares a pool of existing approaches such as Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO), Genetic Algorithms (GAs), Deep Deterministic Policy Gradient (DDPG) and Proximal Policy Optimization (PPO), YOLO and Faster R-CNN against our Dual DOA and SVM [47–49]. The comparison is carried out using algorithmic features such as primary domain, core functionality, input and output types, learning paradigm, known strengths and weaknesses, and their use in supporting autonomous fleets during underwater farming applications.

Figure 4 illustrates a flowchart of the multilayer framework in the context of underwater farming. The projection matrices evolve with UUVs movement and are populated with the optimisation results of the link budget, synchronised autonomy, and object detection, and renewable energy generation and consumption.

Table 4 shows two key algorithms of the multilayer framework to accompany the flowchart in Fig. 4: optimisation of the communications link budget, synchronous autonomy across the school and underwater object detection.

A. *Underwater Acoustic Communications*.

Unlike wireless communications where air is the medium, underwater wireless communications present challenges due to the unique properties of water which absorbs electromagnetic waves. Such an attenuation can reduce or even eliminate the range and data rate of radio frequency signals. Furthermore, underwater currents will affect the motion of UUVs and can cause doppler shift when using RF signals.

To overcome these challenges, researchers have explored various techniques such as sound waves, acoustic modems, ultra-high frequency, and light waves. Each technique has its own advantages, but it also has its limitations. This work explores Adaptive Passive Time Reversal (APTR) algorithm through underwater acoustic MIMO communications for a more efficient long-range high-rate channel estimation and applies spatial division multiplexing as shown on Fig. 5.

The modified underwater acoustic communication can be formulated as per Eqs. (1) to (12). Initial formulation has been informed by [50] and [51]. This has been followed by a stage of transition during which RSS and underwater elevation angle tuning have been considered and incorporated into the formulation. Elevation angle is the vertical angle between the UUVs and the leader UUV, the latter of which is taken as a reference point. Two additional performance indicators have also been added to the formulation: overall spectral efficiency, and effective data rate, the purpose of which is to improve validation of our approach.

$$r_j(t) = \sum_{i=1}^{N} h_{i,j}(t) \times s_i(t) + z_j(t) \tag{1}$$

$$\min_w : \ w_k^H R w_k, \ \text{s.t.}: \ w_k^H d_k = 1 \tag{2}$$

$$RLS = \sum_{i=1}^{N} d_i \, d_i^H + \sigma^2 I \tag{3}$$

$$W_k = [W_{k,1}(f) \ldots W_{i,M}(f)]^T \tag{4}$$

$$d_i = [H_{i,1}(f) \ldots H_{i,M}(f)]^T \tag{5}$$

$$W_k = \left(d_k^H R^{-1} d_k\right)^{-1} R^{-1} d_k \tag{6}$$

$$u'_i(t) = \sum_{j=1}^{M} r_j(t) \otimes w_{k,j}(t) \tag{7}$$

$$RSS = 10 \times n \times \log d - L \tag{8}$$

$$d^2 = r^2 + z^2 \Rightarrow r = \sqrt{\max(0, d^2 - z^2)} \tag{9}$$

$$\theta = \arctan\frac{z}{r} \tag{10}$$

$$\alpha = N \times \frac{T}{T + T_{pr}} \times \frac{K_d}{K} \times r_c \times \beta \tag{11}$$

$$D_{eff} = B_s \times \alpha \tag{12}$$

where $r_j(t)$ denotes receiver array of j^{th} receivers on each UUV, N denotes transmitter channels, M denotes receiver channels, $h_{i,j}(t)$ denotes channel response between i^{th} transmitter and j^{th}receiver, $s_i(t)$ denotes transmitted signal from i^{th} transmitter, $z_j(t)$ denotes background noise, * denotes convolution, $W_{k,j}(f)$ denotes optimal weight function for k^{th} transmission channel in frequency domain, $H_{i,j}(f)$ denotes estimated channel response, w denotes vector of optimal weights, d denotes estimated channel response, RLS denotes cross-spectral density matrix of estimated channel response, $[\,]^T$ denotes transpose, $\sigma^2 I$ denotes small diagonal load on cross-spectral density matrix, $W_{k,j}(t)$ denotes weight function in time domain, $\otimes$ denotes cross-correlation operator, $u'_i(t)$ denotes signal from each UUV transmitter, RSS denotes the Received

Table 3 Dual DOA and SVM against similar approaches

Feature/Algorithm	PSO and ACO	GAs	DDPG and PPO	YOLO and Faster *R*-CNN	DOA and SVM
Primary Domain	Optimization (continuous, combinatorial problems)	Optimization/Search: diverse, but for complex search	Continuous control/reinforcement learning in dynamic environments	Object detection and localization	Signal processing/spatial classification, e.g., acoustic source localization and classification
Core Functionality	Search for optimal solutions by simulating swarm intelligence (particles moving in search space, ants depositing)	Mimic natural selection to evolve solutions over generations	Learn optimal actions in an environment to maximize cumulative reward through trial and error	Detect and localize objects in frames by drawing bounding boxes and assigning class labels	Estimate direction of signals, classify sources based on spatial and signal features, detect and localize objects in frames
Input Type	Problem parameters and objective function	Problem parameters and fitness function	Environment states, e.g., sensor readings, joint angles	Images and video frames (visual data)	Sensor data arrays, e.g., hydrophone and antenna, signal time series, visual inputs
Output Type	Optimal (or near-optimal) values for parameters, routes, schedules	Optimized parameters, best-found solutions	Optimal control actions, e.g., motor commands, steering angles, navigation decisions	Bounding box coordinates, class labels, confidence scores for detected objects	Direction estimates (angles), classified source labels, e.g., UUVs, object detection and localization
Learning Paradigm	Heuristic Search/Optimization	Evolutionary computation/Search	Reinforcement learning, Model-Free	Supervised Learning (Deep Learning)	SVM: supervised learning, DOA: signal processing
Strengths	Global search avoiding local optima, PSO: simple, fast convergence for continuous problems, ACO: effective for combinatorial/pathfinding problems	Robust for complex, non-linear problems, can explore vast search spaces, highly parallelizable	Learn highly complex, adaptive policies, handle continuous action spaces effectively, PPO: stable and sample-efficient	State-of-the-art accuracy for visual object detection, YOLO: real-time speed, Faster R-CNN: higher accuracy for small objects	Excellent for problems requiring spatial localization and classification, can leverage domain-specific signal features, relatively interpretable two-stage process, SVM: robust with high-dimensional data
Weaknesses	No guarantee of finding global optimum, Performance sensitive to parameter tuning, Slow to converge for very complex problems	Computationally intensive, slow convergence for some problems, designing fitness function can be challenging	Require significant computational resources and data, difficult to tune hyperparameters, black-box nature and less interpretable	Require large datasets for training, computationally intensive (Faster R-CNN), YOLO: sacrifices some accuracy for speed, Faster R-CNN is slower	Sequential processing can introduce latency, DOA errors propagate to SVM, requires expertise in both signal processing and ML, may not be end-to-end optimizable
Mean Average Precision	70–78%	74–80%	65–75%	55–84%	80–90%
Energy saving	10–25%	8–15%	5–12%	10–35%	15–40%

Table 3 (continued)

Feature/Algorithm	PSO and ACO	GAs	DDPG and PPO	YOLO and Faster *R*-CNN	DOA and SVM
Supporting autonomous fleets during Underwater Farming Applications	UUV/UAV path planning: optimizing patrol routes for energy efficiency or maximum coverage, sensor network deployment: optimizing fixed sensors placement for best coverage/data collection	Optimizing UUV/UAV mission parameters: evolving optimal strategies for complex inspection tasks under varying conditions, Resource allocation: optimizing task allocation to different vehicles in the fleet	Autonomous UUV/UAV navigation: learning to navigate complex underwater/aerial environments, avoiding obstacles, and dynamically inspecting farm structures, Adaptive sampling: learning optimal sampling strategies for water quality or fish health monitoring	Visual inspection: identifying fish species, detecting net damage, recognizing marine debris, or assessing fish health from visual feeds, Automated counting: counting individual fish within pens or detecting presence of predators	Acoustic monitoring: classifying sounds (fish, UUV, vessel) and localizing their source for anomaly detection or behavioural analysis, sonar target identification: classifying objects in the water column based on acoustic signature and location

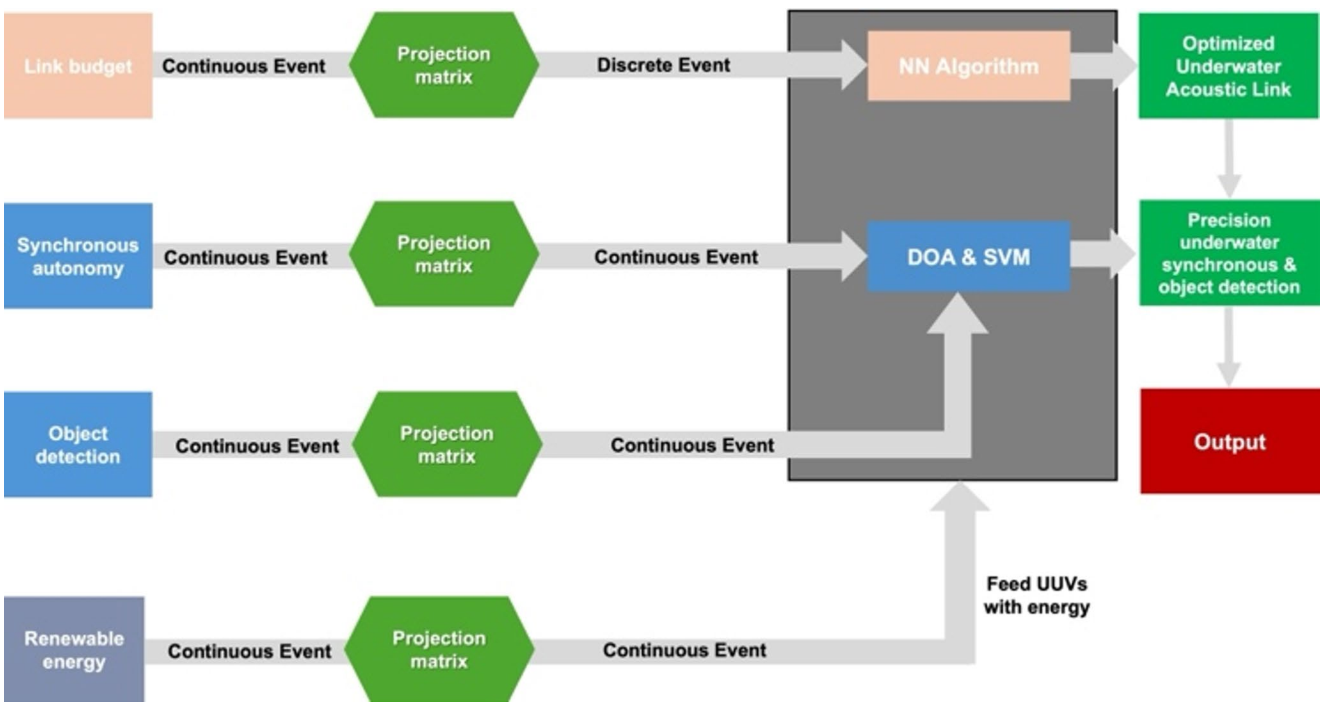


Fig. 4 Flowchart of the proposed multilayer framework

Signal Strength in dBm, n denotes path loss exponent in underwater environment (2 to 4 dB), d denotes separation distance between UUVs, L denotes system losses, z denotes vertical separation between point of reference leader UUV and follower UUVs, d denotes estimated angle range, r denotes horizontal range, α denotes overall spectral efficiency, T denotes signal length, T_{pr} denotes duration of channel probing, K_d denotes data symbol length, K denotes total slot size including training and synchronization overhead, r_c denotes coding rate, β denotes multilevel modulation order, B_s denotes symbol rate, D_{eff} denotes effective data rate.

