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Perspectives Regarding UAS Control in Aquatic Environments (Rivers and Streams) based on Machine Learning

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Abstract

In recent years, the integration of artificial intelligence (AI) and machine learning (ML) in unmanned aerial systems (UAS) has led to increased decision-making autonomy, particularly in complex and dynamic environments. This study proposes an innovative framework for the autonomous operation of UAVs in aquatic scenarios, focusing on the continuous surveillance of a moving vessel. The system uses data from multiple sensors to allow a UAV to stay within a defined perimeter around the vessel, maintain stability above the water, and automatically land on a mobile platform when necessary (e.g., in case of low battery or interference). The decision-making architecture is based on reinforcement learning algorithms for flight control and drone replacement management. The contribution of this study is to propose an intelligent and modular model for the coordination of multi-UAV systems for river missions, with direct applications in surveillance, search and rescue, and environmental monitoring.

Keywords:
Machine Learning; Unmanned Aerial System (UAS); Artificial Intelligence; Aquatic Environments; Sensors.

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With the engineering and technological development of various equipment or devices, unmanned aerial vehicles (UAVs), by their value, are relevant capabilities for many fields or purposes: agriculture, defense, search and rescue missions, etc. By visualizing and researching certain multidisciplinary aspects, the potential optimizations of any product or set of products can be identified. By connecting them within a network, they can communicate efficiently, quickly, and interchangeably, thus providing an essential and secure tool for practicing decision-making management and successfully conducting operations.

The operation of drones in both marine environments is difficult owing to platform (boat) movement, signal instability, weather conditions, and energy limitations. The problem is how we can ensure the continuous presence of an active drone in the air above a boat, maintaining it within a defined perimeter, with automatic localization and landing, as well as automatic replacement in various situations, based on artificial intelligence and autonomous decision management. To address this situation, the following aspects must be analyzed, as shown in the figure below (Figure 1) and as the authors Hassanalian M. and Abdelkefi A. (2017) also mention.

They can be used in areas such as those mentioned above, more specifically for fluvial or maritime surveillance for illegal fishing, smuggling, or national security. For search and rescue at sea, this solution of continuity based on machine learning can be critical in saving human lives. In addition, for environmental monitoring and protection purposes, this system can be used to collect data, such as temperature and the presence of pollutants, based on embedded sensors.
Finally, such a system can be used as a relay node between the ground and the boat, ensuring communication between the two stations in a redundant manner.

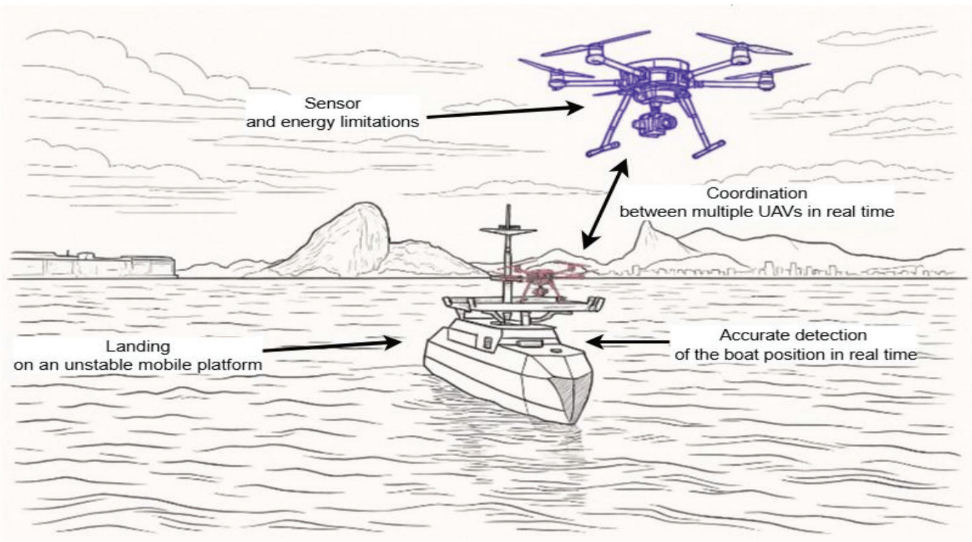

Figure 1 Major obstacles regarding the control of UAS in an aquatic environment
Source: adapted from https://static.wixstatic.com/media/bca94f_496a78a2fa3a4697a9cfc8eb4222ad5a~mv2.jpeg/v1/fill/w_748,h_606,al_c,q_85,usm_0.66_1.00_0.01,enc_avif,quality_auto/bca94f_496a78a2fa3a4697a9cfc8eb4222ad5a~mv2.jpeg

