

## Article

# CFD Analysis of Drag and Internal Volume Tradeoffs in a Compact AUV with a Myring Forebody and Flat Stern

Zhenchao Fu <sup>1</sup>, Jingxing Feng <sup>1</sup>, Zhengyang Zhu <sup>1</sup>, Zhihao Wang <sup>1</sup>, Xiaodong Liu <sup>1</sup>, Yude Shao <sup>1,\*</sup> and Hokeun Kang <sup>2,\*</sup>

<sup>1</sup> College of Ocean Science and Engineering, Shandong University of Science and Technology, Qingdao 266590, China; 18363939462@163.com (Z.F.); 19957361776@163.com (J.F.); 13792580859@163.com (Z.Z.); 19553469951@163.com (Z.W.); liuxiaodong@sdust.edu.cn (X.L.)

<sup>2</sup> Division of Marine System Engineering, Korea Maritime and Ocean University, Busan 49112, Republic of Korea

\* Correspondence: shaoyude@sdust.edu.cn (Y.S.); hkkang@kmou.ac.kr (H.K.)

## Abstract

Low-slenderness-ratio, flat-ended autonomous underwater vehicles must balance hydrodynamic resistance against internal volume retention, yet classical slender-body criteria do not fully represent their coupled forebody wake response. A generalized Myring forebody was assessed for an AUV with  $L = 0.8$  m,  $D = 0.2$  m, and  $L/D = 4.0$  using 53 steady three-dimensional Reynolds averaged Navier-Stokes simulations with the shear stress transport  $k-\omega$  model. Gaussian process regression and the non-dominated sorting genetic algorithm II (NSGA-II) were used only for candidate-region screening; production grid direct CFD samples were used to determine nondominance. Strict fold-wise leave-one-out cross-validation gave  $Q^2 = 0.173$  globally and RMSE = 0.001399 and  $Q^2 = 0.683$  in the predefined 18-sample decision region, indicating local screening utility rather than global surrogate validation. The direct CFD audit identified 13 globally and seven locally nondominated samples; both previously selected test configurations were dominated after CFD back-substitution. Their three grid drag sequences were monotonic but non-asymptotic. Pressure drag comprised 75.88–79.20% of total drag. However, the reduction in the low-drag test configuration relative to the baseline arose mainly from a lower viscous contribution; axial pressure fields therefore indicate redistribution rather than exclusive drag-reduction causation. Paired CFD samples showed that the sign of the drag responded to  $N$  reversal between the two sampled  $L_{nose}$  values, whereas analytical volume increased with  $N$  in both pairs. The results reveal a discrete, configuration-dependent drag volume trade-off and local  $N$ - $L_{nose}$  coupling. The rectangular regions are sampling envelopes rather than validated optimum windows, and the conclusions are restricted to steady, deeply submerged, smooth-wall bare-hull conditions.

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## 1. Introduction

Autonomous underwater vehicles (AUVs) have become important platforms for marine surveying, deep sea observation, seabed resource exploration, pipeline inspection, environmental monitoring, and defense-related operations. For such vehicles, hy-

hydrodynamic drag directly affects propulsion power, cruising speed, endurance, payload capacity, and mission range. Therefore, hydrodynamic shape design remains a central problem in AUV system design and motion control-oriented marine engineering [1,2]. From a classical hydrodynamic perspective, reducing resistance is closely associated with controlling pressure distribution, viscous shear, flow separation, and wake development around submerged bodies. These issues have long been treated as fundamental design concerns in both aerodynamic and submarine hydrodynamic design [3,4].

Conventional underwater vehicles generally employ slender bodies with relatively large length to diameter ratios and gradually tapered sterns. These configurations provide sufficient axial distance for flow acceleration, pressure recovery, and boundary layer development. Smooth axial area variation and continuous afterbody contraction can consequently mitigate adverse pressure gradients and reduce separation-related losses [5,6]. Modern AUV requirements, however, increasingly favor compact hulls with greater internal volume efficiency. Large-capacity batteries, modular acoustic payloads, propulsion integration, and multi-mission equipment must often be accommodated within a restricted overall length. Some compact designs therefore retain a constant-diameter mid-body and terminate in a flat or truncated stern. Although these features facilitate system integration, their hydrodynamic behavior differs from that of classical slender bodies.