B. *UUV Autonomy and Object Detetction.*

This work develops a dual cognitive brain for synchronous autonomy within a school of UUVs and underwater object detection supported by DOA and SVM approach. The DOA is a meta-heuristic and bio-inspired optimization algorithm drawn by the behaviour of dolphins. It mimics the way dolphins use echolocation and social interaction to locate and capture prey in groups. It is an efficient technique that can solve various optimization problems. Furthermore, it can be used for image processing tasks such as image segmentation,

Table 4 Algorithms for the UUVs multilayer framework

Algorithm 1. Optimization of underwater acoustic link

1. Generate transmitter channels N
2. Generate receiver channels M
3. Establish receiver array of j^{th} receivers using $r_j(t)$
4. Check channel response between i^{th} transmitter and j^{th}receiver using $h_{I,j}(t)$
5. Generate initial weights $W_{k,j}$
6. Calculate optimal weight $W_{k,j}(f)$ using: w, d, RLS, $\sigma^2 I$, $\otimes$
7. Each UUV has a signal $u'_i(t)$
8. Check RSS of each UUV using: n, d, L
9. Check α of each UUV using: $T, T_{pr}, K_d, K, r_c, \beta$
10. Check D_{eff} of each UUV using: α, B_s
11. Get output: RLS, RSS, α, and D_{eff}

Algorithm 2. Optimization of synchronous autonomy and object detection

1. Suppose DD_{ij} is distance between UUVs Dol_i and Dol_j
2. Let N be the number of UUVs
3. Check neighbourhood optimal solution using K_i, L_i
4. Use X_{ijt} and E_{ijt} as fitness functions
5. Do random search V_j for N using: M, $TS_{i,j}$, A, R_1, R_2, e, c
6. Get output classifier μ_{ij} using $newDol_i$ for each UUV
7. Assume probability of an object's presence in bounding box is P_f
8. Check overlap between predicted and ground truth boxes B, B_g
9. Predict distance from ground truth using: ρ^2, c
10. Define bounding boxes using: x, y, w, h, and C
11. Get confidence score C

noise reduction, and feature extraction. Figure 6 shows the four phases of the DOA and SVM.

- Phase I Population initialization: This involves generating randomly the initial population of a school of UUVs whereby each vehicle is assigned a position and velocity.
- Phase II Fitness evaluation: Each UUV's fitness is evaluated based on the objective function of the optimization problem.
- Phase III Motion: UUVs update their motion based on the following rules:

1. Search space boundaries: UUVs are kept within the search space boundaries,
2. Best individual position: Each UUV moves towards its best position thus far,
3. Best group position: UUVs also move towards the best position of the entire school,
4. Random motion: A random component is added to the motion to introduce diversity and prevent premature convergence.

- Phase IV Object detection: Feature extraction using underwater cameras and supported by a SVM approach.
- Phases II to IV are repeated until either objects have been detected or the maximum number of iterations has been reached.

The UUVs are equipped with sonars and cameras, to improve object detection accuracy. Furthermore, the use of DOA and SMV supports UUV motion and object detection by optimizing the trajectory of underwater vehicles and search patterns taking into account factors such as obstacle avoidance, energy efficiency, and mission objectives. By adjusting parameters such as school size, exploration,

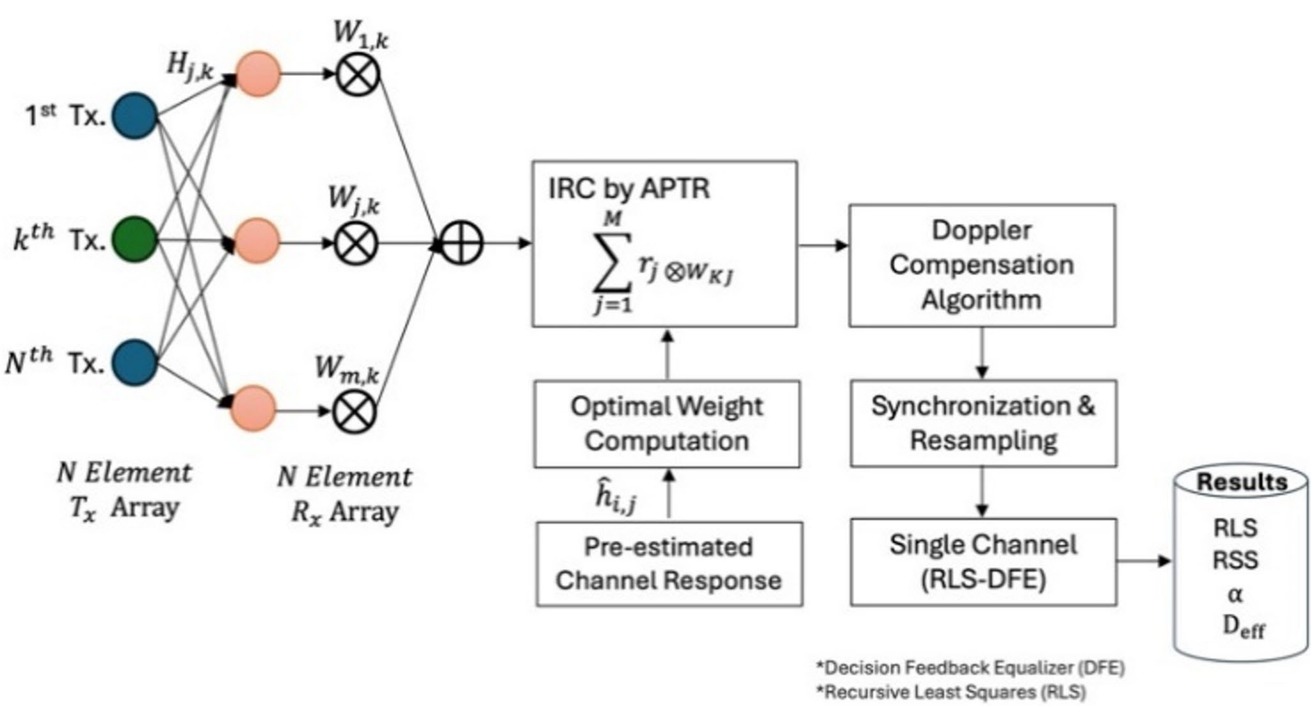


Fig. 5 APTR through underwater acoustic MIMO communications

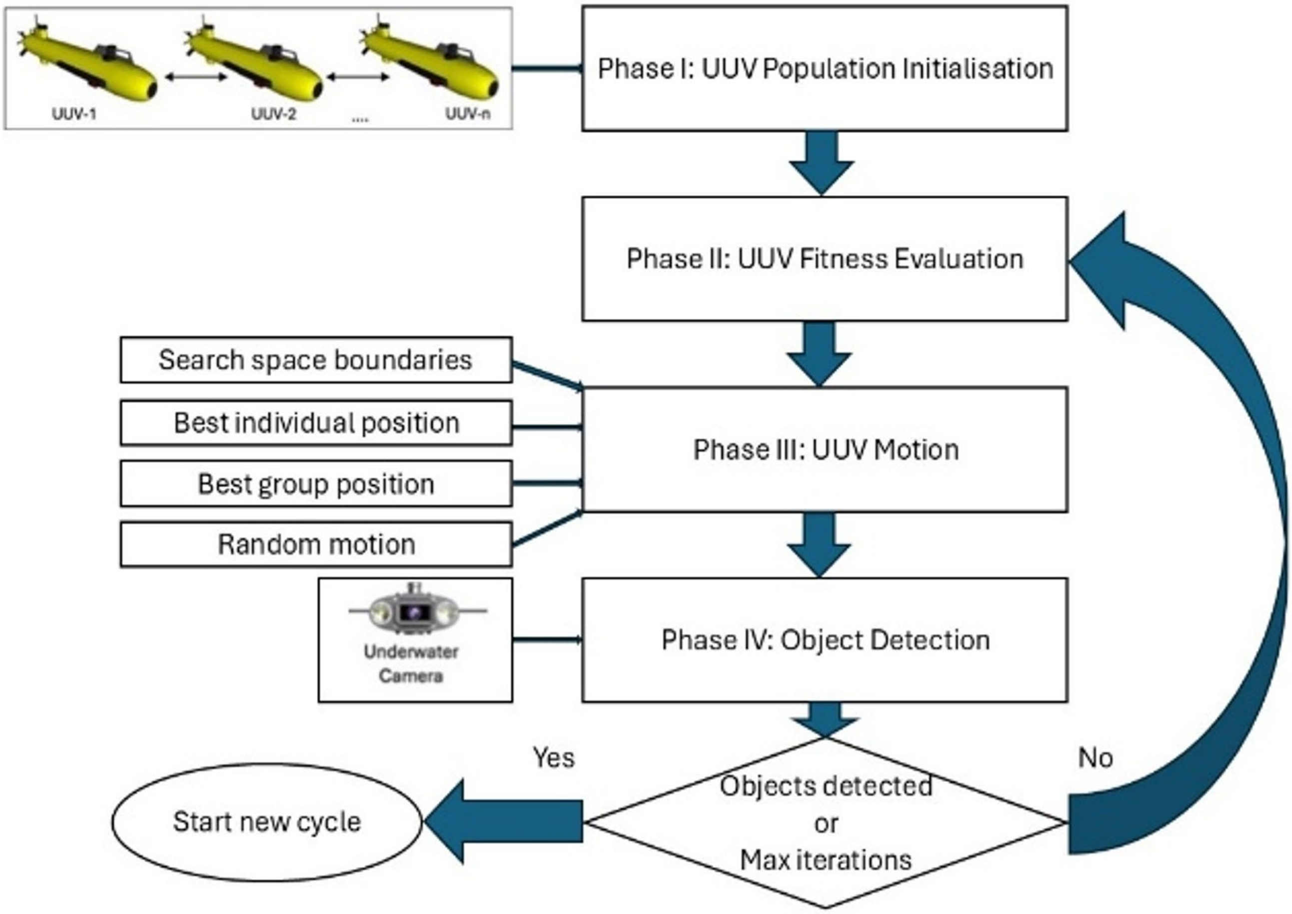


Fig. 6 UUV autonomy and object detection

exploitation, and communication radiuses, UUVs can adapt dynamically to underwater environments. By sharing information among the UUVs, the school can collectively identify and track objects more efficiently.

