Physics-Informed Learning for Passive Prediction of AUV Maneuvering Deviations

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*Abstract*— Most AUVs lack awareness of the very flow phenomena that distort their motion, vortex shedding, asymmetric separation, and turbulence surges, because onboard systems are blind to unsteady fluid–structure interactions. This work introduces a physics-informed surrogate model that reconstructs the passive hydrodynamic response of an AUV directly from its kinematic state.

Trained on 3D CFD simulations, the Machine Learning model predicts both six-axis force–moment vectors and high-order flow-regime indicators, including turbulence intensity, pressure-gradient shifts, and boundary-layer detachment. These emerge not as byproducts, but as physically coupled consequences of motion. Operating in real time and without feedback, the model forecasts how the vehicle will drift, rotate, or lose depth under complex flow, enabling passive prediction of maneuver degradation. The system captures nonlinear behaviors such as yaw–pitch coupling and vortex-induced asymmetry that conventional models fail to resolve. By linking motion to instability without sensors or control, this framework defines a new class of flow-aware underwater autonomy, where trajectory deviation is not estimated after the fact, but foreseen from first principles.

Keywords— Autonomous Underwater Vehicle (AUV); Computational Fluid Dynamics (CFD); Supervised Machine Learning; Hydrodynamic Force Prediction; Data-Driven Modeling; Fluid-Structure Interaction;

# Introduction

Autonomous Underwater Vehicles (AUVs) have evolved into indispensable tools for subsea exploration, inspection, and environmental monitoring. Operating in dynamic and poorly structured marine environments, these systems must navigate while minimizing energy expenditure and acoustic signature, often in the absence of precise environmental sensing. Yet the underwater domain presents a formidable challenge: hydrodynamic loads vary unpredictably with vehicle speed, orientation, and flow regime. Even modest maneuvers can trigger vortex shedding, boundary-layer separation, coupling, or turbulence amplification, phenomena that introduce nonlinear forces and moments which cannot be captured by static coefficients or low-order control models.

Traditional approaches rely on empirical hydrodynamic coefficients or reduced-order approximations that remain valid only within narrow operating envelopes. These models offer no foresight into the emergence of complex fluid behaviors such as flow detachment, dynamic stall, or localized instabilities. Over the past five years, this limitation has motivated a surge of machine-learning surrogates trained on CFD data. Approaches including physics-informed neural networks, convolutional autoencoders, and generative adversarial architectures have shown promise for rapid inference across constrained conditions and specific hull geometries [1]. However, most regress only scalar quantities or control errors, rather than reconstructing the full six-degree-of-freedom load vector. Moreover, they rarely account for the fluid-mechanical origins of instability, limiting their physical interpretability and operational utility.

This study proposes a fundamentally different framework. It introduces a predictive system that infers not only the instantaneous hydrodynamic force and moment vector, but also the complex flow phenomena that generate them. Trained on an extensive set of three-dimensional CFD simulations spanning the full maneuvering envelope of the SPARUS II research platform, the supervised machine learning model captures both global responses and local flow dynamics. These include coupling between axes, adverse pressure gradients, turbulence surges, and onset of boundary-layer separation, signals that precede passive deviations in trajectory and that conventional models overlook entirely.

Unlike previous data-driven methods that treat CFD merely as a provider of output forces, the present framework distills the physical causality embedded in the simulated flow fields. Through offline analysis, the machine-learning model learns how flow structures such as asymmetric vortex shedding or stratified turbulence patterns translate into motion anomalies. It then uses this knowledge to forecast, in real time, the onset and magnitude of passive deviations arising from environmental disturbances. As a result, the system operates not as a reactive controller but as a sensor-free anticipator that reconstructs the underlying fluid–structure interactions driving trajectory errors.

Embedded in a Simulink environment and optimized for onboard deployment, the predictor reproduces key nonlinear behaviors observed in experimental and simulated motion: yaw asymmetries under symmetric thrust, depth excursions under steady-state pitch, and sensitivity to unbalanced flow regimes. These behaviors arise from the model’s internal physics-aware structure, without the need for external correction or empirical tuning.

By bridging high-fidelity CFD with machine-learning interpretation and real-time applicability, this work lays the foundation for next-generation AUV autonomy. It enables planning frameworks and future reinforcement learning controllers to reason not just about position or velocity, but about the fluid-dynamic consequences of their decisions. Such capability supports quieter, more energy-efficient, and more robust underwater navigation in the face of inherently unsteady environmental conditions.

The remainder of this paper is organized as follows. Section II reviews prior efforts in CFD-informed surrogate modeling for underwater systems. Section III describes the SPARUS II platform. Section IV details the learning architecture, feature engineering, and integration procedure. Section V presents predictive results across a suite of representative maneuvers. Section VI discusses broader implications and Section VII suggests directions for future research.