A flat-ended AUV can preserve a larger mid-to-aft cross-sectional area and provide more usable internal space within a limited overall length. Nevertheless, the absence of a tapered pressure-recovery stern also promotes a low-pressure wake behind the truncated aft end. In this situation, the total drag is not determined by the forebody shape alone. Instead, it is governed by the coupled effects of forebody acceleration, suction peak development, pressure recovery near the shoulder region, boundary layer evolution, and aft-end wake loss. The DARPA SUBOFF benchmark has provided a widely used reference geometry for validating numerical methods for axisymmetric underwater bodies, but its relatively slender and non-flat-ended configuration differs fundamentally from the compact, high-volume, flat-ended AUV considered in the present study [7]. Therefore, additional interpretation is required when classical slender-body design principles are extended to low  $L/D$  flat-ended AUVs.

Myring's theory of axisymmetric bodies of revolution provides an analytical basis for parameterizing underwater vehicles' forebodies and afterbodies [5]. Such parameterizations are frequently combined with computational fluid dynamics and multi-objective optimization. NSGA-II provides an established framework for identifying candidate trade-offs when drag reduction conflicts with internal volume retention [8]. For computationally expensive CFD problems, design-of-experiments methods, Gaussian process regression, efficient global optimization and related surrogate approaches can reduce the number of required evaluations and identify promising regions of the design space [9–12].

Previous AUV studies have demonstrated the value of CFD-based parametric optimization for resistance reduction and hull form development. Gao et al. investigated CFD-based AUV hull optimization, Sun et al. developed a bio-inspired surrogate-assisted framework, and Hou et al. combined Kriging with multi-objective optimization for a small underwater vehicle [13–15]. Recent surveys have synthesized CFD-based assessments of AUV hydrodynamic performance and traditional, system identification-, and AI-based approaches for estimating AUV hydrodynamic coefficients [16–19]. Recent application studies have further advanced forebody resistance analysis, continuous adjoint hull-form optimization, and CFD-guided drag-reduction design for underwater vehicles [20–22]. A complementary validated seakeeping study illustrates the broader point that numerical credibility must be established for the specific operat-

ing condition and hydrodynamic response being considered [23]. Together, all this literature confirms that CFD-based optimization and data-assisted screening are well-established engineering tools; however, it does not by itself resolve how forebody geometry, pressure redistribution, viscous effects, flat-base wake loss, and internal volume interact in a compact flat-ended AUV.

The scientific question addressed here is how a compact, flat-ended AUV trades hydrodynamic resistance against gross internal volume when forebody geometry and flat-base wake loss are coupled. The restricted axial length links forebody acceleration, pressure redistribution, boundary layer development, and persistent base wake. Meanwhile, variations in  $N$  and  $L_{nose}$  modify the gross internal volume. The response is therefore examined as a sampled drag volume trade-off rather than as evidence of a single governing drag component or a universally valid optimum region [3–6,13–16].

The present study considers a low-slenderness-ratio, flat-ended AUV with  $L = 0.8$  m,  $D = 0.2$  m, and  $L/D = 4.0$ . Its generalized Myring forebody is parameterized by the nose shape parameter  $N$  and nose length  $L_{nose}$ . A database of 53 steady three-dimensional RANS/SST  $k-\omega$  simulations is used for Gaussian-process-assisted candidate region screening. Final interpretation is based on production grid direct CFD nondominance, CFD back-substitution, three-grid reassessment, fine-grid force decomposition, axial pressure coefficient distributions, and paired finite-change comparisons.

The contribution is threefold. First, the study separates surrogate-based candidate screening from sample-level direct CFD nondominance. Second, it quantifies the drag volume contrast among the baseline and two previously evaluated test configurations while distinguishing absolute pressure drag dominance from the force component responsible for their drag differences. Third, it identifies a discrete direct CFD-supported compromise set and evaluates local  $N$ - $L_{nose}$  coupling using paired finite changes. The resulting evidence defines a sampled, non-rectangular trade-off rather than a universally valid parameter interval.