The synchronous autonomy within a school of UUVs and underwater object detection using the DOA along with the SVM approach can be formulated as per equations (13) to (42) [52–54]. The construction of the mathematical formulation aims at addressing two key objectives: Firstly, the synchronisation of UUVs, and, secondly, the detection of underwater objects. This represents a significant departure from the approaches that have been reviewed in the extant literature which reports using these algorithms in a standalone manner rather than within the context of a cognitive framework.

$$\mathrm{DD_{ij}} = \| \mathrm{Dol_i} - \mathrm{Dol_j} \|, \quad \mathrm{i,j} = 1,2,\ldots,\mathrm{N},\ \mathrm{i} \neq \mathrm{j} \tag{13}$$

$$\mathrm{DK_i} = \| \mathrm{Dol_i} - \mathrm{K_i} \|, \quad \mathrm{i} = 1,2,\ldots,\mathrm{N} \tag{14}$$

$$\mathrm{DKL_i} = \| \mathrm{L_i} - \mathrm{K_i} \|, \quad \mathrm{i} = 1,2,\ldots,\mathrm{N} \tag{15}$$

$$\mathrm{X_{ijt}} = \mathrm{Dol_i} + \mathrm{V_j}\,\mathrm{t} \tag{16}$$

$$\mathrm{E_{ijt}} = \mathrm{Fitness}(\mathrm{X_{ijt}}) \tag{17}$$

$$\mathrm{If\ E_{iab}} = \mathrm{min}_{\mathrm{j}=1,2,\ldots,\mathrm{M};\mathrm{t}=1,2,\ldots,\mathrm{T_1}} \mathrm{Fitness}(\mathrm{X_{ijt}}) \tag{18}$$

$$\mathrm{then\ optimal\ Li\ of\ Doli:\ L_i} = \mathrm{X_{iab}}$$

$$\mathrm{If\ Fitness\ (L_i)} < \mathrm{Fitness\ (K_i)} \tag{19}$$

then $\mathrm{L_i}$ replaces $\mathrm{K_i}$ else $\mathrm{K_i}$ persists

$$\mathrm{TS_{i,j}} = 0 \tag{20}$$

$$\mathrm{Fitness\ (K_i)} > \mathrm{Fitness\ (K_j)} \tag{21}$$

$$\mathrm{TS_{i,j}} > \left\lceil \frac{\mathrm{DD_{i,j}}}{\mathrm{A} \times \mathrm{speed}} \right\rceil \tag{22}$$

$$\mathrm{TS_{i,j}} = \left\lceil \frac{\mathrm{DD_{i,j}}}{\mathrm{A} \times \mathrm{speed}} \right\rceil \tag{23}$$

$$R_1 = T_1 \times \text{speed} \tag{24}$$

$$DK_i \leq R_1 \tag{25}$$

$$R_2 = \left(1 - \frac{2}{e}\right) DK_i, e > 2 \tag{26}$$

$$newDol_i = K_i + \frac{Dol_i - K_i}{DK_i} R_2 \tag{27}$$

$$DK_i > R_1 \tag{28}$$

$$DK_i \geq DKL_i \tag{29}$$

$$R_2 = \left(1 - \frac{\frac{DK_i}{Fitness(K_i)} + \frac{DK_i - DKL_i}{Fitness(L_i)}}{e \times DK_i \frac{1}{Fitness(K_i)}}\right) DK_i, e > 2 \tag{30}$$

$$newDol_i = K_i + \frac{Random}{\| Random \|} R_2 \tag{31}$$

$$DK_i < DKL_i \tag{32}$$

$$R_2 = \left(1 - \frac{\frac{DK_i}{Fitness(K_i)} - \frac{DKL_i - DK_i}{Fitness(L_i)}}{e \times DK_i \frac{1}{Fitness(K_i)}}\right) DK_i, e > 2 \tag{33}$$

$$Fitness\,(newDol_i) < Fitness\,(K_i) \tag{34}$$

$$\mu_{ij} = [\sum{}_{k=1}^{c} (\frac{DD_{ij}}{DD_{ik}})^{\frac{2}{h-1}}]^{-1} \tag{35}$$

where DD_{ij} denotes first distance between two UUVs named as dolphins Dol_i and Dol_j, N denotes number of dolphins (UUVs), K_i denotes neighbourhood optimal solution, L_i denotes individual optimal solution, X_{ijt} and E_{ijt} denote fitness functions, V_j t denotes sound when a dolphin searches randomly in M directions, $TS_{i,j}$ denotes transmission time for sound to move between dolphins, speed is a constant indicating the speed attribute of sound, A is a constant representing acceleration, R_1 denotes search radius for each dolphin (UUV), R_2 denotes calculation of the encircling radius for each dolphin (UUV), e is a constant named 'radius reduction coefficient, $newDol_i$ denotes new position for each dolphin (UUV), μ_{ij} denotes outcome classifier that ranges between 0 and 1, c denotes centroid of cluster and Euclidean distance between two P-dimensional prototype vectors for a detected object, N denotes dataset that includes detected object, h denotes a weighting exponent of a data point which is a real number greater than 1.

A detected image can be divided into an S×S grid, with each cell predicting B bounding boxes, and confidence scores using DOA along with SVM approach. Confidence score C can be computed as per equations (36) to (38) [55–57].

$$C = P_f \times DIoU(B, B_g) \tag{36}$$

$$IoU = \frac{\text{Area of Intersection}}{\text{Area of Union}} \tag{37}$$

$$DIoU = IoU - \frac{\rho^2(B, B_g)}{c^2} \tag{38}$$

where P_f denotes probability of the object's features existence in the bounding box, $IoU(B, B_g)$ denotes overlap between predicted box B and ground truth box B_g, DIoU denotes distant predictions from ground truth, ρ^2 denotes Euclidean distance between the centres of B and B_g, and c denotes diagonal length of the smallest enclosing box covering both B and Bg. The bounding boxes are defined by five parameters: x, y, w, h, and C. In this context, the x and y coordinates denote centre of the bounding box within a cell. The parameters w and h denote width and height of the bounding box in relation to the dimensions of the image.

To evaluate object feature extraction further, confusion matrices and regression analysis of the average fitting value using Mean Squared Error (MSE) are used and can be computed as per equations (39) to (42) [7, 8, 54].

$$Precision = \frac{TP}{TP + FP} \tag{39}$$

$$Recall = \frac{TP}{TP + FN} \tag{40}$$

$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{41}$$

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(Y_i - \widehat{Y}_i\right)^2 \tag{42}$$

where Precision denotes probability of prediction accuracy among positive sample results, Recall denotes probability of actual positive samples predicted as positive samples, TP denotes True Positives, FP denotes False Positives, TN denotes True Negatives, FN denotes False Negatives, F1 denotes weighted average of accuracy and recall, Y_i denotes ground truth value, $\widehat{Y}_i$ denotes predicted value, and n denotes number of predictions [53].

The integrated approach of DOA and SVM is deployed when searching for global optimal solutions, through classification and regression tasks. Hence, for measuring system effectiveness a confusion matrix is used with indicators of synchronisation, autonomy, sensitivity, object detection accuracy, and confusion matrix accuracy.

Figure 7 maps UUV synchronous autonomy using DOA. This requires coordination between the UUV dolphins within their search radius for an optimal solution.

Figure 8 shows the underwater feature extraction by UUVs using SVM. The figure depicts the extraction of HOG features from an input image, which is accomplished in three principal stages: gradient calculation, histogram generation, and block normalization. Subsequent to this, the extracted features are classified against a pre-trained model during the SVM classification stage.

C. *Renewable Energy Generation*.

The approach to generating renewable energy for use on site and on demand is core to the proposal. At the tethered aerostat's altitude of up to 100 m, there are two sources of power, i.e. solar panels and turbines, with which to recharge the UUVs. Figure 9 shows this hybrid renewable power supply system. The outline features a circuit switch and sensors to control the status of each energy source and the buffered energy.

The approach to charging the UUVs via the tethered aerostat using green energy that is transferred to the sea-surface station can be summarized in the following steps:

Step 1 Hybrid renewable energy generation by the tethered aerostat using solar panels and turbines.

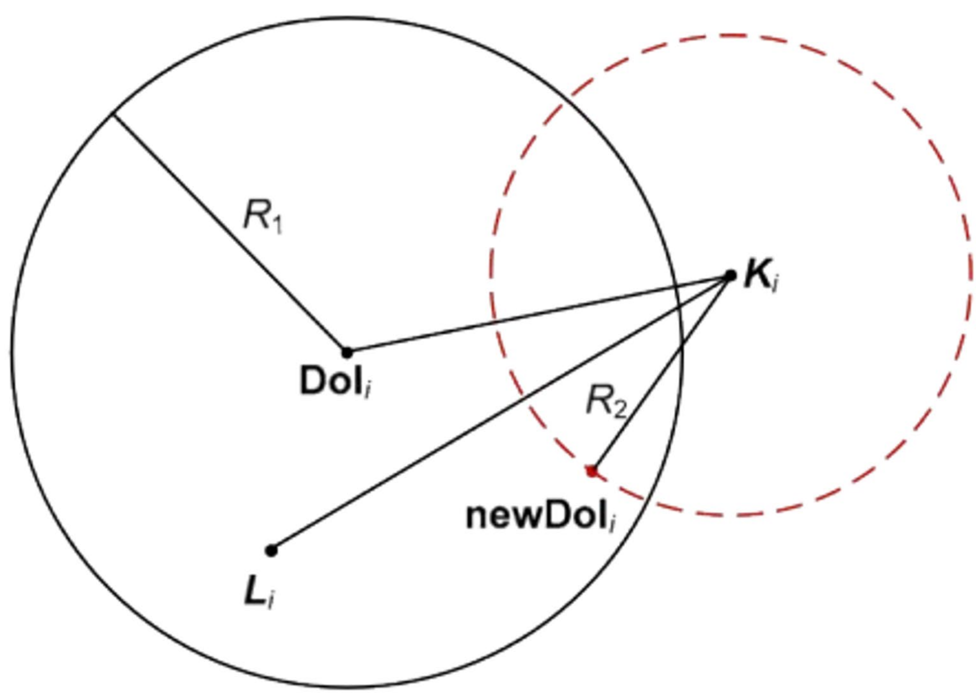
Step 2 Power transmission from aerostat to sea surface platform using a specialized tether.