By studying the available literature and focusing on the latest information, this study explores the application of Machine Learning (ML) and Artificial Intelligence (AI) to enhance UAS control and autonomy within riverine domains, with a special focus on coordination, fault tolerance, and mission continuity.

The paper is structured as follows: introduction, state of the art (literature review), methodology – the framework and conceptual basis –, results and discussion – theory analysis and future work –, and conclusions. The research will contribute to the next steps towards practical simulations, using low-cost UAV devices that are software and hardware-configurable and capable of ML.

1. State of the Art

Analyzing the specialized literature on the subject, it is observed that the issue raised is of major interest among the authors, especially when we consider the evolution of the geopolitical space at a global level, where UAV systems are increasingly used. In current conflicts, drones have proven to be a very effective means of combat, substituting the human factor. From the Network-Centric Warfare (NCW) doctrine, a new current doctrine has emerged, centered on drones, which the Ukrainian Army is implementing by creating company-level combat subunits and even battalion-level units with a specific focus on drone strikes, within combat brigades (Samus 2024, 9).

The authors Wu L., Wang C., Zhang P., and Wei C. (2022) provide a comprehensive analysis of how reinforcement learning (RL) can be applied to enhance the coordination of UAVs based on corrective feedback, thus focusing on improving autonomous landing on mobile platforms (Song 2022). The aforementioned aspects are essential for network coordination in aquatic environments, where manual intervention is usually impossible. The RL method can ensure confidentiality and reduce latency (Chellapandi, et al. 2023, 3-6; Jung, et al. 2024, 1-23; Negru, et al. 2024, 1-23) – an important aspect regarding the security of UAVs, as well as operating them in unfriendly environments, where connection fluctuations may occur.

A study that addresses the visual challenges specific to the maritime environment (e.g., water reflections) and irregular target movements demonstrates that convolutional neural networks (CNN) can be used by a UAV swarm to successfully track certain targets (Zhao, et al. 2024, 3-18; Maharjan, et al. 2022, 1-24) while the study *"A Survey on UAV-Aided Maritime Communications: Deployment Considerations, Applications, and Future Challenges*" (Nomikos, et al. 2023, 56-78) analyzes the use of UAVs as aerial nodes in maritime communications through trajectory optimization and the use of ML for resource management and edge caching. This is highly relevant for UAVs in hostile environments, where connectivity requires adaptive learning-based solutions.

The authors Sarkar N. I. and Gul S. (2023) provided a review covering over 100 papers on AI-based autonomous UAV networks, focusing on planning, routing, resource management, and energy efficiency. They emphasized the need to optimize these elements through ML with direct application to complex aquatic scenarios.

Recent studies on the action of drones on river courses, such as in "*Synergistic Reinforcement and Imitation Learning for Vision-driven Autonomous Flight of UAV Along River*" (Wang, Li, and Mahmoudian 2024) state that combining RL with imitation learning (IL) allows UAVs to navigate autonomously along rivers, relying on artificial vision, with a higher learning speed and increased accuracy. It also suggests a synergistic method that combines imitation learning and reinforcement learning for UAV navigation and obstacle avoidance in riverine environments. It addresses difficulties in partially observable, non-Markovian settings and improves performance and convergence rates by using a trainable simulation environment.

The authors Haris Malik and Hou Jin (2020, 1-22) present an actual problem, namely obstacle detection and safe navigation, this time of unmanned ground vehicles (UGVs), in situations where they have to follow a pre-established route. On the route that the vehicle had to follow, dangerous obstacles were mounted, which would have endangered the device. For the good implementation of artificial intelligence that makes efficient decisions based on the obstacles encountered, aspects regarding the distance, size, crowding, shape, and angle of the steering wheel were analyzed, intending to improve the navigation skills of the autonomous vehicles. This paper has applicability in the chosen topic, as obstacles represent a critical factor that the drone's AI must detect and avoid.