The remainder of this paper is organized as follows. Section 2 defines the geometry, numerical method, validation hierarchy, sampling strategy, surrogate model, and direct CFD comparison framework. Section 3 presents the surrogate diagnostics, direct CFD dominance audit, three-grid reassessment, force decomposition, pressure recovery characteristics, and paired finite changes. Section 4 discusses the physical interpretation, engineering implications, predictive limitations, and applicability of the results. Section 5 summarizes the principal conclusions.

## 2. Materials and Methods

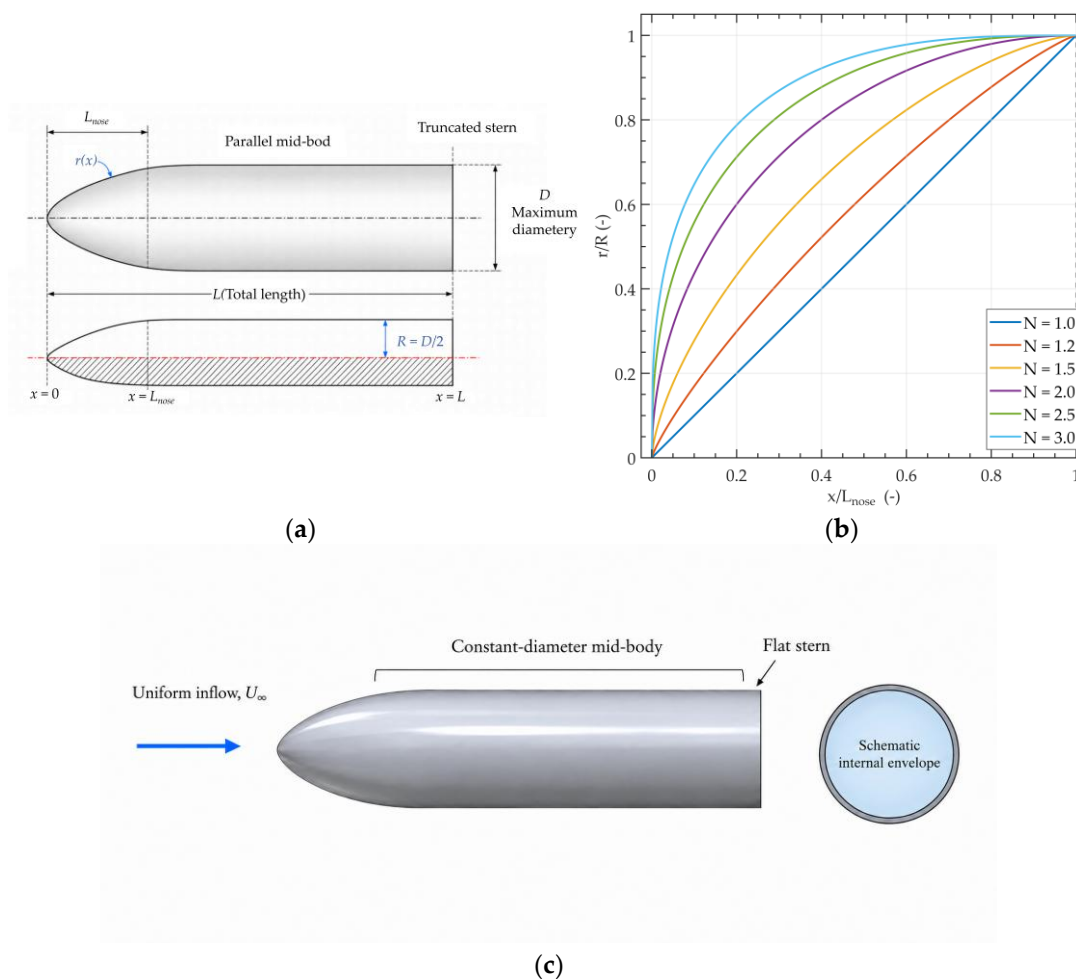
### 2.1. Low- $L/D$ Truncated AUV Geometry and Generalized Myring Parameterization