Step 3 Energy reception and storage by the sea surface platform “sink” that acts as a stable buoy and manages and stores energy in large battery banks, e.g., lithium-ion batteries.

Step 4: UUVs initiate recharging sequence: trigger, navigation, and docking. When the charge of a UUV falls below a predefined threshold, its navigation systems can direct it to the surface charging platform. After precise underwater docking manoeuvres, the UUV aligns itself with a submerged charging coil of the platform, and energy is transferred electromagnetically across a small gap without direct physical contact (inductive charging). The battery status is monitored continuously to ensure safe and efficient power transfer.

The entire process is designed for continuous, autonomous operation. The aerostat constantly harvests and transfers energy, the sea surface platform stores it, and AUVs visit the platform periodically for recharging. This integrated system aims to significantly extend the endurance and autonomy of underwater vehicles by leveraging energy from an aerial platform and an intermediate sea surface charging station, reducing the need for frequent human intervention or return to port.

Fig. 7 Synchronous autonomy



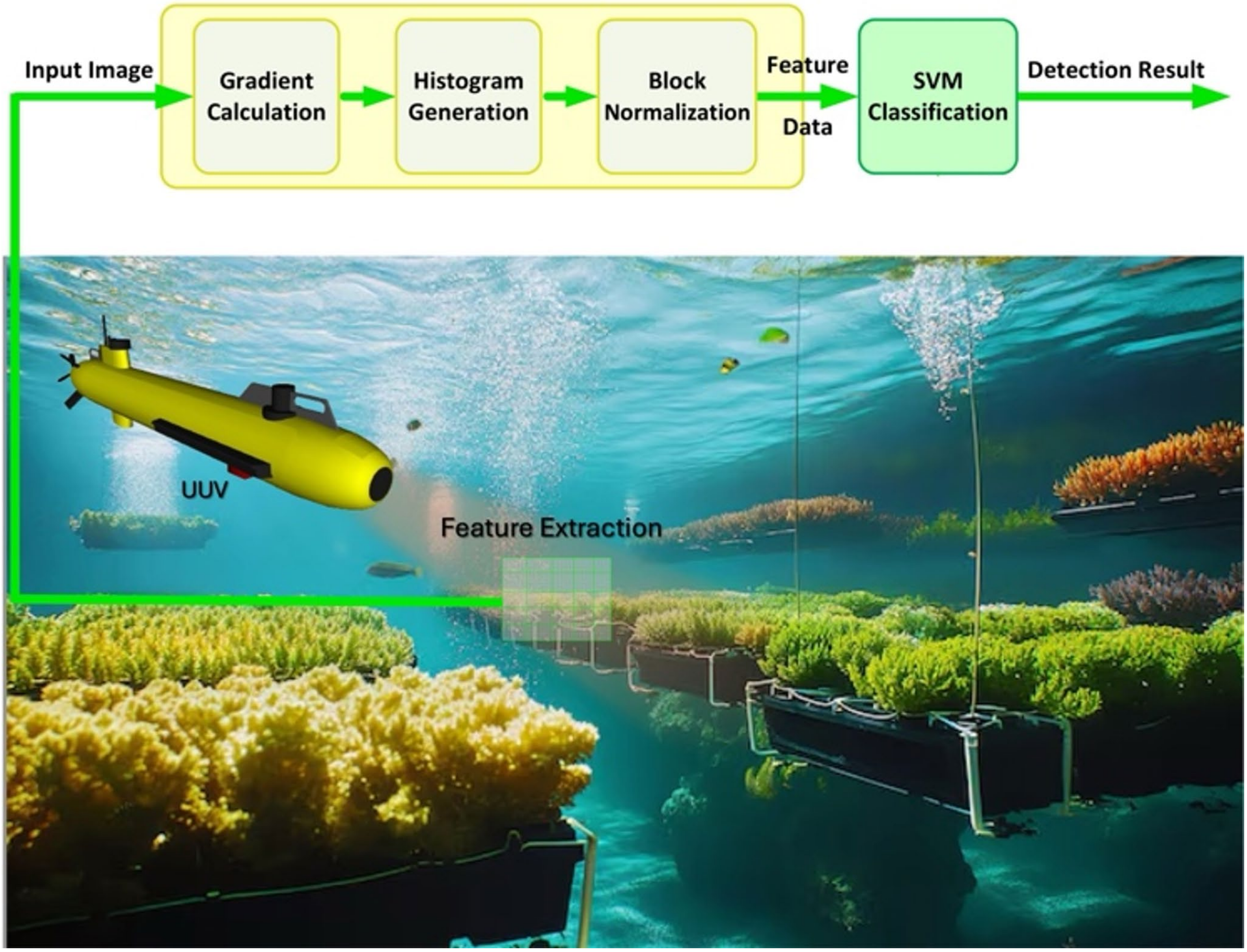


Fig. 8 Underwater feature extraction using SVM

The truth values shown on Table 5 outline the logical connections between the hybrid renewable power supply system components and sensors. S2 denotes sensor for wind power availability, S3 denotes sensor for photovoltaic availability, S4 denotes sensor for low charged battery status, S5 denotes sensor for high-charge battery status, B(t) denotes output power from battery with low-charge, B(t+1) denotes output power from battery with high-charge, W denotes output power from wind turbine, P denotes output power from solar panel, C denotes battery in charging mode [55–59].

The output energy from solar panels can be calculated mainly based on their size, which depends on the amount of sunlight during daily sunlight hours. This can give two main indicators, solar panel capacity and efficiency. These factors signal how efficient it is to convert sunlight into usable energy. The energy from solar panel can be formulated as per Eqs. (43) and (44) [58–62].

$$\mathrm{P_{spo}} = \mathrm{DH} \times \mathrm{W} \times 75\% \tag{43}$$

$$\mathrm{E_{sp}} = \frac{(\mathrm{P_{max}} / \mathrm{A})}{1000} \times 100\% \tag{44}$$

where $\mathrm{P_{spo}}$ denotes output power of solar panels, DH denotes average hours of sunlight, W denotes solar panel rated watts assuming an energy loss of 25%, $\mathrm{E_{sp}}$ denotes solar power efficiency, $\mathrm{P_{max}}$ denotes maximum solar panel power, A denotes total solar panels area (width $\times$ length), 1000 is the conversion factor for transforming power output per unit area from watts per square meter to %. Wind turbines are an alternative renewable energy source for the proposal. The output of the wind turbines can be calculated mainly based on their size and altitude from the ground. The higher the altitude of wind turbines is, the higher their productivity will be since they are dependent on high wind speeds. The clean energy from wind turbines can be formulated as per Eqs. (45) and (46) [58–63].

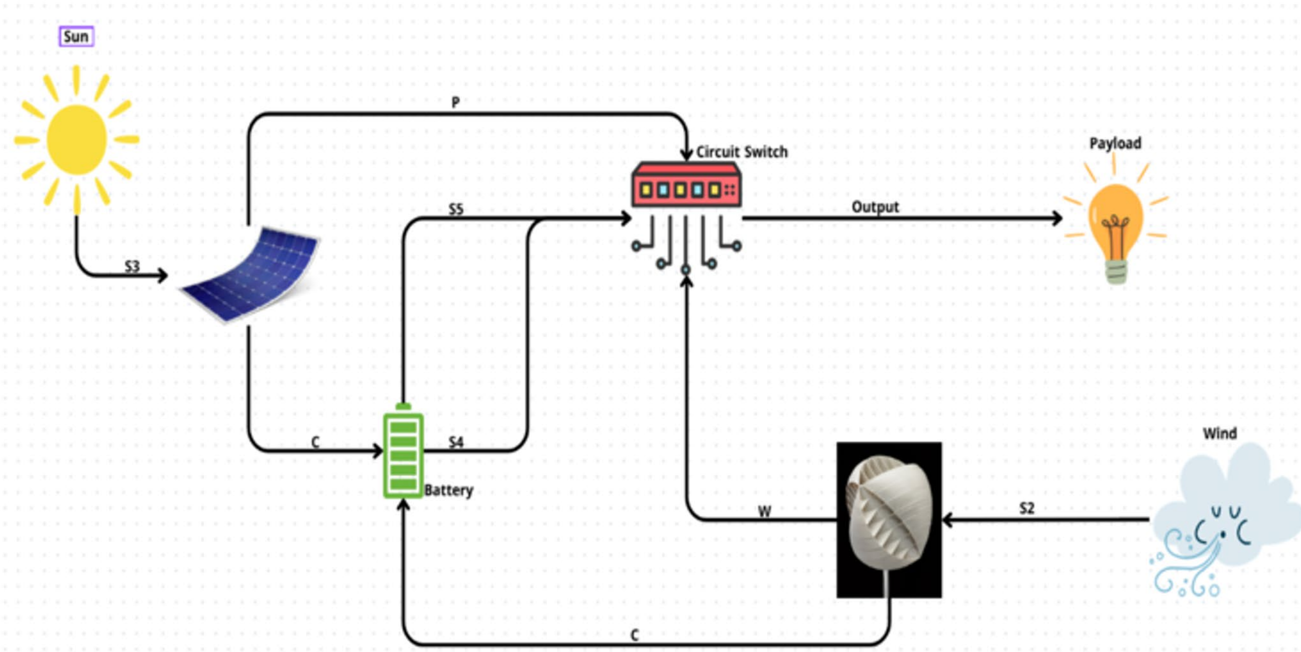


Fig. 9 Hybrid renewable power supply system

Table 5 Truth table of logical connections between the hybrid renewable power supply system components

S2	S3	S4	S5	B(t)	B(t+1)	W	P	C	Function
0	0	0	0	0	0	0	0	0	System Off
0	0	0	1	-	-	-	-	-	Not Valid
0	0	1	0	1	0	0	0	0	Buttery on then off
0	0	1	1	1	1	0	0	0	Battery on then on
0	1	0	0	0	0	0	1	1	Solar on battery +
0	1	0	1	-	-	-	-	-	Not Valid
0	1	1	0	x	0	0	1	1	Solar on Battery +
0	1	1	1	x	0	0	1	0	Solar On
1	0	0	0	x	0	1	0	1	Wind On Battery +
1	0	0	1	-	-	-	-	-	Not Valid
1	0	1	0	x	0	1	0	1	Wind On Battery +
1	0	1	1	x	0	1	0	0	Wind On
1	1	0	0	x	0	1	1	1	Wind, Solar On, Battery +
1	1	0	1	-	-	-	-	-	Not valid
1	1	1	0	x	0	1	1	1	Wind, Solar On, Battery +
1	1	1	1	x	0	1	1	0	Best case Full function system

$$\mathrm{P_{wto}} = \mathrm{C_p} \times {}^{1}\!/_{2} \times \rho \times \mathrm{A_r} \times \mathrm{V}^3 \tag{45}$$

$$\mathrm{E_{wt}} = \frac{\mathrm{P_{wto}}}{\mathrm{P_T}} \times 100\% \tag{46}$$

where $\mathrm{P_{wto}}$ denotes output power of wind turbines, $\mathrm{C_p}$ denotes maximum power coefficient, ρ denotes Air density, $\mathrm{A_r}$denotes rotor swept area, V denotes wind speed, $\mathrm{E_{wt}}$ denotes solar power efficiency, $\mathrm{P_T}$ denotes power available through wind.