Moving on to the aerial realm, the authors Antonopoulos A., Lagoudakis M.G., and Partsinevelos P. (2022, 1-23) describe the development and deployment of an integrated UAV navigation system that provides real-time localization using optical, depth, and inertial data as well as the Global Navigation Satellite System (GNSS). To facilitate seamless integration into various systems and unfamiliar environments, the implemented system is built on top of a Robotic Operating System (ROS) environment package.

The Hierarchical Deep Q-Network (H-DQN), a solution based on hierarchical deep reinforcement learning, is used in a Semi-Markov Decision Process (SMDP) context (Qin, et al. 2022, 1-15). The Quality of Services (QoS) and energy security can be balanced with this technique. Additionally, it adjusts well to changing conditions using a variety of sensors and requirements. The concept applies to UAS-IoT with minimal power supplies, autonomous drone operations in areas with limited infrastructure, and environmental monitoring.

An algorithm for UAV navigation and obstacle avoidance in flood scenarios is covered in another paper that focuses on deep reinforcement learning (DRL) and its application to UAVs (Garg and Jha 2024, 1-12). This algorithm allows multiple UAVs to be controlled autonomously in order to collect obstacle data and determine safe routes for waterborne evacuation vehicles.

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In the paper *"Neural network model for autonomous navigation of a water drone"* (Chekmezov and Molchanov 2024, 4-16), a neural network model for autonomous navigation of a water drone in a simulated fluvial environment is presented. Reinforcement learning is used to improve obstacle avoidance and water current adaptation, guaranteeing efficient navigation in dynamic conditions. Going further towards the subject of UAV simulation, it comes to studies that focus on software-in-the-loop simulation for testing vision algorithms with a quad-rotor UAV, utilizing Gazebo for simulation and PX4 for flight control (Nguyen and Nguyen 2019, 429-432; Nguyen Nguyen, and Ha 2019, 615-627). These aspects can also be utilized for further simulation within this article.

UAV security is another important factor that should not be overlooked. Another paper implements a three-class machine learning model on a UAV using a Raspberry Pi processor to classify GPS spoofing attacks in real-time, using GPS-specific features for effective detection and classification in location-dependent applications (Nayfeh et al. 2023, 289-292). With the use of a convolution neural network (CNN) feature extractor and machine learning classifiers, a study presents a low-cost Raspberry Pi 4-based system that uses ML for UAS detection and classification, attaining 100% accuracy in two-class detection and 90.9% in UAS type classification (Swinney and Woods 2022, 14). Furthermore, the paper "Autonomous *Control with Vision and Deep Learning: A Raspberry Pi Edge Computing Platform for Obstacle Detection in SUAV Path*" (Ullah, et al. 2024, 1-9) shows that this feature can be used for obstacle detection in Small Unmanned Aerial Vehicles (SUAVs) deployed on a Raspberry Pi. This setup enhances navigation safety through real-time obstacle avoidance in complex environments. In terms of security, for active countermeasures, C-UAS (anti-drone systems) can be used, which are a basic requirement for ground forces to be able to operate on the modern battlefield (Watling and Bronk 2024).

To sum up this subchapter, with a focus on energy efficiency, real-time adaptation, and security, the reviewed literature reveals a strong research focus on applying machine learning – specifically, deep neural networks, reinforcement learning, and imitation learning – to improve UAV autonomy, navigation, obstacle avoidance, data collection, and communication in challenging and dynamic aquatic or hostile environments. Also, one major issue that has been noted is the necessity of giving careful consideration to the credibility and dependability of machine learning in UAV operations and applications (Kurunathan et al. 2024, 1-28).

2. Methodology

2.1. The framework

The study is based on research into the concept behind implementing artificial intelligence in quadcopter devices that will be able to respond to user requirements, in different amphibious environments, and for various purposes. To understand the concept behind improving UAS control, the initial objective was to find answers to several questions:

- What must the drone system contain to be capable of machine learning?
- What type of machine learning can be used?
- What parameters must be taken into account when used in unfriendly environments?
- What applications can be used to subsequently simulate these networks' frames?
- How can machine learning algorithms be integrated to allow UAVs to adapt in real time to uncertain conditions in river environments, in military situations?