# Related work

Hydrodynamic modeling of autonomous underwater vehicles has traditionally relied on pre-calibrated coefficients derived from experiments, CFD or simplified potential flow theories. While useful for coarse approximations, these models often fail to capture the nonlinear, unsteady, and environment-dependent nature of real-world underwater motion. To improve fidelity, recent studies have turned to CFD-based force estimation. Han et al. [2], for instance, performed six-degree-of-freedom CFD simulations of full-body underwater maneuvers, explicitly resolving the coupling between yaw, pitch, roll, and depth during turning. While their approach highlights the complex inertial and hydrodynamic interactions that emerge during realistic trajectories, it relies on high-fidelity simulations and remains unsuitable for real-time forecasting.

In response, several works have explored surrogate modeling strategies grounded in physics-based principles. Ramirez et al. [3] developed a multi-output Gaussian Process Regression (GPR) model that reconstructs the six-degree-of-freedom hydrodynamic response of an AUV from onboard sensor data. Their framework was trained entirely on experimental measurements obtained during controlled pool trials, capturing real-world dynamics through DVL and IMU readings. While effective for estimating net forces and moments under measured conditions, the model lacks sensitivity to the underlying flow-field phenomena, such as turbulence intensity, pressure gradients, or separation, that often precede degraded performance. In contrast, the present work leverages CFD-derived flow descriptors to enable early detection of flow-regime transitions and trajectory instability.

A related effort by Zhou et al.[4] introduced a physics-informed generative adversarial network (PI-GAN) trained on steady-state CFD simulations to estimate hydrodynamic forces acting on AUVs under varying flow conditions. Their model integrates geometric and flow features to predict force coefficients without solving the Navier–Stokes equations at runtime, significantly reducing computational cost. By embedding physical priors in the training process, the system preserves consistency with CFD results across multiple operational states. However, their focus remains on reconstructing time-averaged hydrodynamic loads from fixed inputs. However, the present work forecasts evolving trajectory deviations and local flow-regime descriptors in real time, enabling early detection of unsteady behaviors such as vortex buildup, separation, or dynamic asymmetry that impact maneuvering performance.

Other relevant contributions include Yin and Pavesi [1], who investigated how laminar-to-turbulent transition affects the unsteady force response of a pitching hydrofoil, using high-fidelity CFD to capture transient flow features such as separation bubbles and reattachment. While their analysis provides valuable insight into flow-regime transitions, it focuses on a simplified geometry and post hoc force evaluation. The present work targets real-time prediction of such phenomena on full AUV bodies, enabling early awareness of instability drivers during operation.

Building on this foundation, the present study proposes a novel surrogate framework focused not on reconstructing the vehicle’s dynamic input-output map, but on predicting the onset of deviation and instability before it materializes. By training the model on rich CFD data and targeting descriptors of flow condition degradation, the proposed system achieves a passive predictive capability that bridges the gap between classical hydrodynamic modeling and real-time flow-aware behavior anticipation.

# THE SPARUS II AUV

The present study focuses on the SPARUS II Autonomous Underwater Vehicle, a torpedo-shaped, modular platform developed by IQUA Robotics for both academic and operational missions. It is widely employed in control and hydrodynamic research due to its compact form, open software architecture, and partial hovering capabilities.

The SPARUS II measures 1.6 [m] in length, has a hull diameter of 230 [mm], and weighs approximately 52 [kg] in air. It can operate at depths up to 200 [m] and at surge velocities ranging from 0 to 2 [m/s] [6]. The platform is actuated in three degrees of freedom: two stern-mounted horizontal thrusters control surge (via symmetric thrust) and yaw (via differential thrust), while a central vertical tunnel thruster provides heave control. Each thruster is limited to 40 [N]. No active actuation is available for sway, pitch, or roll, classifying the vehicle as under-actuated.

This under-actuation imposes constraints on maneuverability, particularly under crossflows or during aggressive turns. As a result, lateral drift and attitude deviations must be indirectly corrected using surge and yaw inputs, leading to degraded path fidelity. These characteristics emphasize the importance of accurate, real-time prediction of hydrodynamic responses, especially at off-design pitch and yaw angles, when direct control is unavailable.

The vehicle is equipped with standard navigation sensors, including an IMU, depth sensor, Doppler velocity log (DVL), and USBL localization system. A configurable payload bay supports up to 8 liters in volume and 7 kg in air, enabling deployment of sonar, cameras, or scientific instruments. All software components are built upon the Robot Operating System (ROS), allowing flexible integration with navigation and control modules.

All simulations and predictive modeling in this work are confined to the vehicle’s operational envelope: pitch angles between ±40°, and forward velocities between 0 and 2 [m/s]. These values correspond to realistic low-speed maneuvering scenarios such as near-seafloor surveys and obstacle-aware navigation. Within this envelope, complex hydrodynamic effects such as flow separation, vortex-induced forces, and nonlinear coupling can emerge, motivating the need for robust predictive modeling.

# Methodology

Effective autonomy in dynamic, unstructured underwater environments demands more than reactive control. It requires the ability to anticipate how flow conditions will evolve, and how they will affect the vehicle's motion, before the consequences become observable. This study introduces a novel methodology for building a physics-informed predictive model that does not merely estimate hydrodynamic loads, but learns to recognize the early flow phenomena that cause them. By extracting turbulent signatures, pressure-gradient patterns, and separation dynamics from high-fidelity CFD simulations, the model internalizes the precursors of instability and degraded performance. These learned physical cues enable the system to forecast deviations in trajectory, orientation, and flow regime well in advance, even under previously unseen maneuvers.