The total power of the hybrid system can be calculated as per Eq. (47).

$$E_{hybrid} = \frac{P_{usable}}{P_{input}} \times 100\% \tag{47}$$

4 Simulation and discussion

This section discusses the predicted results of the proposed solution starting with the use of APTR through underwater acoustic MIMO communications, followed by the dual cognitive brain for setting up synchronous autonomy and underwater object detection using DOA and SVM, and generation of renewable energy by the tethered aerostat via solar panels and turbines [63–66].

Figure 10 shows the UUV simulation using MATLAB Simulink toolbox. The toolbox helps with monitoring the performance of the UUVs at the planning stage, for communication, and integration of the different design aspects in the underwater environment. It also helps with assessing the autonomy algorithm for navigation and path planning for underwater farming missions.

Figure 11 illustrates the geometric optimization problem between UUVs using the same toolbox. The simulation considers the distance and centres of mass and buoyancy for UUVs and calculates the error between these two frames at a scaled value. By minimizing the cost function, the converged result gives a reasonable stability and minimum error. It also considers acoustic communications at 50 kHz frequency and at depths of 4–7 m band.

Figures 12, 13 and 14 show the predicted results with the proposed use of APTR through underwater acoustic MIMO communications.

Figure 12 shows the spectral efficiency of acoustic MIMO antennas against directional antennas. The spectral efficiency curve grows linearly with the number of acoustic MIMO. The spectral efficiency initially increases rapidly with as number of MIMO users increases, that is due to spatial multiplexing transmitting multiple data streams concurrently over a single frequency band such as 50 kHz, that raises the overall data rate. However, beyond a certain point, the rate of increase slows down and the curve eventually saturates. The result show reasonable spectral efficiency for the scattered UUVs.

Figure 13 shows the RSS performance results of the underwater acoustic MIMO communications against directional antennas. The RSS is a critical factor that impacts the system's capacity, reliability, and overall data rate for the underwater environmental. Indeed, this environment has an impact on RSS due to ambient noise, and geometric spreading loss including absorption and scattering loss. Noticeably, RSS decreases as distance increases. The line-of-sight (LoS) connectivity between the scattered UUVs using MIMO antenna is superior that directional one. The RSS of MIMO floats with an acceptable average of −61.8dB and

