

ENHANCING AUTONOMOUS UNDERWATER VEHICLE RELIABILITY THROUGH FUNCTIONAL DECENTRALIZATION AND MULTI-AGENT INTERACTION

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Abstract

The article presents a comparative analysis of existing control architectures – including centralized, two-tier, hybrid, and modular peer-to-peer – demonstrating their limitation in meeting modern requirements for scalability, energy efficiency, and survivability under conditions of environmental uncertainty and the “information explosion”. To address these challenges, the authors propose an architecture based on the principles of a “non-strict hierarchy”, where each subsystem functions as a partially autonomous intelligent agent. The core of the system is a multi-agent intelligent model integrating communication and behavioral logic, domain ontologies, and advanced planning functions. The proposed structure is organized into functional clusters, including external communication, operational control, and executive devices, which facilitate the efficient distribution of computational loads across autonomous modules (agents). Furthermore, to resolve the critical issue of consensus in multi-agent systems, a method involving priority functions and tasks is introduced. The study concludes that this decentralized organizational approach minimizes the impact of hardware failures and communicational latencies, ensuring robust real-time decision-making in complex robotic environments

Key words

Autonomous Unmanned Underwater Vehicles (AUVs), Multi-Agent System (MAS), Distributed Control System, Decentralized Architecture, Fault Tolerance, Non-strict Hierarchy.

1 Introduction

Autonomous Unmanned Underwater Vehicles (AUVs) are extensively utilized for diverse applications, includ-

ing bathymetric surveys [Danilova,2021], resource exploration [Vavilov and Glushchenko,2024], and strategic military operations [Shatokhin et al.,2024]. A prominent contemporary trend involves the development of modular systems, such as YelloCube, where individual modules are equipped with dedicated microcomputers and interact via Peer-to-Peer (P2P) networks based on Robotics Operation System (ROS) [Novozhilov et al.,2022]. In addition, self-adaptation frameworks, such as SUAVE [Silva et al.,2023], are actively being researched to enable AUVs to maintain autonomous decision-making capabilities despite hardware failures or degraded environmental visibility [Shatokhin et al.,2024]. Current paradigms in AUV control system design prioritize the development of robust architectures and the synthesis of control algorithms capable of processing multimodal data. This data reflects the environmental state, onboard equipment status, and real-time navigation parameters. According to work [Iskanderov,2025], the functional requirements for next-generation AUV control systems include:

1. **Computational Efficiency:** Optimizing resource utilization and ensuring rapid data access through distributed computing;
2. **Scalability and Flexibility:** Maintaining operational adaptability during standard missions and emergency scenarios;
3. **Functional Reliability:** Implementing dynamic redundancy for resources, algorithms, and data;
4. **Energy Management:** Facilitating dynamic resource reallocation based on task priority. ;
5. **Signal Integrity:** Enhancing processing speeds and noise immunity.

The architecture of an AUV control system is largely dictated by the required degree of autonomy [Mahyud-

din and Arshad,2025][Novozhilov et al.,2022][Osa and Samuels,2023][Silva et al.,2023][Gomez-Bravo et al.,2023][Xu et al.,2025][Sukonkin et al.,2013]. Classical centralized monolithic architectures utilize a single hardware-software complex, favoring compact vehicle designs[Novozhilov et al.,2022][Osa and Samuels,2023]. However, as mission complexity increases, this approach imposes prohibitive computational demands and raises production costs.

Two-level control systems differentiate between mission planning (lower level) and technical state analysis or control synthesis (upper level) [Silva et al.,2023]. Despite enabling adaptation to disturbances, these systems are often hindered by limited computational capacity in the adaptive module and data redundancy. Hybrid architectures integrate remote and autonomous operation via an operational control layer that allows "hot" switching between algorithms [Gomez-Bravo et al.,2023]. Nevertheless, communication latencies between operator commands and execution cycles can result in significant trajectory deviations at high velocities. Modular peer-to-peer architectures distribute tasks among dedicated processors (control, sensor, and navigation modules) to improve fault tolerance [Xu et al.,2025][Sukonkin et al.,2013]. However, these systems often rely on a single communication bus, which restricts bandwidth, and typically retain high-level decision-making with the human operator.