The methodology proceeds in three main stages: (A) generation of a high-resolution CFD dataset that captures both global responses and localized flow precursors, (B) supervised learning of a surrogate model capable of generalizing the full fluid–structure relationship in real time, and (C) integration of the model into a six-degree-of-freedom simulation framework that reproduces the vehicle’s passive motion under predicted hydrodynamic conditions. This design forms the foundation for a new class of anticipatory, flow-aware maneuvering systems.

## High-Fidelity CFD Dataset Generation

A dataset of high-resolution CFD simulations was constructed to capture the steady and unsteady hydrodynamic response of an AUV subject to a wide range of motion conditions and environments. These include variations in pitch and yaw, transient accelerations, and angular rate changes. The simulations were conducted in ANSYS Fluent, solving the unsteady Reynolds-Averaged Navier–Stokes (URANS) equations with the SST k–ω turbulence model, chosen for its robustness in resolving separation zones and near-wall behavior under dynamic flow.

Unlike traditional hydrodynamic databases, which record only net forces or use simplified geometry, our dataset preserves full flow field information. Each simulation retained surface pressure distributions, turbulence intensity (e.g., TKE), vorticity zones, and indicators of boundary-layer detachment. These are not secondary effects, they are early markers of dynamic instability, energy loss, and degraded maneuverability.

A broad matrix of simulation scenarios was constructed by varying translational velocities, angular rates, and orientation angles across operationally relevant ranges. Crucially, the sampling strategy included motion states near known hydrodynamic regime transition, such as high pitch rates combined with lateral translation, which are known to trigger laminar separation bubbles (LSBs), asymmetric flow detachment, and unsteady wake dynamics. Recent studies have shown that rapid pitching induces the bursting and reattachment of LSBs, leading to vortex shedding and lift hysteresis [1]. These phenomena are central to maneuver-induced instabilities and justify the need for high-fidelity CFD data capable of capturing such transitions in full detail.

The input features included translational velocity components in the surge, sway, and heave directions (denoted u, v, w), angular velocity components about the roll, pitch, and yaw axes (p, q, r), and absolute orientation angles relative to the inertial frame (φ, θ, ψ). These features were selected both for their physical relevance and for their direct observability using standard onboard navigation sensors such as inertial measurement units (IMUs) and Doppler velocity logs (DVLs). Derived quantities, including the velocity magnitude and angular momentum surrogates, were retained when their inclusion improved predictive performance. Each input vector was paired with a corresponding output composed of two complementary components. The first was the net hydrodynamic load acting on the vehicle at that instant, expressed as forces and moments along all three axes (Fx, Fy, Fz, Mx, My, Mz). The second component described localized flow conditions near the vehicle’s surface, including turbulence intensity, surface pressure gradients, and binary and probabilistic indicators of flow separation. These descriptors were extracted directly from CFD post-processing to preserve the physical context underlying the observed loads.

This dual-target formulation enabled the model to associate kinematic states not only with mechanical outcomes but also with the flow-structure phenomena that precede them. As such, the model acquired sensitivity to early-stage hydrodynamic disturbances, including asymmetric detachment or boundary-layer instability, even under conditions not explicitly represented in the training data. Rather than approximating forces through empirical fitting, the training process preserved the nonlinear coupling between motion and fluid response, supporting generalization across a wide range of realistic maneuvers.

## Surrogate Model Selection and Evaluation

The complexity of the prediction task in this system lies not only in estimating the net forces acting on the vehicle, but in anticipating the fluid–structure conditions that precede degraded performance. Flow separation, asymmetric wake formation, and boundary-layer instability are all highly nonlinear phenomena that emerge from specific combinations of motion states. Capturing these transitions requires a regression model that is both accurate and physically coherent, one that does not simply interpolate, but reflects the structure of unsteady hydrodynamic behavior.

Rather than relying on traditional interpolation schemes, which assume local continuity and smooth variation, we adopted a Supervised Machine Learning (SML) approach tailored for learning high-dimensional, nonlinear input–output mappings. Hydrodynamic responses to AUV maneuvers often exhibit abrupt regime transitions—such as laminar separation bubble bursting, vortex shedding, and lift hysteresis—that violate the smoothness assumptions required for simple interpolation. Standard interpolators tend to produce unstable or unphysical results near these critical boundaries, lacking both physical awareness and uncertainty quantification. In contrast, supervised learning models can infer the structure of the underlying physics from rich CFD-derived datasets and generalize beyond observed data points. This capability is essential for accurately modeling unsteady fluid–structure interactions across the AUV's operational envelope.

Accordingly, we conducted a broad model selection study spanning over thirty supervised learning algorithms, including linear, kernel-based, ensemble, and neural methods. While some models achieved reasonable average performance, their prediction surfaces exhibited undesirable properties for dynamic use, such as oscillatory artifacts, poor generalization in high-gradient regions, or sensitivity to sparsity.