The research object is a low slenderness ratio, flat-ended AUV. The hull consists of a generalized Myring forebody and a parallel mid-body segment, while the stern is represented by a vertical flat-end cross-section rather than a conventional conical or tapered afterbody. The main geometric parameters include the total hull length  $L$ , maximum diameter  $D$ , maximum radius  $R = D/2$ , nose length  $L_{nose}$ , axial coordinate  $x$ , and local radius  $r(x)$ . In this study,  $L$  is fixed at 0.8 m and  $D$  at 0.2 m, corresponding to  $L/D = 4.0$ . CFD calculations use Ansys Fluent 2022 R1 software.

The fixed  $L/D = 4.0$  hull is used as an intentionally compact reference archetype rather than as a universal representation of modular AUVs. With  $L = 0.8$  m and  $D = 0.2$  m, the baseline geometry provides an integrated internal volume of approximately 0.02223 m<sup>3</sup> (22.23 L), while retaining a constant-diameter mid to aft compartment and a planar aft interface compatible with modular payload or propulsion integration. This geometry deliberately suppresses the conventional tapered afterbody pressure recovery length, thereby exposing the coupling among forebody pressure recovery, flat-base wake loss,

and packaging volume. The resulting numerical values should therefore be interpreted within this severe compact-hull design regime [1,4–6,16,20].

Figure 1 illustrates the geometric parameterization. The nose starts at  $x = 0$  and smoothly connects to the parallel mid-body segment of maximum radius  $R$  at  $x = L_{nose}$ . The parallel mid-body extends to  $x = L$  and terminates at a flat stern. The shape parameter  $N$  controls the sharpness or bluntness of the generalized Myring forebody. Under the same  $L_{nose}$  and  $R$ , a smaller  $N$  produces a sharper nose, which can reduce the high-pressure stagnation region but reduces usable forebody volume. A larger  $N$  produces a more rounded nose, which can preserve more internal volume but may strengthen the local pressure gradient and pressure drag. Therefore,  $N$  and  $L_{nose}$  are selected as the primary design variables.



**Figure 1.** Geometric definition and generalized Myring forebody parameterization of the low-slenderness-ratio, flat-ended AUV. (a) Definition of the overall length  $L$ , nose length  $L_{nose}$ , maximum radius  $R$ , constant-diameter mid-body, and planar stern. (b) Normalized forebody profiles  $r/R$  as functions of  $x/L_{nose}$  for  $N = 1.0, 1.2, 1.5, 2.0, 2.5$ , and  $3.0$ ; the dashed line at  $x/L_{nose} = 1$  marks the forebody mid-body junction. (c) Schematic representation of the uniform-inflow direction, constant-diameter mid-body, flat stern, and geometric internal envelope. The internal envelope denotes gross geometric accommodation rather than usable payload volume. Panels (a,c) are schematic.

The forebody radius is described by the generalized Myring equation

$$r(x) = R \left[ 1 - \left( 1 - \frac{x}{L_{nose}} \right)^N \right]^{1/N}, \quad 0 \leq x \leq L_{nose} \quad (1)$$

where  $x$  is the axial coordinate,  $L_{nose}$  is the nose length, and  $N$  is the Myring shape parameter. When  $N \approx 1$ , the nose tends toward a conical or sharp profile; when  $N = 2$ , the nose approaches a semi ellipsoidal profile; and when  $N > 2$ , the nose becomes more rounded. For the parallel mid-body segment,

$$r(x) = R, \quad L_{nose} < x \leq L \quad (2)$$

The design-variable ranges are  $1.0 \leq N \leq 3.0$  and  $150 \text{ mm} \leq L_{nose} \leq 350 \text{ mm}$ . The internal volume of the complete 360-degree body of revolution is obtained by geometric integration,

$$V = \pi \int_0^{L_{nose}} r^2(x) dx + \pi R^2 (L - L_{nose}) \quad (3)$$

The integral can also be written in analytical form as

$$V = \pi R^2 \left[ (L - L_{nose}) + L_{nose} \cdot \frac{1}{N} B\left(\frac{1}{N}, 1 + \frac{2}{N}\right) \right] \quad (4)$$

where  $B$  is the Beta function. In the sampling and surrogate-modeling stages,  $L_{nose}$  is expressed in millimeters. In geometry generation and volume integration, it is converted to meters. MATLAB R2025a numerical integration and the analytical expression were cross-checked to avoid volume errors caused by unit inconsistency. The fixed geometric quantities, design variable bounds, and objective definitions used throughout the study are summarized in Table 1.