The paper uses qualitative research methods, as, based on the analysis of the specialized literature and the created syntheses, new answers are sought to the previously formulated research questions, the objective of the research being the generation of new theoretical knowledge and the establishment of a conceptual framework for the implementation of artificial intelligence in unmanned aerial systems.
The data collection method was represented by documentary analysis, by collecting data and extracting essential information from different sources, in order to see the trends and research directions of various authors in the field. Thematic analysis was used as the qualitative analysis method.

This approach was chosen to highlight information of interest regarding the chosen topic, as well as to establish the basis for future research, which would include simulations and practical methods using real devices. The contribution leads to the systematization of aspects related to UAV control, which makes it possible to more easily simulate UAS in a virtual environment, respecting critical parameters. After simulating them in the virtual space, one can move on to the practical programming of a real device by "injecting" artificial intelligence to reduce the gap between the user's requirements and the device's intelligent sensors.

Limitations of the study include the lack of physical equipment for simulation and direct testing, thus leading to the lack of practical experiments, which are necessary to validate the results in a virtual and then a real environment.

2.1. Conceptual basis

Analyzing the specialized literature of the authors, it can be seen that they converge towards common principles and approve the need to improve some elements of UAS, but there are too few discussions about a single conceptual framework that would unify all these elements of UAS to obtain a viable and efficient solution in the area of aerial drone systems. Such a framework can be used with the ROS system, which is built to provide a modular approach for robotic applications. The individual development of functional blocks can be very useful, especially when designing highly complex applications. This approach allows for simple development, since each block has a very specific task (Antonopoulos, et al. 2022, 5).

Thus, based on the modular model of ROS and with the observations of other authors regarding some modules that should be developed, such as the ML inference engine (Foehn, et al. 2022, 2), the battery monitoring module (Barrientos, et al. 2011, 13) and the surveillance module (Queralta, et al. 2020, 11), in order to enable the intelligent and autonomous operation of UAVs in aquatic environments, a modular architecture is proposed that supports multi-agent coordination, real-time decision-making and autonomy based on ML. A similar modular architecture has been developed, but for search and rescue (SAR) operations (Queralta, et al. 2020, 1-2). The contribution of the present work is based on this validated approach, but adapted to the challenges of aquatic, riverine environments, with an emphasis on the ML-based decision module.

The architecture includes both on-board and edge-level components, combining sensor fusion, ML inference, control logic, and inter-agent communication, where data collected by sensors are processed locally (on-board), and decisions regarding flight, landing, or mission handover are made autonomously with the support of an ML module. This modular UAV-vessel approach was chosen because it allows the integration of critical functions, such as sensors, control, power, communications, and ML, in a scalable and robust framework, capable of responding to the specificities of fluvial environments. It is also justified by recent literature showing that modularity and distributed processing enhance the autonomy and resilience of UAS in multi-agent coordination (Antonopoulos, et al. 2022; Foehn, et al. 2022; Jung, et al. 2024).
Within this architecture, there will be two subsystems: the UAV and the central river vessel. The two subsystems are interconnected by a communication link (C2) and, in fact, constitute the overall unmanned aerial drone (UAS) system. Each subsystem is characterized by several specific modules (Figure 2), as follows:

The sensor module (GPS, IMU – Inertial Measurement Unit, barometer, on-board cameras) ensures the localization and perception of the surrounding environment, being the foundation of sensor fusion processes (Du, et al. 2020). The collected data are then processed by an ML inference module, which evaluates operational states (e.g., proximity to the vessel, battery level, landing safety, etc.). The role of this module is justified in the work of Foehn, et al. (2022), who demonstrate that running ML models directly on the UAV has rapid implications at the level of reaction in dynamic environments.