Among all candidates, Gaussian Process Regression (GPR) emerged as uniquely suited to this task. Its interpolation behavior remained smooth and consistent even in regions of rapid dynamic variation, such as during pitch surges, yaw reversals, or combined angular–translational transients. Unlike purely numerical models, GPR maintains global coherence in the predicted response surface and provides a principled uncertainty measure that regularizes predictions where training data are sparse. These properties are critical for dynamic integration, where unstable estimates can accumulate into trajectory drift or misinterpretation of flow regime onset. More importantly, GPR aligned with the physical logic of the system. By learning not only net force outcomes but also precursors such as surface pressure gradients and turbulence intensity, the model acquired sensitivity to early-stage flow disturbances. This anticipatory capacity allows the system to identify unfavorable orientations, degraded hydrodynamic conditions, or maneuver inefficiencies before they escalate into performance loss.

Model 2.21, based on GPR, consistently achieved the best performance across all evaluation criteria. On the validation set, it attained an RMSE of 0.401, MAE of 0.270, and of 0.99985. These results were almost mirrored on the test set, with RMSE = 0.308, MAE = 0.240, and R² = 0.99938, demonstrating both generalization and robustness as shown in Figure 1–Figure 4. Inference speed exceeded 2000 predictions per second as shown in Figure 6, confirming the model’s suitability for embedded, real-time applications. More critically, GPR’s structure aligned with the physical logic of the system. By learning the continuous relationship between motion and flow features, not only the force outcome, the model became sensitive to the early signatures of instability. This anticipatory capacity enables the system to identify dangerous orientations, degraded flow conditions, or inefficient maneuvers before they manifest in macroscopic error. For this reason, the selection of GPR was not a post-hoc optimization decision, but a central design element. It reflects the need for a model that encodes fluid dynamics and supports integration into a larger system that operates under real-time, unstructured, and physically uncertain conditions.

תמונה שמכילה טקסט, צילום מסך, קו, תרשים

תוכן בינה מלאכותית גנרטיבית עשוי להיות שגוי.

Figure 1- Root Mean Squared Error (RMSE) across all tested models during validation

תמונה שמכילה טקסט, צילום מסך, תרשים, קו

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Figure 2- Root Mean Squared Error (RMSE) across all tested models during test

תמונה שמכילה טקסט, צילום מסך, תרשים, קו

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תמונה שמכילה טקסט, צילום מסך, תרשים, קו

תוכן בינה מלאכותית גנרטיבית עשוי להיות שגוי.

Figure 4- Mean Absolute Error (MAE) comparison on the test set

תמונה שמכילה טקסט, צילום מסך, גופן, קו

תוכן בינה מלאכותית גנרטיבית עשוי להיות שגוי.תמונה שמכילה טקסט, צילום מסך, קו, מקביל

תוכן בינה מלאכותית גנרטיבית עשוי להיות שגוי.

Figure 6- Execution speed of the selected surrogate model on embedded hardware

The model’s multi-output structure enables it to reconstruct not only global hydrodynamic forces, but also localized flow-regime indicators. These include surface pressure gradients, boundary-layer separation markers, and turbulence-related quantities that are known to precede hydrodynamic degradation.

As an illustrative example, Figure 7 shows the predicted versus actual values of turbulent kinetic energy (TKE) over a representative subset of test samples that were held out during training. TKE is widely recognized as a proxy for turbulence intensity and unsteady flow activity, particularly in regions near flow separation, vortex shedding, or adverse pressure gradients. The model achieves excellent agreement across most of the domain, with predicted values closely following the identity line.

A slight dispersion appears at higher TKE values, where predictions begin to deviate modestly from ground truth. This behavior is physically consistent with the nature of turbulence: high-TKE regions are typically associated with chaotic, intermittent structures that are more sensitive to small variations in kinematic input and more difficult to generalize from sparse CFD data.

Nonetheless, the model’s ability to reconstruct these indicators from compact motion states demonstrates its internalization of flow–structure coupling mechanisms, enhancing both its interpretability and its potential for early instability forecasting.