**Table 1.** Geometric constants, design variables, and objective functions.

| Category          | Symbol     | Value/Range | Unit           | Description                      |
|-------------------|------------|-------------|----------------|----------------------------------|
| Total length      | $L$        | 0.8         | m              | AUV total length                 |
| Maximum diameter  | $D$        | 0.2         | m              | Maximum body diameter            |
| Maximum radius    | $R$        | 0.1         | m              | $D/2$                            |
| Slenderness ratio | $L/D$      | 4.0         | —              | Low- $L/D$ configuration         |
| Shape parameter   | $N$        | 1.0–3.0     | —              | Generalized Myring nose exponent |
| Nose length       | $L_{nose}$ | 150–350     | mm             | Axial nose length                |
| Objective 1       | $C_D$      | Minimize    | —              | Total drag coefficient           |
| Objective 2       | $V$        | Maximize    | m <sup>3</sup> | Internal volume                  |

## 2.2. Governing Equations and Turbulence Model

The numerical simulations are based on the three-dimensional incompressible Reynolds-averaged Navier–Stokes (RANS) equations. The continuity and momentum equations are written as

$$\frac{\partial \bar{u}_i}{\partial x_i} = 0 \quad (5)$$

$$\rho \bar{u}_j \frac{\partial \bar{u}_i}{\partial x_j} = - \frac{\partial \bar{p}}{\partial x_i} + \frac{\partial}{\partial x_j} \left[ \mu \left( \frac{\partial \bar{u}_i}{\partial x_j} + \frac{\partial \bar{u}_j}{\partial x_i} \right) - \rho \overline{u_i u_j} \right] \quad (6)$$

The incompressibility assumption is appropriate for the single operating condition considered in the present study. For fresh water near 25 °C, the acoustic speed is approximately  $c = 1.50 \times 10^3 \text{ m/s}$ , giving  $Ma = U/c \approx 1.3 \times 10^{-3}$  at  $U = 2.0 \text{ m/s}$ . The corresponding free-stream dynamic pressure is  $q_\infty = 0.5 \rho U^2 = 1.996 \text{ kPa}$ . Using the acoustic estimate  $K = \rho c^2 \approx 2.24 \text{ GPa}$  for the bulk modulus, a hydrodynamic pressure variation of order  $q_\infty$  gives  $\Delta \rho / \rho \sim 9 \times 10^{-7}$ ; even a deliberately conservative pressure excursion of  $5q_\infty$  gives only  $\Delta \rho / \rho \approx 4.5 \times 10^{-6}$ . Density variations associated with the resolved hydrody-

dynamic pressure field are therefore negligible, supporting the incompressible RANS formulation adopted here [24,25]. This justification is restricted to the present low-Mach, single phase external flow model in which cavitation is not represented and should not be interpreted as an assessment of compressibility at arbitrary hydrostatic depths or under cavitating conditions.

Because the low  $L/D$  flat-ended AUV may experience strong adverse pressure gradients near the forebody to mid body transition and in the truncated stern wake, the SST  $k-\omega$  turbulence model is adopted. The SST  $k-\omega$  model combines the near-wall advantages of the  $k-\omega$  formulation with the far-field robustness of the  $k-\varepsilon$  formulation, and is widely used for engineering flows involving adverse pressure gradients and separation [26–28]. Recent high-fidelity simulations of marine energy devices have further shown that wave–current coupling, imposed platform motion, and wake vortex interaction can substantially modulate hydrodynamic loads and wake structures in complex marine external flows [29]. This reinforces the need for a turbulence-modeling strategy that can provide stable predictions for adverse-pressure-gradient and wake-dominated flow features, although the present study focuses on steady RANS-based resistance prediction rather than fully resolved unsteady turbine–wave interaction.