In order for algorithm-level decisions to be translated into precise movements, the architecture must include a flight control module. This connects the ML or RL algorithms to the autopilot system, using ROS 2 or PX4 (Nguyen and Nguyen 2019), thus translating intelligent behaviors into executable commands. Autonomy monitoring is ensured by a battery module, a necessary component for energy management and critical decision-making, an essential element in the structure of an intelligent UAS. Also, data exchange with other UAVs and the central vessel, in line with the inter-agent coordination concepts presented by Queralta, et al. (2020), would be achieved using a communications module, closing the architecture at the UAV level.

As for the central vessel/ship, it is practically a control station, and the subsystem includes a UAV surveillance module, responsible for monitoring the active drones and triggering handover procedures, launching a new UAV when one returns for loading or fails, thus ensuring mission continuity. This functionality is similar to the drone swarm coordination strategies researched by Jung, et al. (2024, 7).
The difference between the two subsystems is that while the UAV platform has the ML module to make very fast decisions related to maintaining position, avoiding collisions, adjusting altitude, etc.

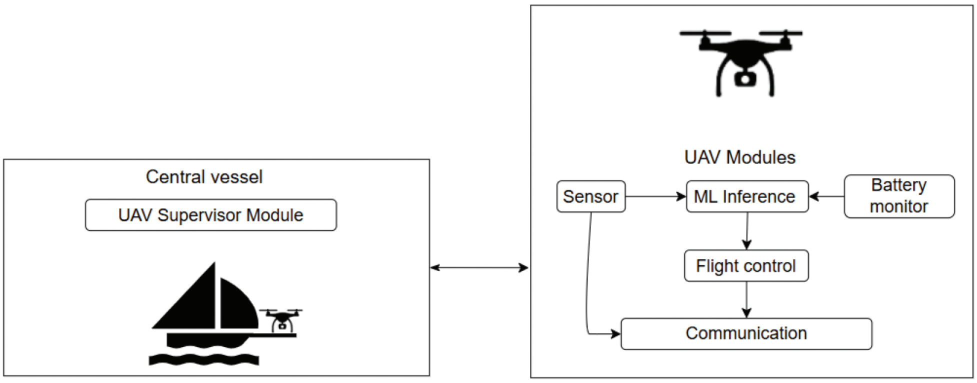

Figure 2 Architecture components of the UAS

The operational workflow, based on the diagram above, involves the UAV continuously sensing the position, altitude, and battery level, while the ML Inference Engine determines if the UAV is in a safe operational state. If a critical state is detected, the drone executes an autonomous landing on the fluvial vessel, whereas the supervisor module of the vessel triggers the launch of a standby UAV to continue the mission. This architecture can be implemented in ROS 2 with PX4 (MathWorks n.d.) and simulated in Gazebo using realistic riverine and aerial dynamics data.

The table below represents a light RL design focused on rewards (Guo, et al. 2023; Kong et al. 2023; Tovarnov and Bykov 2022) to better understand the reinforcement learning-based UAV control with perimeter maintenance in a fluvial environment (Table no. 1).

TABLE NO. 1

Light RL design on UAV control

State (S)	Action (A)	Reward (R)
While distance < 10 m to vessel & battery > 30%	Maintain position	+5
Distance between 10 m and 15 m	Adjust position	+1
Distance > 15m	Return towards the vessel	0
Battery < 20%	Land on the vessel's platform	+5 / -5
Collision	Any or N/A	-10

This approach introduces autonomy that adapts to real-time environmental changes (Table no. 2), including river current dynamics and narrow corridors, without the need for fixed, rule-based thresholds.

TABLE NO. 2

Light RL design based on environmental changes

State (S)	Action (A)	Reward (R)
Wind speed < 5m/s	Maintain normal flight	+3
Wind speed between 5m/s and 10 m/s	Adjust heading/thrust	+1 / -1
Wind speed > 10m/s	Initiate emergency landing	+ 5 / - 5
Visibility < 100m	Reduce speed, activate extra sensors	+3
Temperature between -10℃ and 40℃	Adjust battery saving mode/land	-3
Humidity > 90%	Enable sensor protection mode	+1 / -3

3. Results and discussion

3.1. Analysis of the theoretical and conceptual framework

Analyzing the specialized literature, as well as the previously proposed framework, the following answers to the research questions posed in Chapter 2 are found:
First of all, to allow the integration of machine learning, a drone must present an architecture similar to the one described, which combines both hardware and software elements. The components/modules were described in the previous chapter. Regarding the type of ML that can be used, taking into account the nature of the aquatic environment, characterized by variability and uncertainty, the most suitable type of machine learning is reinforcement learning (RL. This allows UAS to learn through interaction with the environment, adapting to new situations and optimizing decisions based on reward or penalty points, the goal being to maximize the score obtained. In more complex applications, more complex variants of ML, such as Deep Q-Network or hybrid learning, can also be used.