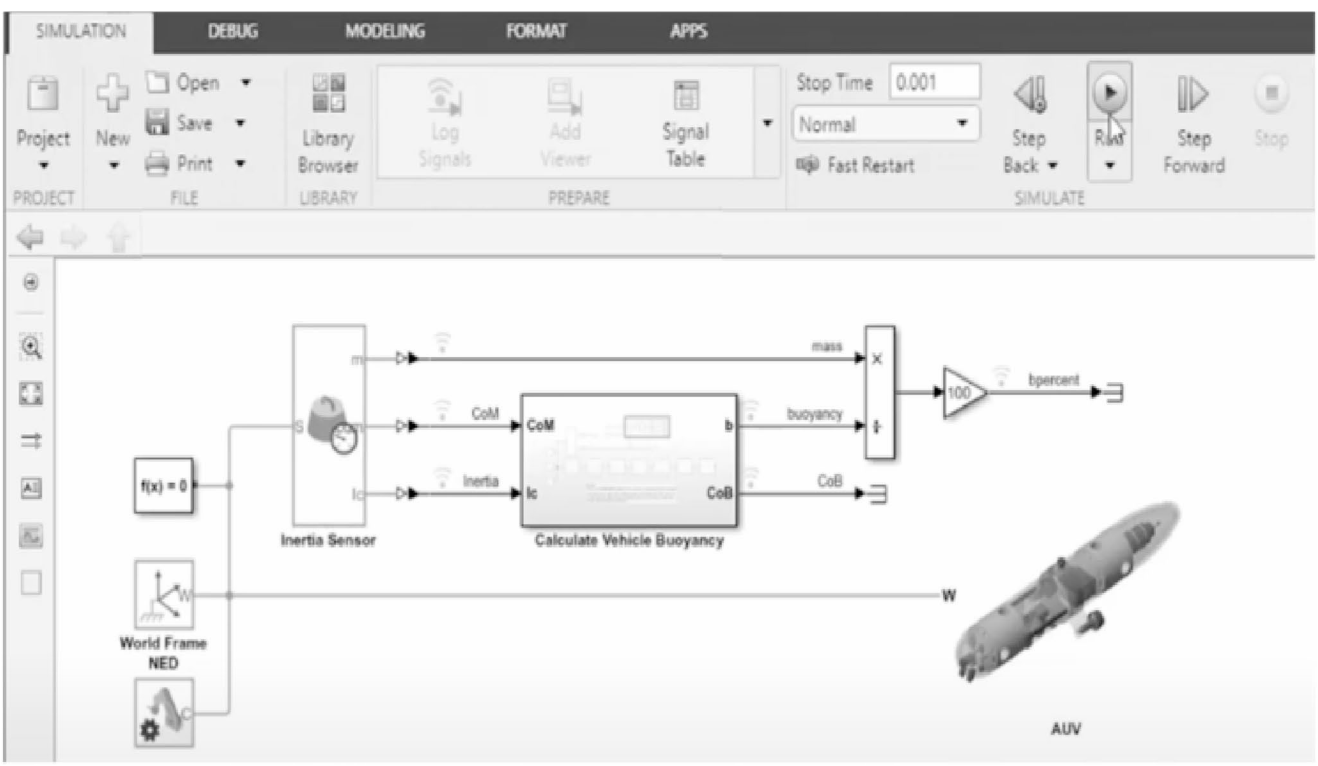


Fig. 10 The MATLAB simulink toolbox

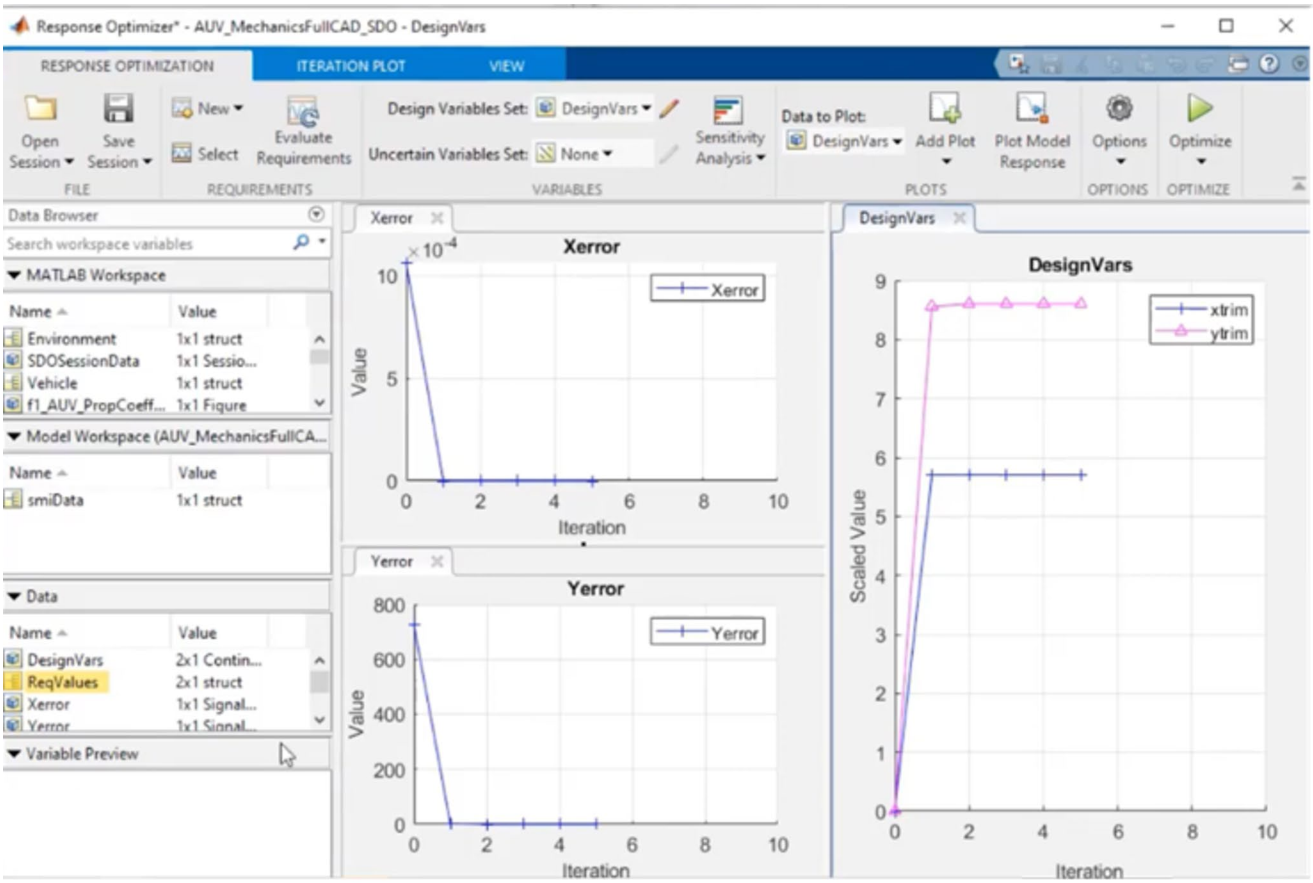


Fig. 11 The MATALAB simulink toolbox

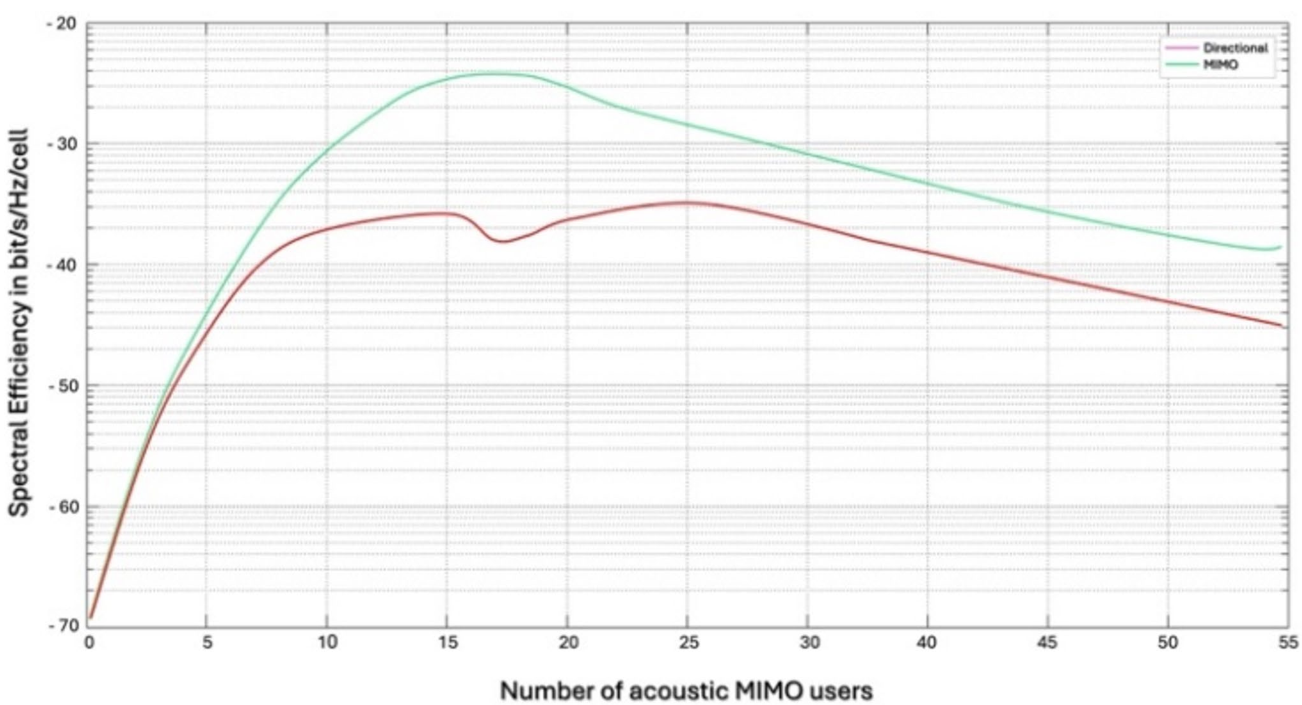


Fig. 12 Spectral efficiency of acoustic MIMO antenna against directional antenna

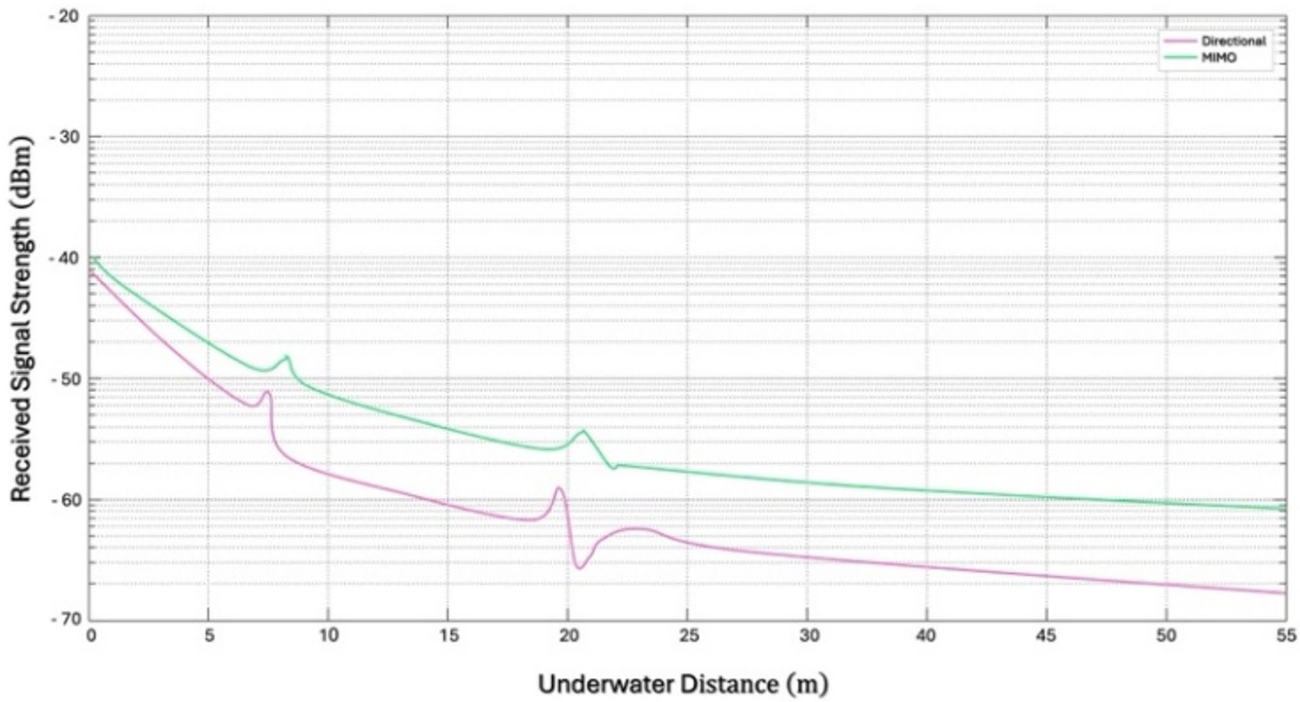


Fig. 13 RSS of acoustic MIMO antenna against directional antenna

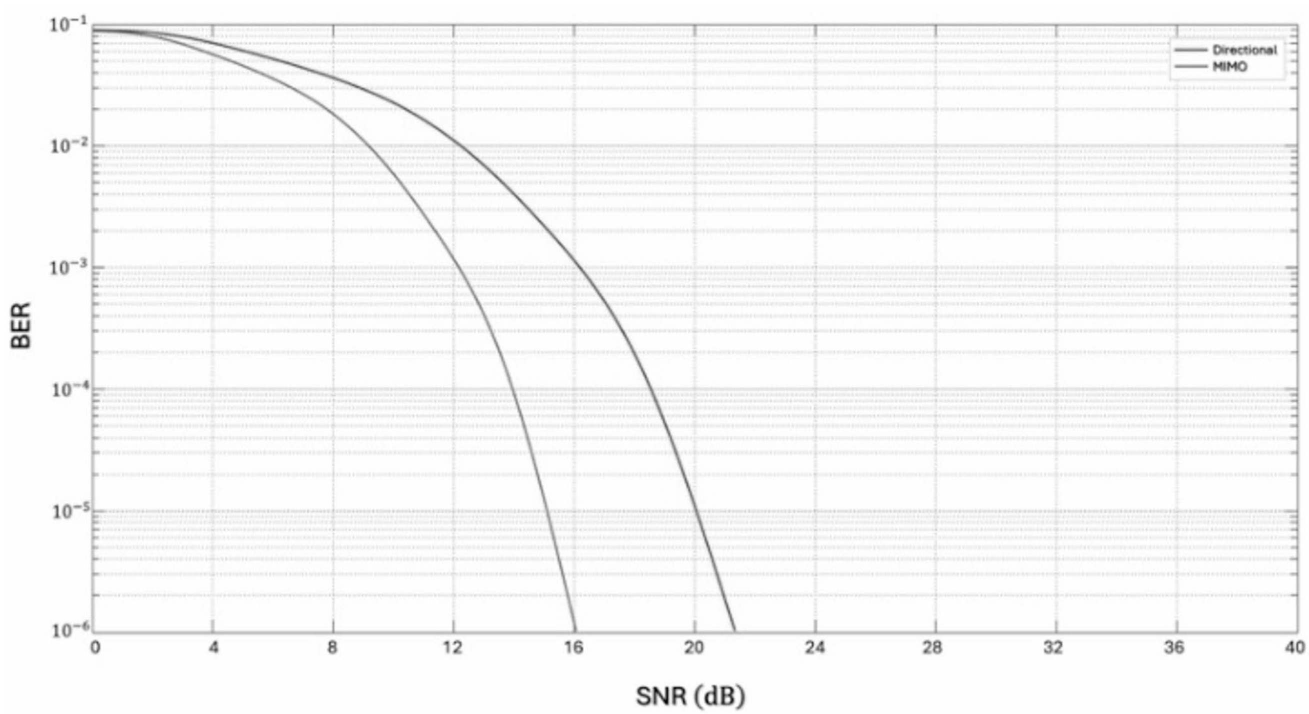


Fig. 14 SNR vs. BER of acoustic MIMO antenna against directional antenna

with moderate power consumption and efficient underwater communications.

Figure 14 shows Signal-to-Noise Ratio (SNR) vs. Bit Error Rate (BER) performance results for the underwater acoustic MIMO antenna against directional antennas. Both SNR and BER are ultimate performance metrics in digital communication systems, including underwater acoustic MIMO communication systems, that measure the quality of

Fig. 15 Underwater object detection using SMV

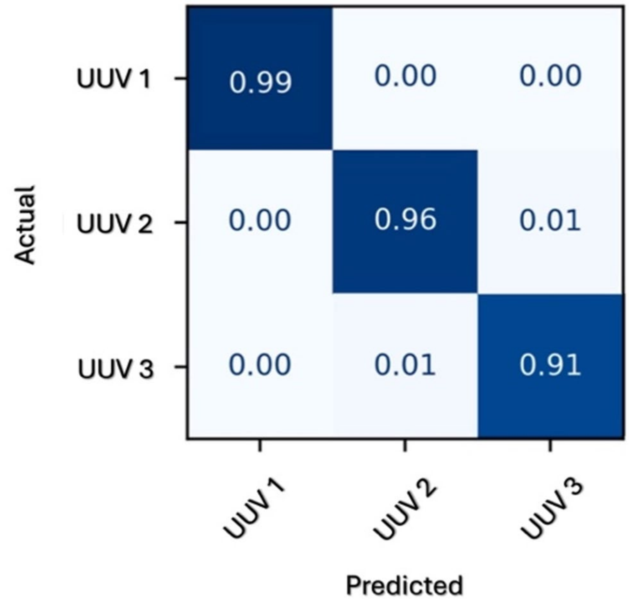


Fig. 16 Confusion matrix on synchronous autonomy sensitivity using DOA

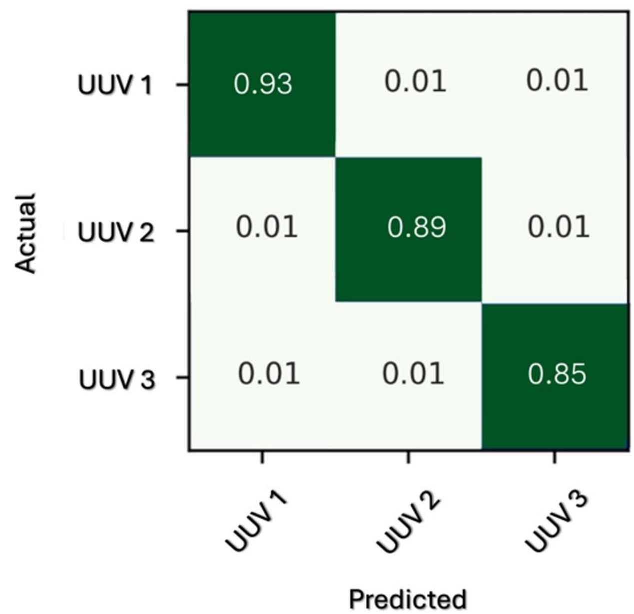


Fig. 17 Confusion matrix on object detection using DOA

a received signal as well as effective data rate in relation to BER. Predicting SNR and BER results is carried out using the "semilogy" function in MATLAB. The obtained results show that the lowest BER achieved is $1x10^{-6}$, which indicates a reasonable performance for the MIMO antenna. BER values decrease and wireless link performance increases which suggest a channel with low error rates that uses minimum transmission power. The signal data rate was high due to the diversity gain which results in maximizing capacity.