Traditional architectures primarily rely on Guidance, Navigation, and Control (GNC) principles, where autonomy is limited once the mission is defined. In dynamic environments, centralized models become inefficient due to the complexity of real-time parameter integration. Consequently, the transition to decentralized multi-agent systems (MAS) is regarded as a critical factor in enhancing AUV survivability and efficiency [Chernyshev,2023][Neira et al.,2021]. Intelligent agents are characterized by autonomy, proactivity, reactivity, social behavior, mobility, and asynchrony [Osa and Samuels,2023]. While MAS offer significant advantages, they also present challenges regarding interaction complexity, behavioral formalization, and potential information loss during agent exchange [Martynova and Rosengauz,2016][Yan,2025].

In this study, AUV reliability is defined as the capacity to maintain functionality under uncertainty and in emergency conditions. Given that the number of agents in such systems is typically small—constrained by vehicle size and task scope—signal transmission delays are negligible relative to decision-making cycles. To resolve potential conflicts or achieve consensus among partially independent agents, this work proposes a method based on the prioritization of functions and tasks. This approach addresses the requirements for modern automated control systems within limited computational

powers and energy constraints. While multi-agent approaches have been explored, some models suffer from excessive functional decomposition, such as allocating separate agents for infrequently used systems. This redundancy can complicate consensus-reaching and increase hardware requirements, ultimately reducing system reliability [Bykova et al.,2020].

Framing AUV fleets and complex onboard systems as distributed marine cyber-physical systems expands the range of applicable multi-agent control principles featured in recent literature. Robust multi-agent interaction in uncertain and time-varying network layouts has been a focal point of recent studies within the field of cyber-physical control. For instance, [Imangazieva,2025] demonstrated a novel robust time-varying chain multi-agent control methodology that successfully counteracts unmeasured perturbations and nonstationarity across chained agents by implementing an auxiliary loop mechanism and state observers. This demonstrates the viability of utilizing local neighbor metrics to damp system-wide noise. Similarly, decentralized communication constraints are highly prevalent in other modern cyber-physical applications [Moseyko et al.,2023] developed an adaptive exchange protocol for multi-agent interaction under arbitrary observation noise, proving that decentralized load balancing and feedback control are critical when handling severe data throughput limits. Integrating these paradigms into AUV architectures can similarly allow functional components to autonomously track target paths while actively compensating for environmental disturbances and acoustic transmission delays.

Crucially, this work addresses the intersection of decentralized control theory with the specific physics of the underwater environment. Unlike terrestrial or aerial multi-agent systems where electromagnetic waves propagate predictably and with low attenuation, the underwater environment acts as a highly non-linear, non-stationary dissipative physical medium. Hydroacoustic wave transmission inherently faces multi-path propagation, frequency-dependent absorption, Doppler distortions, and low propagation speeds (≈ 1500 m/s). Rather than treating these constraints purely as information channel constraints, this paper frames them as boundary conditions of the physical medium. The new physical insight advanced here lies in the formalization of how decentralized functional clusters minimize energy dissipative cycles and mitigate severe physical transmission delays. This effectively bounds the entropy of the overarching cyber-physical system.

The objective of this research is to develop and substantiate a distributed multi-agent management architecture. This architecture aims to ensure adaptive vehicle behavior and maximize the probability of mission success through functional decentralization and intelligent agent interaction.