To answer the third research question, the parameters that need to be considered in hostile aquatic environments include atmospheric conditions (wind speed and direction, atmospheric pressure), hydrological conditions (water currents, water level, turbulence generated by obstacles), as well as static and dynamic obstacles (bridges, bank vegetation, other boats). Internal technical parameters, such as battery level, communication signal stability, and GPS positioning accuracy, are also determinants for mission success. Integrating this data through sensor fusion and using it in ML algorithms allows UAS to make robust decisions and reduce vulnerability to hostile conditions.

Aerial drone systems in river environments can be validated and tested within applications such as ROS 2 integrated with PX4, which allows for modular development of UAV components. A gazebo can also be used for simulations in which environmental factors can be modified to reflect obstacles and adverse weather conditions specific to the river environment. These types of applications increase the realism and practical value of research involving drone systems in general.

Last but not least, to integrate ML algorithms into this drone technology, it is necessary to implement artificial intelligence at the UAV device level, through the presented architecture, but also at the level of the entire system, including the control station or center. The UAV, through a lightweight ML model, becomes capable of micro-decisions that must be taken in a very short time, while the system, through the control station and the data collection center, must be capable of the macro-decision perspective, having the overall situation of all drones in the field simultaneously, as well as the ever-updating Common Operational Picture (COP) (Figure 3). A combined use of all unmanned platforms would lead to an operationally efficient multi-domain system that provides a more complete common operational picture, due to its presence in the three environments – land, air, and sea. Each platform has its own areas that can be developed, many aspects being common, as can be seen in the compendium produced within the UNIDIR framework (Grand-Clément 2023, 12-16).

Figure 3 Common Operational Picture (COP) using aerial drone systems
Source: https://www.magaero.com/wp-content/uploads/2023/02/KINETIC-STRIKE-TRAINING-PROGRAM-KSTP-Image-1643901249160-RT.jpg

Aquatic environments and watercourses (rivers, canals, estuaries) present a series of particularities in terms of their influence on unmanned aerial platforms. They are distinguished by narrow spaces, variable dynamic conditions, and the short distance to the shore. Water currents, through their speed and direction, have an impact on ships that are landing platforms for drones; this requires the UAV to constantly calculate its position and trajectory. Approaching the shore practically implies the possible proximity to obstacles or objects that may represent obstacles, whether it is man-made infrastructure or vegetation specific to the site. The infrastructure can also represent a source of electromagnetic interference that disrupts the quality of communications between the UAV platform and the control station.

By integrating ML and artificial intelligence in general, drone systems can learn to react optimally to currents, based on previously simulated scenarios and stored in their unit. They can also make decisions in real time based on AI, detecting and avoiding obstacles autonomously, without human intervention. This ensures resilience for both the civilian and military sectors by anticipating risks and reducing reaction times across the entire drone system, which can include an increased number of such mobile aerial platforms.

3.2. Results on autonomous control of UAV in riverine environment based on rewards

A distance of up to 10 meters from the vessel is considered safe, as long as the battery is over 30%. This being the variant that the UAV must learn to obey, it will be scored the most, and the drone will have to maintain its position. If the distance increases, through the flight control module, the drone will have to adjust its position and will be scored only one point. If the distance exceeds the maximum value of 15 meters, then it is outside the aerial perimeter established for the vessel. In this case, the UAV must return to the designated area. If the battery drops below 20%, which is a critical level since the battery autonomy of drones is not great, it must land on the vessel's platform simultaneously with the second UAV that is on standby and which now has to activate and fly, replacing the one with the low battery. If the first drone lands successfully, it will be scored +5 points. If it fails to land properly or in a timely manner, it receives a score of -5. Ultimately, in the case of a collision between drones or with the environment, a penalty of -10 points was applied.