## Real-Time Integration and Predictive Flow Simulation

To evaluate the surrogate model under physically realistic and dynamically uncertain conditions, a high-fidelity simulation framework was developed to replicate the six-degree-of-freedom (6DOF) motion of an Autonomous Underwater Vehicle subjected to variable flow environments. This framework extends beyond conventional trajectory simulation by incorporating not only the vehicle’s inertial dynamics but also the surrounding flow regime, as predicted in real time by the trained surrogate model. Rather than estimating hydrodynamic loads in isolation, the system captures how motion-induced flow phenomena, such as laminar separation bubble (LSB) bursting, asymmetric wake formation, vortex shedding, and nonlinear coupling between angular and translational motions—emerge and evolve throughout the maneuver. In the offline phase, a comprehensive library of three-dimensional CFD simulations was constructed to span a wide range of AUV orientations, velocities, and angular rates, including high-gradient transitions known to trigger hydrodynamic instability. Each CFD timestep yielded both global load outputs (forces and moments) and local flow-field descriptors, including surface pressure gradients, turbulence intensity, boundary-layer separation zones, and wall shear behavior. These were used to train a Gaussian Process Regression (GPR) model capable of mapping the vehicle’s motion state to its instantaneous fluid-structure response. In the online phase, the trained model was embedded within a Simulink-based 6DOF simulation environment. At each timestep, sensor-derived motion states—comprising linear and angular velocities and orientation—are passed to the model, which returns both net hydrodynamic loads and distributed flow indicators in real time. This enables the AUV’s motion to evolve passively under the influence of a learned, physics-informed flow field, without relying on empirical approximations or static force libraries. The Simulink implementation ensures modularity, numerical robustness, and compatibility with embedded real-time control platforms and hardware-in-the-loop (HIL) testing. By coupling predicted flow dynamics with motion equations, the system transitions from reactive estimation to anticipatory inference, enabling the early detection of performance degradation and maneuvering instabilities—even in unstructured or previously unmodeled flow conditions. The overall system architecture—comprising an offline CFD-driven learning phase and an online inference phase—is illustrated in Figure 6

# תמונה שמכילה שרטוט, קו תוכן בינה מלאכותית גנרטיבית עשוי להיות שגוי.Results

The following results present the passive motion trajectories of the AUV in five distinct maneuvering scenarios in water depth, simulated using the real-time surrogate prediction system. In all cases, the vehicle evolved freely, without control input or force correction, under the influence of hydrodynamic conditions predicted at runtime from its instantaneous motion state. Unlike classical simulations that apply pre-fitted force models or simplified assumptions, this system computes at each step a full fluid–structure response: not only net forces and moments, but physically interpretable features such as surface pressure asymmetries, boundary-layer separation indicators, and localized turbulence onset. These features emerge dynamically from the predicted motion–flow coupling and are used to propagate the AUV’s state through six-degree-of-freedom rigid-body dynamics. The maneuvers were intentionally selected to challenge the model across regimes where traditional approaches tend to fail—rapid pitch, lateral drift, yaw asymmetry, and orientation changes that trigger nonlinear wake phenomena.

This analysis is not limited to evaluating prediction accuracy, but aims to demonstrate how the integrated model reproduces physically realistic flow-induced behaviors under open-loop conditions. The system captures key phenomena, such as vortex shedding, asymmetric separation, and coupled motion responses, without relying on onboard sensing or active control. Each scenario highlights the model’s ability to anticipate degradation and instability before they manifest at the trajectory level.

* 1. *Passive Straight-Line Maneuver at Low Propulsive Intensity*

תמונה שמכילה כתב יד

תוכן בינה מלאכותית גנרטיבית עשוי להיות שגוי.The AUV was initialized with symmetric lateral thrust of 10 [N] per thruster (25% of maximum), intended to maintain a straight trajectory under passive conditions. The simulation assumes a calm sea state, with no external flow disturbances or ambient turbulence. The vehicle's motion evolves solely in response to predicted internal fluid–structure interactions. This maneuver aimed to produce straight-line motion under symmetric low-thrust actuation without control. As can be seen in Figure 8, the AUV gradually rises 1 [m] over time, indicating a loss of depth despite the absence of external disturbances. Figure 11 shows a horizontal deviation of approximately 1 [m] from the desired path, suggesting a slow lateral drift. These deviations are explained by the angular response in Figure 12, where pitch and yaw exhibit small oscillations that decay but do not fully stabilize. These residual oscillations likely result from unsteady flow effects such as pressure asymmetries and dynamic separation, which introduce transient moments even under symmetric actuation. Without active control to suppress them, these small angular deviations accumulate and lead to significant trajectory drift over time.

* 1. *Passive Straight-Line Maneuver at High Propulsive Intensity*

To examine the influence of thrust intensity on passive stability, this scenario replicates the configuration of sub-section (A) but increases the lateral thruster output to 35 [N] per side (approximately 85% of maximum capacity). The simulation was conducted under calm sea conditions and without any control input.

תמונה שמכילה קו, תרשים

תוכן בינה מלאכותית גנרטיבית עשוי להיות שגוי.תמונה שמכילה קו, תרשים, עלילה, טקסט

תוכן בינה מלאכותית גנרטיבית עשוי להיות שגוי.As can be seen in Figure 10, the vehicle exhibits substantial trajectory deviation, both vertically and laterally. The AUV loses over 15 [m] in depth and drifts approximately 15 [m] sideways, as shown in שגיאה! מקור ההפניה לא נמצא.. The angular response in Figure 13 reveals stronger and more persistent fluctuations in pitch and yaw compared to the low-thrust case, with larger תמונה שמכילה אומנות ילדים, צבעוני, מלבן, שרטוט

תוכן בינה מלאכותית גנרטיבית עשוי להיות שגוי.amplitude and slower decay. These fluctuations amplify unsteady flow effects, such as asymmetric separation and pressure imbalances, which in turn generate asymmetric forces and cumulative drift. While the magnitude of the deviation may seem large for a 2.5 [mins] maneuver, it is physically consistent with the dynamics of an uncontrolled system operating at high velocity, where small residual angles can rapidly translate into significant spatial displacement due to flow–structure coupling. This result demonstrates that higher thrust, without active stabilization, can degrade trajectory integrity and increase susceptibility to nonlinear hydrodynamic instabilities.