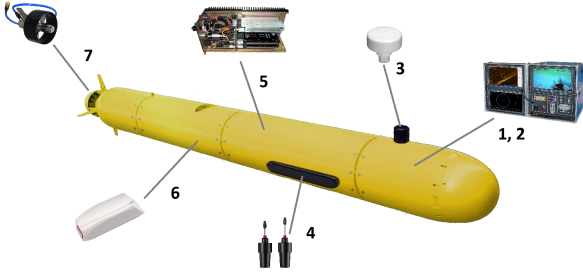


Figure 1. Simplified architectural layout of the AUV

2 Methodology for Control System Design

2.1 Intelligent Agent Model for AUV Control

The proposed multi-agent infrastructure for marine cyber-physical systems is based on the **Main Intelligent Agent** (MIA) model. The MIA is defined as a formal tuple:

$$MIA = \langle LA, CM, BM, O, AD, SA_{head} \rangle \quad (1)$$

1. *LA* (Logical Attributes): Information attributes defining the agent's identity.
2. *CM* (Communication Model): Protocols for inter-agent interaction.
3. *BM* (Behavioral Model): The logic governing agent actions.
4. *O* (Ontology): A knowledge graph used for semantic reasoning.
5. *AD* (Additional Functions): Auxiliary operations and processing tasks.
6. *SA_{head}* (Strategic Architecture): The internal decision-making core.

The main components of the model include information attributes *LA*, a communication model *CM*, a behavioral model *BM*, a knowledge graph *O*, additional functions *AD*, and the internal structure of the main agent *SA_{head}*.

The *SA_{head}* component encapsulates the strategic mission objectives of the AUV and decomposes them into control logic for the subordinate elements of the management system. It is formalized as:

$$SA_{head} = \langle TP, TA, TV, FP \rangle \quad (2)$$

where *TP* represents the set of behavioral strategies (goals), *TA* denotes acceptable behavior scenarios, *TV* is a library of pre-defined scenarios, and *FP* is a function for scenario generation based on situation recognition and predefined response rules. Within the multi-agent system (MAS), specialized agents—such as the coordinator, ontology manager, and communicator—utilize this model to access the knowledge base and

optimize decision-making in both nominal and emergency scenarios.

2.2 Architecture of the Distributed Control System

This study proposes a **multi-agent distributed control system** (DCS) that integrates classical hierarchical modular structures with partially autonomous agents. The fundamental components of the AUV include the control unit, navigation system, antenna array, sensor suite, power compartment, buoyancy modules, and the propulsion-steering complex (Figure 1) [Boreyko et al., 2018][Neira et al., 2021].

Traditional AUV control logic typically segregates onboard data processing (navigation and computing) from telemetry, communications, and propulsion management. However, such rigid separation often leads to computational load imbalances across system components. The proposed architecture employs a non-strict hierarchy, ensuring systemic consistency and uniformity of agent behavior while facilitating proactive horizontal interaction. This approach minimizes the necessity for vertical data transmission to higher-level agents, thereby reducing latency.

It is important to note that the basic physical partition of the AUV onboard hardware components (including the propulsion-steering complex, navigation unit, power compartments, and sensor suite) remains uniform across traditional monolithic or hybrid designs. The unique structural feature characteristic specifically of the decentralized class of control problems proposed here is the transition from a rigid physical assignment to an adaptive functional cluster organization. Unlike standard architectures where subsystems lack direct lateral communication, our system establishes 'non-strict hierarchical' boundaries. This architecture treats each sub-assembly as a semi-independent computing module capable of horizontal peer-to-peer data validation and dynamic load reassignment without needing permission cycles from a centralized top-tier processor.

2.3 Conceptual Framework: Modules and Clusters

The system is organized around two fundamental structural concepts:

1. **Module (Agent)**: A logically distinct element of the distributed system equipped with its own computing resource. Modules are classified as independent or semi-independent based on their degree of intelligence and interaction capabilities. Each module manages one or more physical endpoints of the AUV;
2. **Cluster**: A functional grouping of one or more modules responsible for interrelated control tasks. The use of clusters facilitates scalable system modification and allows for the application of object-oriented programming principles in the control software development.

3 Multi-Agent Distributed AUV Control System

The design of the proposed multi-agent distributed control system (DCS) for Autonomous Unmanned Underwater Vehicles (AUVs) is based on a hierarchical modular architecture. This structure (Figure 2) incorporates partially autonomous agents to enhance both functional reliability and operational efficiency.