Figures 15, 16, 17 and 18 show the predicted results with the proposed synchronous autonomy and underwater object detection across the school of UUVs using DOA and SVM.

Figure 15 shows underwater object detection using SMV. The complex nature of the underwater environment medium distorts and scatters light, which leads to a low-resolution, blurry, and colour-shifting in images. Feature extraction techniques including texture, shape, and colour analysis are

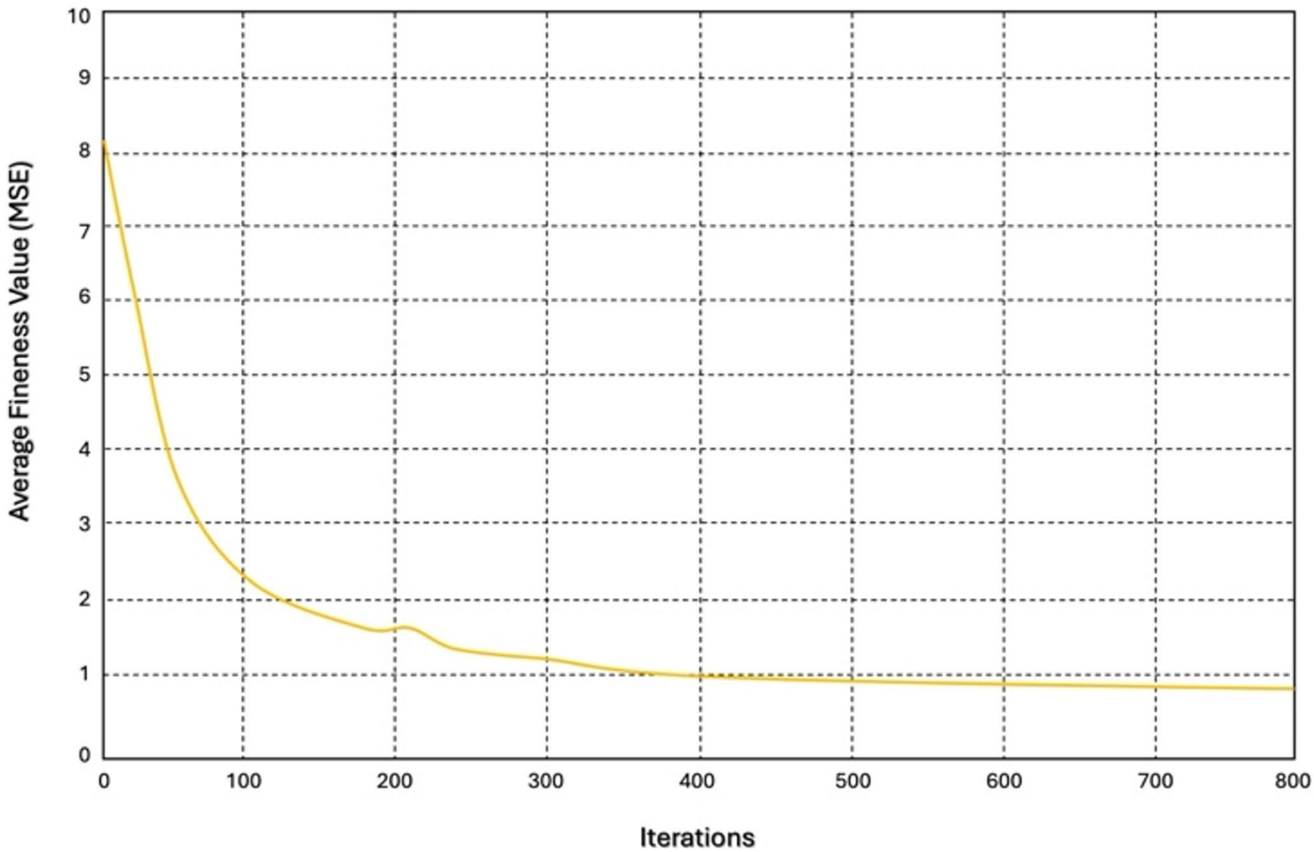


Fig. 18 Average fitting value (MSE) against number of iterations

used to identify plant features. This work deploys a secondary dataset for training, testing and validation to achieve the predicted results. The results exhibit various degrees of accuracy in revealing the health of the underwater world with confidence scores ranging between 91% and 96%.

Figures 16 and 17 show the confusion matrixes with the proposed use of DOA. The matrix in Fig. 16 considers the sensitivity of the synchronous autonomy between the UUVs at different depths. Although the water depth reduces, the synchronous autonomy accuracy reduces slightly, yet the overall, accuracy floats between 0.91 and 0.99. Figure 17 shows the ability of UUVs to carry out object detection using DOA. Again, despite the slight reduction in accuracy, the overall accuracy floats between 0.85 and 0.93.

Figure 18 pitches average fitting values against number of iterations. The curve visualizes the convergence behaviour with iterative optimization of DOA and SVM. As the number of iterations increase, the average fitting value, often a measure of error or deviation from optimal, decreases.

Figures 19 and 20 map the predicted results with the generation of hybrid renewable energy through solar panels and wind turbines.

Figure 19 simulates the hybrid renewable energy system using the MATALAB Simulink toolbox. The Simulink model has been produced under various operating conditions, such as varying solar irradiance, wind speed, and load demand. The results have then been used to analyse the performance of the renewable energy system.

Figure 20 illustrates the output from the hybrid renewable energy system over a 24 h period using the MATALAB Simulink toolbox. The output from solar panels and wind turbines are plotted both separately and combined. The graph reveals that the combined output exceeds the demand for energy.

Figure 21 shows a sensitivity analysis which has been carried out using “what-if”, the purpose of which is to determine how changes in independent input variables influence the output of our model and in turn help us decision-makers to understand the potential impact of different scenarios and assess upto a certain degree the robustness and reliability of our model by testing its sensitivity to different assumptions.

The Total Mission Score (TMS) can be calculated as per equations (48) to (51).