This entire concept automatically teaches technological systems through reinforcement learning to behave according to the highest score, modeling it by the characteristics set by the human mind. However, atmospheric conditions cannot be ignored in this regard. Each UAV has specific sensors to measure environmental parameters (e.g., an anemometer for wind speed, barometric sensors for atmospheric pressure, GPS for real-time localization, and LiDAR for obstacles). The data are used in ML algorithms to adapt the flight according to the real conditions, because it affects both the UAV dynamics model and autonomous decisions (e.g., landing when the wind is too strong). The learning process can also benefit from simulated failure cases in which UAVs deviate from optimal behavior. Penalizing these scenarios helps the agent learn robust fallback strategies more quickly. Although the simulation was based on idealized physics, future work should include validation with real telemetry data from UAV flights in aquatic environments to ensure the fidelity of the learned behavior.

It is important that both external environmental factors (e.g., air currents, vegetation, etc.) and internal conditions of UAV systems (battery level, stability of communication links, etc.) be within a unified risk assessment framework, as shown in a research article in the field of safety and security (Terje 2007, 745–754). The machine learning-based drone model should not only focus on optimizing navigation, but also on continuously assessing the risks and vulnerabilities specific

to the environment in which it operates, so that it is resilient, safe, and accurate.
From an operational perspective, the proposed architecture and the use of reinforcement learning directly contribute to the Military Decision-Making Process (MDMP), as can be easily seen below (Table 3). Thus, it is observed that UAS can operate on the MDMP principle or can be used in the decision-making process by military personnel.

TABLE NO. 3

The correlation between the military decision-making process and the modular UAS architecture

No.	Stage	Correlation
1	Receipt of Mission	UAVs can be quickly integrated into a specific mission, understanding and adapting to the requirements received from the higher echelon, including time, space, and resource constraints.
2	Mission Analysis	Integrated sensors and ML modules provide essential data about the environment (water currents, natural obstacles, weather conditions), facilitating the identification of critical tasks and the anticipation of risks in the operating space. Essential for the S2 compartment when UAS provides information.
3	Course of Action – COA Development	By using RL and prediction algorithms, UAVs can generate multiple courses of action (shortest or personalized path, maintaining the perimeter, landing on the ship, handover between drones), which can be adapted in real time. Also, courses of action established by the echelon can be implemented directly in UAS.
4	COA Analysis	ML-based simulations allow testing and evaluation of each course of action in complex river conditions, identifying strengths, vulnerabilities, and potential risks before implementation.
5	COA Comparison	Data resulting from previous assessments can be compared with each other, within several courses of action, providing the commander with an objective picture of the optimal solution. If this stage is integrated into the UAV subsystem, then it will be able to choose the best possible option.
6	COA Approval	Through UAS, synthesized data and recommendations can be transmitted, facilitating the selection process of the most viable course of action to the commander.
7	Orders Production	The integration of UAVs into a coordinated and robust network allows the translation of the approved decision into an executable operational plan, where each drone receives clear roles, synchronized with the overall mission.

3.3. Future work

Having the data on the aspects that need to be considered regarding the control of a drone through ML, the author can move on to the next step, which involves the hardware implementation of a physical drone capable of ML. Such a UAV device is built modularly, starting from a physical frame, such as those in the figures below (Figures 3 and 4), on which standardized electronic hardware is mounted.

This system is controlled by an open-source flight controller (e.g., Pixhawk), which runs firmware such as PX4 or ArduPilot, some of the most advanced and popular software systems for autonomous drones. This flight controller makes use of information from the PX4 repository to improve ArduPilot UAV mission safety and operational effectiveness (Tovarnov and Bykov 2022). The platform can be built manually, with components also available separately. After assembling the

Figure 3 **F450 Quadrotor Drone**
(Source: https://www.jsumo.com/f450-droneunassembled-4337-15-K.jpg)

Figure 4 **QAV250 Quadrotor Drone**
(Source: https://encrypted-tbn0.gstatic.com/images?q=tbn:ANd9GcQ5J_RzkS0IFLSAmAWAFVVrQ1P5YIDShJKriQ&s)

parts, connecting the motors, electronics, and sensors, and mounting them on the platform, it can be configured at the software level with applications such as QGroundControl (QGC).