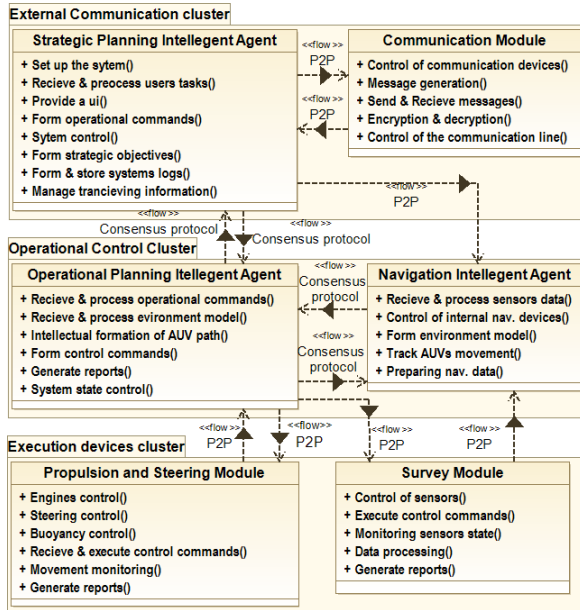


Figure 2. Block diagram of the multi-agent Distributed Control System (DCS) for AUVs

3.1 Computational Load Distribution

In the proposed DCS, agent modules function as semi-independent computing complexes. This allows for dynamic load balancing and ensures the relative isolation of subsystems, preventing cascading failures. The architecture categorizes agents into three functional clusters:

1. External Communication Cluster:

- (a) **Strategic Planning Module (Independent):** Responsible for high-level mission management, including task decomposition and data aggregation from subordinate agents;
- (b) **Communication Module (Semi-independent):** Manages external wireless links (radio and satellite) and establishes secure communication sessions.

2. Operational Management Cluster:

- (a) **Operational Planning Module (Independent):** Decomposes strategic objectives into specific commands for executive devices based on real-time environmental data;

- (b) **Navigation Module:** Performs navigation tasks using telemetry (gyroscopes, altimeters) and maintains a dynamic model of the external environment.

3. Actuator and Telemetry Cluster:

- (a) **Propulsion and Steering Module (Semi-independent):** Control the propulsion-steering system and other mechanical actuators;
- (b) **Survey Module (Semi-independent):** Collects and pre-processes raw data from onboard sensors and systems.

3.2 Functional Reliability through Prioritization

To resolve conflicts and reach consensus among partially independent agents, a priority-based function assignment method is introduced. This ensures behavioral consistency during module-level conflicts.

The **Strategic Planning Module** serves as the primary priority agent. It interprets the global mission and transmits behavior scenarios to other modules. It manages transitions between various operational modes, including service, positioning, depth maneuver, cruising, bottom-tracking, scanning, and emergency ascent (Figure 3).

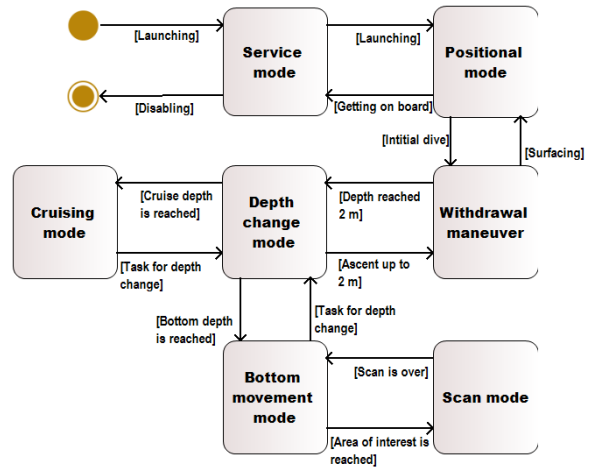


Figure 3. State transition diagram of AUV operational models

The **Communication Module** ensures link reliability via radio-frequency [Uribe and Grote.,2009] or optical channels [Nakamura et al.,2015]. It implements encryption, decryption, and noise-reduction algorithms. To avoid hardware redundancy, its logic can be integrated into the Strategic Planning agent if direct operator contact is not required for a specific mission phase.