## Passive Yaw Maneuver under Asymmetric Actuation

In this maneuver, an intentional asymmetry was introduced: the port-side thruster was set to 10 [N] while the starboard thruster remained inactive. This configuration was designed to induce a passive starboard turn without control input or external disturbances, under calm sea conditions.

תמונה שמכילה קו, תרשים, עלילה, שרטוט

תוכן בינה מלאכותית גנרטיבית עשוי להיות שגוי.Figure 16 presents the resulting three-dimensional trajectory. The AUV deviates significantly from the intended straight path, completing a wide passive arc to starboard. Over a 5 [mins] interval, the vehicle accumulates more than 15 [m] of lateral offset and descends by over 40 [m] in depth. These deviations are further illustrated in the top-view projection shown in Figure 17. The angular response in Figure *14* reveals pronounced and persistent oscillations in both pitch and yaw. These oscillations do not converge, but instead sustain a fluctuating pattern throughout the trajectory. This behavior suggests that the unbalanced thrust triggered not only a yawing motion but also an unstable pitch–yaw coupling that remained unchecked due to the absence of corrective control.

תמונה שמכילה קו, תרשים, עלילה

תוכן בינה מלאכותית גנרטיבית עשוי להיות שגוי.As shown in Figure 17, the AUV initially veers to the right due to its inertial response and initial yaw moment, but over time, the trajectory curves back to the left, forming a partial arc. This behavior is consistent with the application of thrust on the port side only, combined with complex hydrodynamic effects such as delayed flow separation, asymmetric wake formation, and nonlinear yaw coupling. The net result is a passive turning motion that naturally evolves into a broader circular path. Such dynamics are expected in the absence of control input, especially in the presence of unsteady flow regimes.

תמונה שמכילה צילום מסך, כחול חשמלי, כחול מג'ורלי, טקסט

תוכן שנוצר על-ידי בינה מלאכותית עשוי להיות שגוי.

תמונה שמכילה טקסט, צילום מסך, אומנות ילדים

תוכן שנוצר על-ידי בינה מלאכותית עשוי להיות שגוי.

To better understand the underlying causes of this instability, flow visualizations based on CFD predictions were examined. Figure 18 displays unsteady streamline behavior behind the sail, highlighting vortex shedding and flow separation patterns that fluctuate over time. These unsteady features are known to generate asymmetric pressure distributions and time-varying lateral forces.

Together, these results demonstrate how asymmetric actuation, when combined with unsteady flow behavior and uncontrolled angular dynamics, can produce compounding deviations in both trajectory and orientation. This maneuver serves as a validation of the system's ability to capture complex, physically consistent responses even under passive and open-loop conditions.

## Passive Straight-Line Maneuver under Lateral Harmonic Disturbance

This scenario repeats the symmetric high-thrust maneuver detailed in sub-section (B), in which both horizontal thrusters deliver a constant force of 35 [N]. However, an additional unsteady lateral excitation is introduced: a time-dependent sinusoidal force is applied along the global Y-axis to emulate oceanic side disturbances, such as oscillatory currents or wave-induced sway. No active feedback control is applied, allowing the AUV to respond passively to the combined effect of propulsion and disturbance.

The resulting 3D trajectory is shown in Figure 19, where the AUV initially follows a straight descent similar to the baseline case, but gradually deviates into a wavy lateral path due to the externally imposed oscillation. This behavior is more clearly observed in the top-view projection (Figure 20), where the vehicle exhibits an undulating motion along the Y-direction, overlaid on its forward progression. The trajectory confirms the expected phase-locked lateral sway induced by the harmonic force.

Angular motion profiles are shown in Figure 21. The yaw angle (bottom plot) displays increased variability and high-amplitude fluctuations beyond ±15°, indicating unmitigated rotational response to the lateral forcing. This is accompanied by a corresponding modulation in the pitch angle (top plot), where the amplitude envelope expands significantly after 200 [sec], suggesting coupling effects between sway and heave due to unbalanced hydrodynamic loading and flow separation.

Notably, both angular responses become increasingly irregular as the simulation progresses, hinting at the onset of unsteady flow regimes and potential nonlinear resonance effects. These dynamics reflect the AUV's natural response to persistent lateral excitation, highlighting the limitations of passive navigation in disturbed environments.

This test case serves as a benchmark for evaluating flow sensitivity, disturbance amplification, and the need for real-time corrective strategies. It underscores the importance of predictive modeling in the context of real-sea conditions, where such external influences can accumulate and destabilize the trajectory unless explicitly addressed by the guidance system.

תמונה שמכילה קו, תרשים, עלילה, מדרון

תוכן בינה מלאכותית גנרטיבית עשוי להיות שגוי.