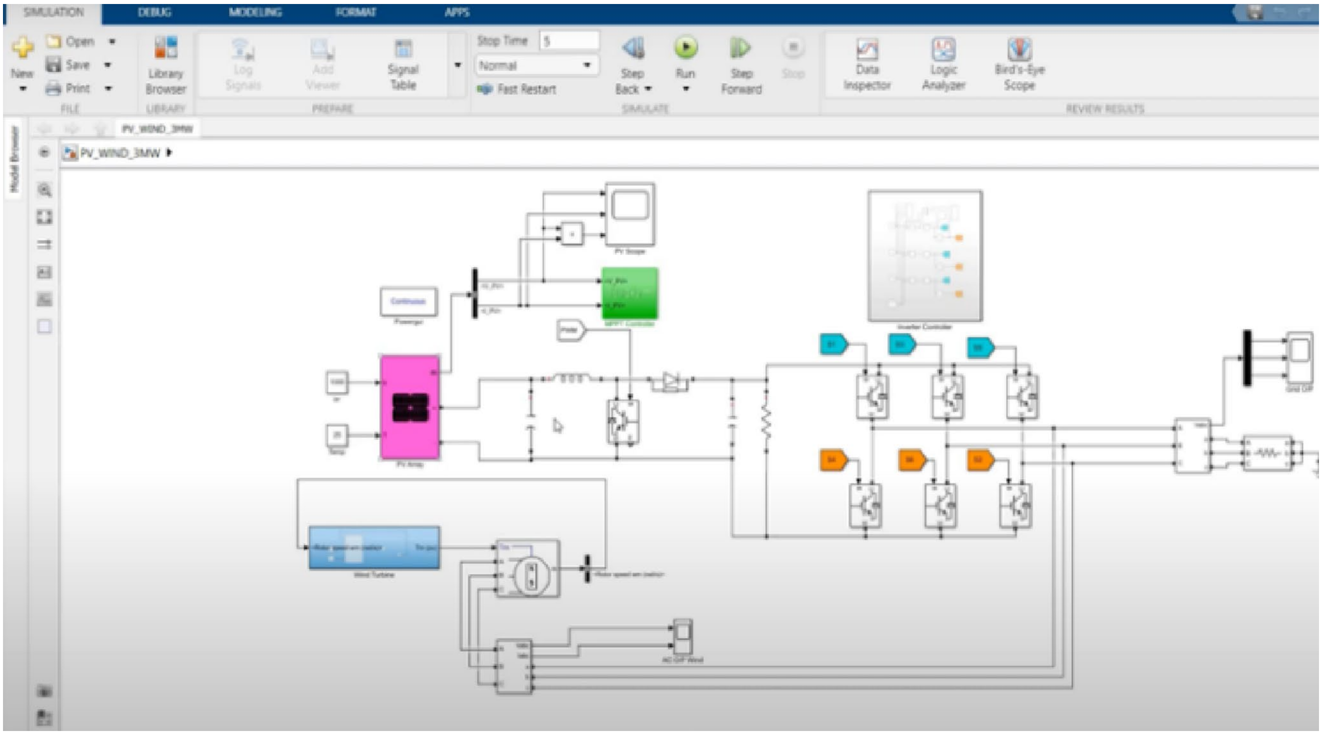


Fig. 19 Generation of hybrid renewable energy

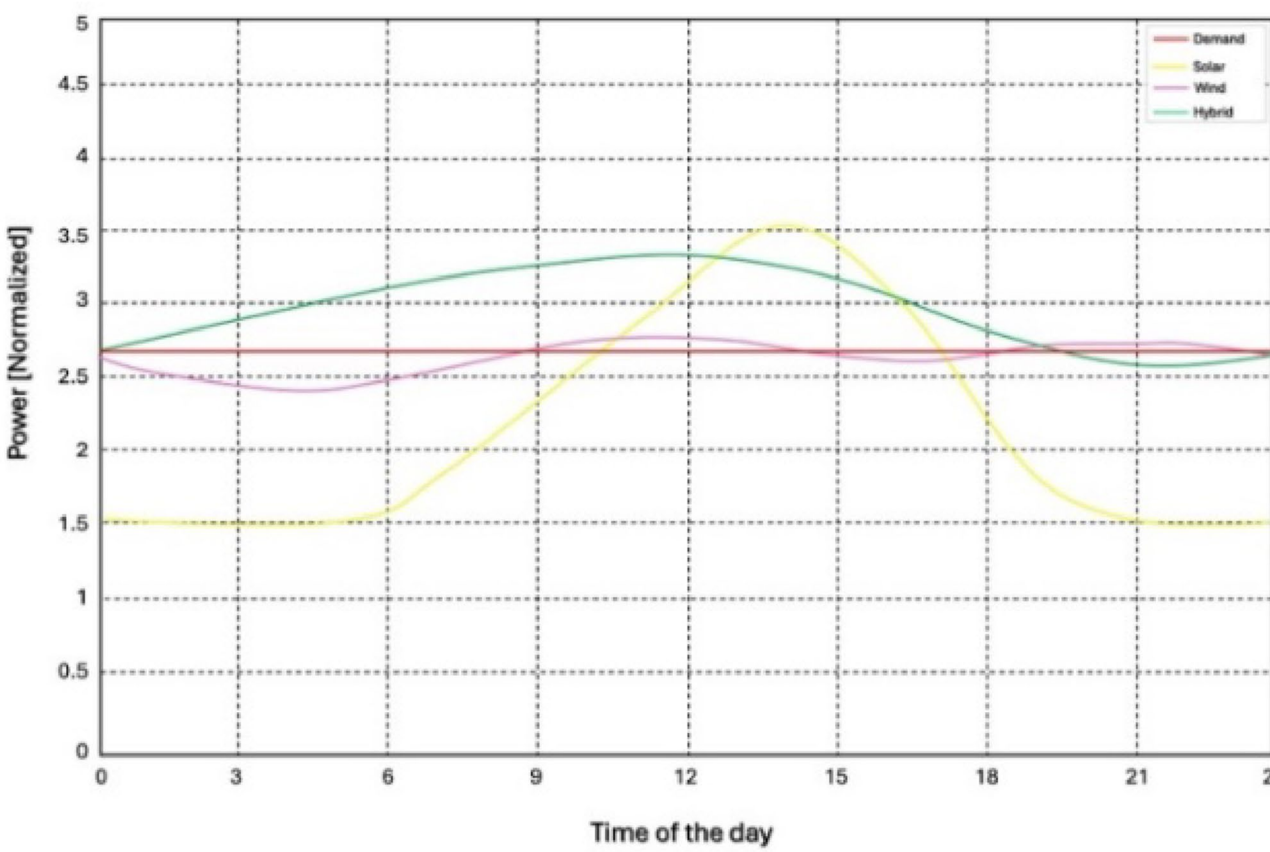


Fig. 20 Output from the hybrid renewable energy system

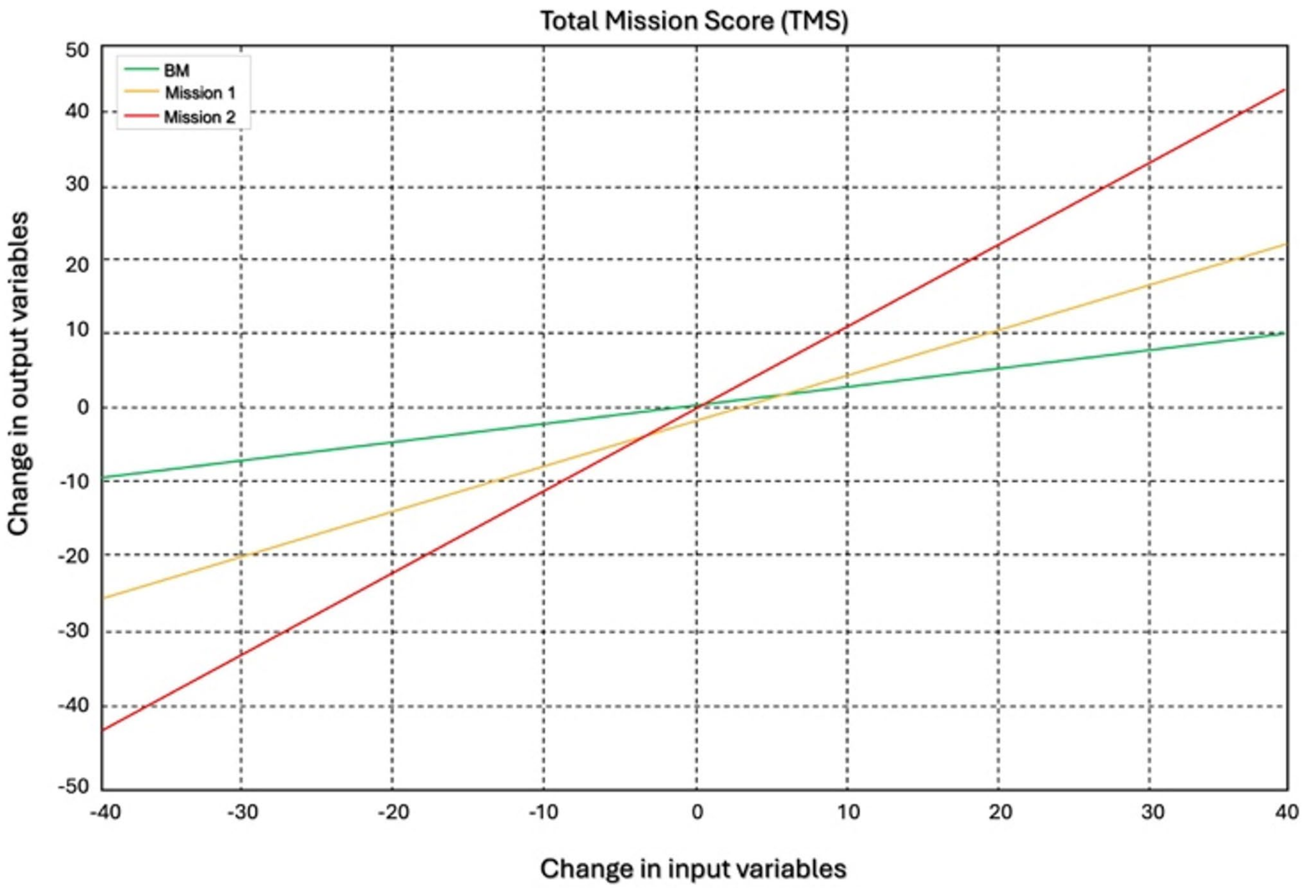


Fig. 21 What-if sensitivity analysis

$$\mathrm{M}_1 = 1 + \frac{\left(\frac{\mathrm{RSS\ value}}{\mathrm{distance}}\right)_{\mathrm{UUV}}}{\left(\frac{\mathrm{RSS\ value}}{\mathrm{distance}}\right)_{\mathrm{best\ UUV}}} \tag{48}$$

$$\mathrm{M}_2 = 2 + \frac{(\mathrm{No.\ of\ UUVs\ in\ sync} \times \mathrm{Accuracy\ \%} \times \mathrm{Mission\ time})_{\mathrm{UUV}}}{(\mathrm{No.\ of\ UUVs\ in\ sync} \times \mathrm{Accuracy\ \%} \times \mathrm{Mission\ time})_{\mathrm{Best\ UUV}}} \tag{49}$$

$$\mathrm{BM} = \frac{\mathrm{Best\ UUV\ time}}{\mathrm{UUV\ time}} \tag{50}$$

$$\mathrm{TMS} = \mathrm{M}_1 + \mathrm{M}_2 + \mathrm{BM} \tag{51}$$

Our sensitivity analysis focuses on various parameters across multiple missions. M_1 refers to Mission 1, and its focus is the RSS acoustic value over distance. To test this, it uses 2 variables to compare the performance of a random UUV against that of the best UUV. M_2 refers to Mission 2, and its focus is the synchronized motion of UUVs, the accuracy percentage of underwater detection, and the UUVs mission time. To test this, it uses 3 variables to compare the performance of a random UUV against that of the best UUV. The Baseline Mission (BM) refers to the testbed time for the two missions.

These missions have been modelled using the MATLAB plotting approach, where the values of input variables can be varied to see the effect on output variables. The variables have been varied between −50 to +50, which can help deduce the best UUV performance and the impact from every change on the overall result.

Figure 21 shows the two main missions as well as the BM and TMS scores. All missions have positive slops which suggests a direct or at least a proportional relation to the variables. Thus, when input variables change, the change directly affects the mission score.

5 Conclusion

Integration of AI and Simulation and the modelling of content have long been regarded as established tools and techniques across may application areas [67, 68], but recently environmental sustainability has been dominating the agenda. UUVs are widely regarded as a solution to challenges arising from underwater sea missions, as they offer a host of benefits and innovations which are widely regarded as a cornerstone of marine sustainability. Through automating tasks and data collection, a school of UUVs can significantly enhance efficiency in complex and challenging underwater environments around the shores or inland in rivers and lakes. This work epitomises what is possible by putting together a school of UUVs with support from DOA and SVM, that communicate acoustically and receive renewable energy from an aerial platform through a sea surface station and then exemplifies that with underwater sea missions. The predicted results show that the communication link budget parameters, accuracy of autonomous coordination across the school and object detection underwater are reasonable. Taking a step forward would require generation of detailed seafloor maps for studying of the seafloor bed and ease of navigation. Moreover, a wider range of UUVs payloads, such as gyroscopes, acoustic modems, or doppler velocity loggers will enhance their functionality and scope.

Acknowledgements The authors extend their appreciation to Taif University, Saudi Arabia, for supporting this work through project number TU-DSPP-2024-139. Also, the authors are thankful to Abdulrahman Karem, Omar Alghamdi, and Talal Althobiti for their support during preparation of the various simulations.

Author contributions The authors have contributed equally to drafting this manuscript. The authors have read and approved the final manuscript.

Funding statement This research was funded by Taif University, Taif, Saudi Arabia, Project No. TU-DSPP-2024-139.

Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare that there is no conflict of interest regarding the publication of this paper.

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