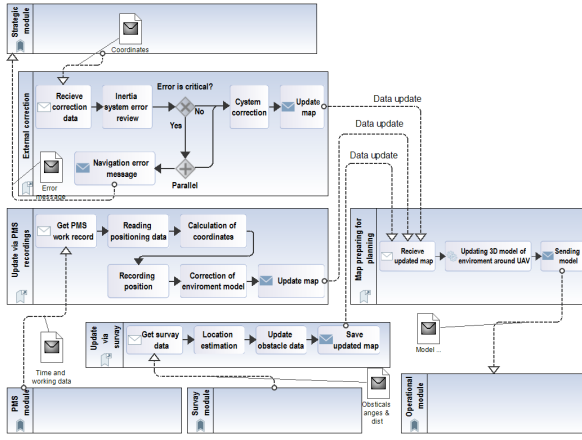


Figure 5. Sequence diagram of message exchange between navigation processes and external sensors

3.3 Navigation, Mapping, and Environmental Survey

The **Operational Planning Module** acts as the central hub for intelligent information processing. It generates control commands for the Propulsion and Steering System (PSS), manages the mapping system, and performs route planning. For pathfinding in complex environments, two-step algorithms such as ALT [Goldberg and Harrelson.,2005][Fuchs.,2010] or Reach [Goldberg et al.,2016] are utilized to minimize computational overhead. The interaction protocol for this module is illustrated in the Use Case diagram (Figure 4).

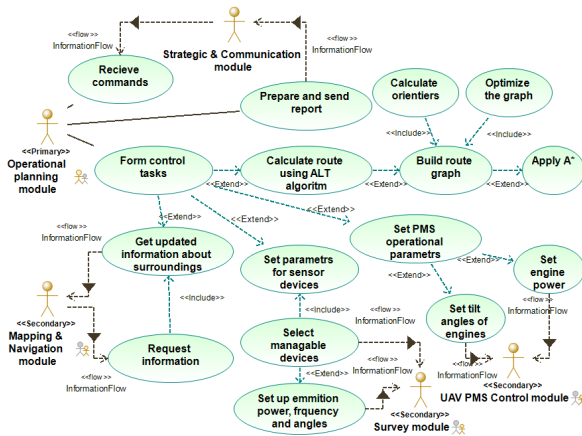


Figure 4. Use case diagram for the Operational Planning Module

The **Strategic Planning Module** accepts local tasks for individual agent modules and transmits information about current results and equipment status. Between the PMS and operational planning modules, data packets contain thruster angles and powers, time and distance

traveled. The list of devices, frequency and power of radiation is sent by the review module. The mapping and navigation module sends sector mapping results in response to a request to select an area of interest.

The **Navigation Module** aggregates data from inertial sensors (gyrocompasses, depth gauges) and refines an a priori depth map. To optimize memory utilization, the system employs sector-based division of the map [Niyazi et al.,2025]. Multi-scale mapping is used: larger sectors for cruising at depth to save memory, and fine-grained sectors for bottom-traversal. The message exchange protocol for navigation processes is depicted in Figure 5.

The **Survey Module** processes inputs from hydroacoustic (sonars, echo sounders) and optical (lasers, cameras) sensors. Its primary role is to perform sector-based scanning and keel-clearance measurements to detect obstacles. Depending on the environmental context, the module dynamically adjusts sensor settings (Figure 6) to balance survey quality with energy efficiency.

The proposed multi-scale mapping and dynamic sensor regulation (Figure 6) directly advance the physics-informed management of onboard resources. Hydroacoustic and optical sensor configurations are coupled directly to the thermodynamic and mechanical states of the AUV. High-frequency active sonars demand significant electrical energy, accelerating battery thermal dissipation and reducing operational range. By dynamically switching into physics-optimized behavioral states (e.g., swapping a wide-angle active sonar configuration for a low-power single-beam echo sounder during deep cruise phases), the system structurally scales down its interaction with the medium. This ensures that the vehicle's localized behavior responds directly to physical variables such as changing hydrostatic pressure fields and boundary layer currents, optimizing the propulsion-steering system's mechanical efficiency.