Figure 19- AUV trajectory in 3D under lateral harmonic disturbance

תמונה שמכילה קו, תרשים, עלילה, מקביל

תוכן בינה מלאכותית גנרטיבית עשוי להיות שגוי.

Figure 20- AUV trajectory top-view under lateral harmonic disturbance

תמונה שמכילה עלילה, קו, תרשים

תוכן בינה מלאכותית גנרטיבית עשוי להיות שגוי.

Figure 21- Time evolution of pitch and yaw under disturbed conditions under lateral harmonic disturbance

## Response to Longitudinal Sea Disturbance: Pitch-Dominant Forcing and Emergent Coupling

This maneuver reuses the symmetric 35 [N] thrust configuration from sub-section (B) but introduces a passive, unmodeled sea disturbance that induces rotational imbalance. No active control was applied, and all external forces originated from fluid interactions.

As shown in Figure *22*, the AUV exhibits a noticeable downward and lateral drift. Over the course of the trajectory, the vehicle descends by approximately 25 [m] and deviates laterally by 12 [m], despite the symmetric actuation. Figure *23* confirms this lateral shift in the top-view, where the AUV gradually veers to starboard without any yaw command.

The angular response in Figure *24* reveals a strong dynamic coupling: although no torque was applied about the yaw axis, the yaw angle plunges to (−35)°, while the pitch gradually increases to over 30°. This highlights an emergent feedback mechanism in which pitch-driven flow imbalances, caused by local separation and unsteady pressure gradients, induce significant yaw torque and trajectory divergence.

The results emphasize the surrogate model’s ability to capture non-trivial hydrodynamic coupling effects, underscoring the necessity of incorporating such behaviors into real-time control or forecasting architectures.

תמונה שמכילה תרשים, קו, שרטוט, ציור

תוכן בינה מלאכותית גנרטיבית עשוי להיות שגוי.

Figure 22- Predicted 3D trajectory under longitudinal sea disturbance

תמונה שמכילה קו, עלילה, תרשים

תוכן בינה מלאכותית גנרטיבית עשוי להיות שגוי.

Figure 23- top-view of the trajectory under longitudinal sea disturbance

תמונה שמכילה תרשים, קו, עלילה

תוכן בינה מלאכותית גנרטיבית עשוי להיות שגוי.

Figure 24- Angular evolution: pitch (top) and yaw (bottom) response over time under longitudinal sea disturbance

# Conclusions and Discussions

This study investigated the passive hydrodynamic response of an Autonomous Underwater Vehicle under a range of symmetric and perturbed thrust scenarios, leveraging a surrogate model trained on high-fidelity CFD data. Each maneuver was designed to isolate specific flow–body interactions and evaluate the system’s behavior in the absence of control.

In Maneuver (A), symmetric low-thrust actuation (10 [N] per side) resulted in a gradual loss of depth and a lateral deviation of approximately 1 [m], despite calm sea conditions and an ostensibly balanced configuration. These deviations arose from small residual oscillations in pitch and yaw, induced by asymmetric wake dynamics and flow separation effects that remain unsuppressed without active control.

In Maneuver (B), increasing the symmetric thrust to 35  [N] per side amplified these effects significantly: the vehicle exhibited over 15 [m] of depth loss and approximately 15 [m] of lateral drift. The stronger thrust triggered higher Reynolds number regimes causing more turbulence, leading to intensified vortex shedding and more pronounced pitch–yaw coupling, demonstrating the nonlinearity of the system's response.

In Maneuver (C), thrust was applied solely to the port-side thruster (10 [N]), while the starboard thruster remained inactive. This asymmetric actuation generated a curved trajectory, with the AUV veering progressively to starboard. The resulting path, approximately circular in nature, is a direct consequence of the unbalanced lateral moment introduced by the single-sided thrust. Physically, the applied force at an offset from the vehicle’s center of mass induces a continuous yaw moment, causing the AUV to rotate passively in the horizontal plane. Despite the absence of any explicit yaw input or rudder control, the vehicle maintains this turning pattern purely due to the induced torque and hydrodynamic interaction with the surrounding flow. The deviation observed, approximately 15 [m] lateral displacement and 40 [m] depth variation, reflects both the sustained yaw rotation and the coupled pitch-yaw dynamics, driven by unsteady pressure distribution and boundary-layer separation near the hull. The depth loss is explained by the asymmetric thrust inducing a yaw–pitch coupling, which alters the local angle of attack and causes unbalanced pressure distribution along the hull, leading to a net downward force.

Maneuver (D) introduced a lateral, harmonic disturbance along the Y-axis to emulate wave-induced sway. Although the thrust conditions were identical to Maneuver (B), the AUV experienced more than 15 [m] of lateral displacement and clear yaw oscillations, despite no direct torque input in the yaw direction. This behavior highlights resonance-like amplification in the sway–yaw plane and underscores the model’s ability to capture multi-axis responses to external excitations.