This device is capable of executing multiple and various commands: autonomous flight, maintaining the perimeter, event detection, immediate and automatic reactions, automatic landing, handover between drones, etc. Furthermore, this UAV type is suitable for virtual simulations, using applications such as Gazebo and AirSim, where environmental parameters can be applied. Being open-source it means that the system has full control over the communication firmware, presenting compatibility with single-board computers (SBC) such as Raspberry Pi or Jetson. It presents a considerable advantage when it comes to low cost and accessibility, as well as its popularity. Implementing artificial intelligence based on machine learning and configuring the aspects presented above could make drones much more efficient and usable in agriculture, optimizing the time of activities in precision agriculture (Petre, et al. 2022, 105). As for the disadvantages, perhaps the biggest one is the low battery autonomy and the physical protection, which can yet be improved by utilizing additional protections for the platform's case. Due to technological limitations of batteries, drones cannot carry an additional or increased payload, as this disrupts their accuracy (Boşcoianu, et al. 2024, 12). Also, battery limitations are the cause of the major problem among drones, regardless of the field in which they operate, being one of the weaknesses of these technologies, which are still at the beginning of their development (Iagăru, et al. 2023, 296).

Future work will involve using real, low-cost, ML-capable physical drones and analyzing their behavior while they are being subjected to the experiment in amphibious environments and being programmed according to the requirements presented in this paper.

Conclusions

Integrating machine learning techniques into UAS control presents promising opportunities for improving autonomous operations in complex aquatic environments, such as rivers and streams. These environments pose unique challenges, including water currents, variable weather conditions, and spatial constraints caused by vegetation and infrastructure.

Within the modular architecture, both the military decision-making process and the possibility of automatic learning based on rewards and penalties can be integrated at the AI module level. Through this ML-based UAS control, inter-agent coordination between UAVs is achieved, characterized by the transmission of data both to the central platform (ship) and to a field data collection center, thus making it possible to create and consolidate the common operational picture in real time and in a continuous, updated manner, based on the handover process between drones. This process supports the success of ISR (Intelligence, Surveillance, Reconnaissance), search and rescue, and military support operations. Also, through these handover mechanisms and battery monitoring, the energy management of UAS can be ensured, making it possible to extend the operational duration without direct human intervention, reducing logistical costs and risks for military personnel involved in the actions.

ML-based control strategies enable UAVs to adapt to such uncertainties in real time by learning robust flight behaviors, coordinated multi-agent navigation, and context-aware decision-making. Key insights include the development of adaptive algorithms for maintaining formation and position relative to moving platforms, reliable autonomous landing on ships in fluctuating water conditions, and seamless handover protocols to extend mission duration. Furthermore, the integration of real-time environmental sensors into ML models improves their resilience to atmospheric disturbances and hydrological variability.

The research questions were fully answered by defining the UAS architecture and selecting appropriate ML types. The specific parameters of the hostile river environment were identified, as presented in the table. Some specific applications of virtual simulations have been mentioned that can be used to validate the perspective of integrating UAS with ML and their use in adverse conditions, based on environmental factors that can be easily modified within these simulations. However, to be able to integrate UAS with ML, an AI module is needed, separately, at the level of the UAV itself, as well as at the system level, more precisely at the level of the control station and the data collection center, so that the perspective offered by the system is a complete one. However, the research questions are limited to a more theoretical level due to the lack of equipment and the actual simulation of the presented modular architectural framework.
Future research should focus on improving simulation environments that accurately model aquatic dynamics, combined with UAV behavior, expanding the datasets for training ML controllers in various scenarios, and validating the approaches through implementations in real conditions.

By harnessing the potential of ML, unmanned aerial systems can achieve a higher level of autonomy, safety, and efficiency, opening up new applications in environmental monitoring, search and rescue, and inspection of aquatic infrastructure in various fields, including the military. However, to use it in the military field, an additional research perspective should be developed on the development of standardized protocols that ensure reliable and low-latency communication between UAVs and river platforms, allowing coordinated behaviors and the integration of systems from different suppliers at an international level.

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