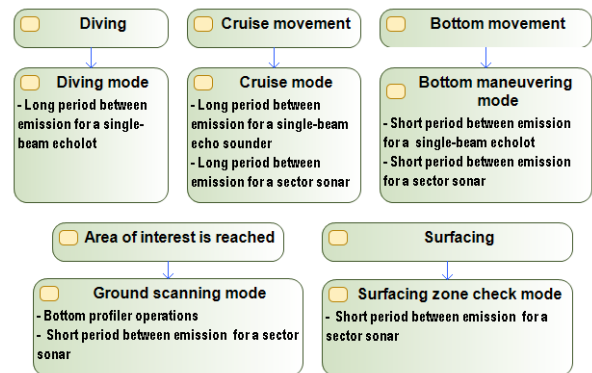


Figure 6. Onboard equipment configurations mapped to behavioral scenarios

3.4 Propulsion and Steering System (PSS)

The **PSS Module** regulates movement along the planned trajectory with high positioning accuracy. Buoyancy control is handled by a specialized subordinate module. The PSS also monitors the state of all executive systems, initiating emergency ascent protocols if critical failures are detected. The architecture of this module, exemplified by an 8-thruster configuration (four vertical, four horizontal), is detailed in the class diagram (Figure 7).

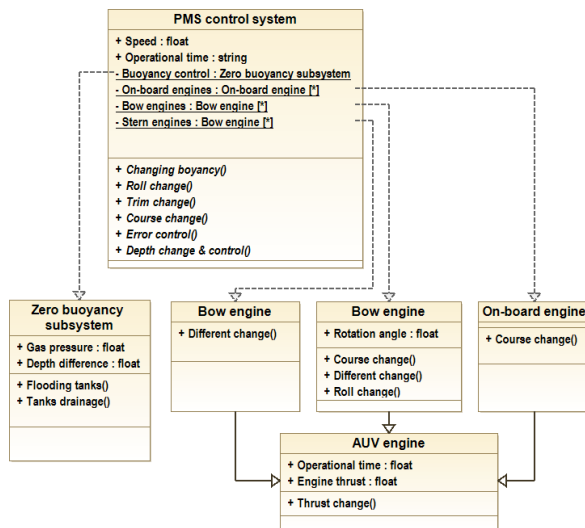


Figure 7. Class diagram of the Propulsion and Steering System (PSS) module

4 Conclusion

This paper addresses the critical issue of reliability in traditional hierarchical control systems for Autonomous Unmanned Underwater Vehicles (AUVs) during long-term autonomous missions under environmental uncertainty. By adopting a multi-agent system (MAS) paradigm, each module within the distributed control architecture is treated as a partially autonomous intelligent agent. This approach facilitates the decomposition of complex strategic objectives into a series of manageable subtasks, which are executed independently within a framework of predefined operational scenarios and constraints. The implementation of a multi-agent approach in AUV control system design provides several key advantages:

1. **Computational Efficiency:** The distribution of processing tasks across multiple modules prevents bottlenecks and ensures real-time responsiveness;
2. **Energy Optimization:** Enhanced decision-making speed and resource allocation directly contribute to

improved energy efficiency, extending mission duration;

3. **Fault Tolerance:** Functional decentralization ensures that the system remains resilient even in the event of individual module failures.

While multi-agent systems generally face challenges regarding behavioral formalization, communication latencies, and consensus-reaching, these limitations are effectively mitigated in the context of AUVs. Given the finite number of control modules, the interaction schemes can be rigorously formalized using mathematical tools such as Petri nets. Furthermore, the proposed mechanism of function and task prioritization significantly simplifies the consensus-reaching process among partially independent agents, ensuring coherent system behavior in conflict scenarios.

In summary, the proposed methodology for developing a multi-agent distributed control system effectively addresses the constraints of limited computational and energy resources. Through structural fault tolerance and dynamic resource distribution, this approach substantially enhances the functional reliability and operational survivability of modern AUVs.

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