Maneuver (E) applied a time-varying torque solely around the pitch axis, simulating longitudinal wave effects. Despite the perturbation being confined to a single rotational degree of freedom, the AUV exhibited complex cross-axis behavior, including yaw excursions up to (-35)°, a vertical drop exceeding 25 [m], and lateral drift of over 12 [m]. These responses reflect strong internal coupling mechanisms within the hydrodynamic system, as well as the surrogate model’s capacity to reproduce them with high fidelity.

These responses arise not only from cross-axis coupling, but also from unsteady flow phenomena such as asymmetric vortex shedding, fluctuating dynamic pressure fields, and boundary-layer separation induced by the oscillatory pitch motion. Together, these effects lead to emergent instabilities across multiple degrees of freedom, which the surrogate model captures through its physically grounded training.

By comparing the different maneuvers, several key insights emerge regarding the nonlinear sensitivity of the AUV to thrust levels, environmental disturbances, and internal flow–body interactions

The transition from Maneuver (A) to (B) underscores the system’s nonlinear sensitivity to thrust magnitude: increasing the symmetric thrust input led to significant increase in both depth loss and lateral deviation. This amplification arises not from linear scaling of forces, but from vortex growth, boundary-layer instability, and the onset of asymmetric wake dynamics, effects that intensify rapidly with increasing Reynolds number.

Comparing Maneuvers (B) and (D) further reveals the profound impact of lateral sea disturbances. While the thrust profile remains unchanged, the introduction of a time-varying side force excites sway–yaw resonance modes, destabilizing the pressure field around the hull and inducing persistent lateral drift and yaw oscillations.

Comparing Maneuvers (B) and (E) reveals how pitch-only disturbances can cascade into full 3D trajectory deviations through hydrodynamic coupling. While both maneuvers shared identical thrust conditions, the introduction of a pitch-axis torque in (E) induced severe yaw excursions, vertical descent, and lateral drift—despite the absence of any yaw control or lateral forcing. This contrast underscores the surrogate model’s capacity to predict emergent cross-axis instabilities arising from local changes in angle of attack, flow separation dynamics, and unsteady pressure gradients. The results demonstrate that even rotational disturbances confined to a single axis can propagate through the vehicle's hydrodynamic structure, destabilizing multiple degrees of freedom and magnifying trajectory deviation far beyond what thrust magnitude alone would suggest.

By jointly analyzing the CFD simulations and the surrogate model outputs, this study reveals how localized flow phenomena, such as boundary-layer separation, turbulent surges, and asymmetric pressure gradients, serve as precursors to macroscopic trajectory deviation. These flow-regime features, often undetectable by conventional sensors, emerge as physically meaningful indicators of instability well before significant position or orientation errors manifest. The surrogate model distills high-dimensional CFD data into actionable insight, mapping compact kinematic inputs to both six-axis force–moment responses and early flow-instability signatures. By forecasting these indicators in real time, the system enables control-free anticipation of deviation trends under complex ocean conditions, laying the foundation for flow-aware planning and robust underwater autonomy.

Crucially, the model’s generalization ability stems not from overfitting to training data, but from its grounding in physical principles extracted from 3D CFD. As a result, it retains predictive power even in unseen conditions, such as compound disturbances or nonlinear coupling effects. This approach uniquely balances physical interpretability, generalization beyond the training set, and computational efficiency.

The presented system therefore introduces a new layer in flow-aware underwater autonomy, one where passive forecasting of emergent hydrodynamic behavior informs, rather than replaces, control decisions. It lays the foundation for intelligent maneuvering strategies that integrate hydrodynamic foresight into planning and evaluation frameworks.

# Future Work

Two companion manuscripts, already underway, will elevate the passive forecaster introduced here into a decisive engine for autonomous decision-making. The first, an instability-assessment study now in internal review, distills the current unsteady descriptors (vortex-shedding phase, turbulence bursts, separation–reattachment dynamics, pressure-gradient hot spots, and their epistemic bounds) into a streamlined, controller-rate vector S(t) that captures both the intensity and morphology of evolving hydrodynamic instability across the vehicle’s full operating envelope. Preserving this vector structure safeguards the mechanistic pathways through which unsteadiness erodes energy efficiency, acoustic discretion, and tracking precision, while a mesh-aware Gaussian-process formulation satisfies tight on-board latency and memory budgets. Once validated against an expanded CFD corpus that now includes wave–current coupling and density stratification, S(t) will be released as a stand-alone module, providing any guidance layer with an instantaneous, quantitative measure of hydrodynamic margin.

The second manuscript, slated for immediate submission thereafter, embeds S(t) within a model-based reinforcement-learning framework. During offline policy search, each candidate thrust sequence is evaluated simultaneously for propulsive work, trajectory fidelity, and the projected evolution, plus epistemic risk, of S(t). By elevating flow stability to a first-class reward signal, the agent uncovers maneuvers that are simultaneously energy-optimal, acoustically discreet, and robust to environmental variability, a performance trifecta impossible when optimization relies solely on net loads. Together these studies transform today’s descriptive surrogate into a fully flow-aware autonomy stack: the forthcoming instability module delivers real-time, quantitative risk, and the reinforcement learner exploits that insight to synthesize stealthy, power-efficient, and trajectory-faithful paths.

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