The Reynolds number based on the total hull length is

$$Re = \frac{UL}{\nu} \approx 1.6 \times 10^6 \quad (7)$$

The drag coefficient, pressure coefficient, and drag decomposition are defined as

$$C_D = \frac{D_T}{0.5\rho U^2 A_{ref}} \quad (8)$$

$$C_p = \frac{P - P_\infty}{0.5\rho U^2} \quad (9)$$

The total drag was decomposed by the direct integration of the mean surface traction over the complete wetted hull surface  $S_w$ , comprising the forebody, the constant-diameter side surface, and the planar flat base. With  $\mathbf{n}$  denoting the unit normal directed from the solid into the fluid,  $\boldsymbol{\tau}$  the mean viscous stress tensor, and  $\mathbf{e}_x$  the unit vector aligned with the incoming flow, the total drag and its pressure and viscous contributions are written as

$$D_T = \int_{S_w} \{[-(p - p_\infty)\mathbf{n} + \boldsymbol{\tau} \cdot \mathbf{n}] \cdot \mathbf{e}_x\} dS = D_p + D_v \quad (10)$$

$$D_p = \int_{S_w} [-(p - p_\infty)\mathbf{n}] \cdot \mathbf{e}_x dS, D_v = \int_{S_w} (\boldsymbol{\tau} \cdot \mathbf{n}) \cdot \mathbf{e}_x dS \quad (11)$$

Here,  $S_w$  is the complete wetted hull surface,  $p_\infty$  is the imposed far field pressure reference, and the sign convention is chosen such that a positive  $D_T$  denotes the drag magnitude in the incoming flow direction, equivalent to the resistance opposing vehicle motion.

$$C_{D,k} = \frac{D_k}{\frac{1}{2}\rho U^2 A_{ref}}, k \in \{T, p, v\} \quad (12)$$

$$\eta_p = \frac{D_p}{D_T} = \frac{C_{D,p}}{C_D}, \eta_v = \frac{D_v}{D_T} = 1 - \eta_p \quad (13)$$

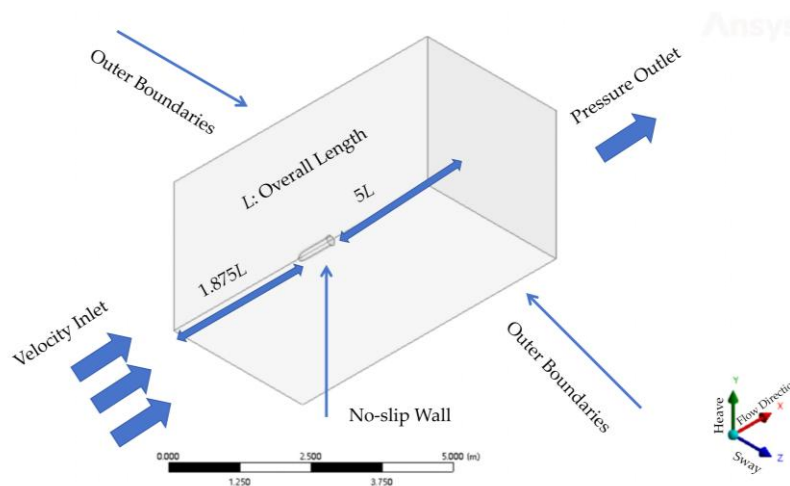
The axial pressure and viscous forces were extracted separately from the solver wall-force reports using the direction vector (1, 0, 0). All integrations were performed over the same complete wetted surface, rather than over selected forebody or base patches. The reference area was the maximum cross-sectional area,  $A_{ref} = \pi R^2 = \pi D^2/4 = 0.0314 \text{ m}^2$ , and the same values of  $A_{ref}$ ,  $\rho$ ,  $U$ , and  $p_\infty$  were applied to every target hull configuration and mesh level. Thus, the reported component differences arise from the computed wall tractions rather than from changes in the normalization convention

[24,25,30]. The SUBOFF reference area convention remains as specified separately in Section 2.4.1.

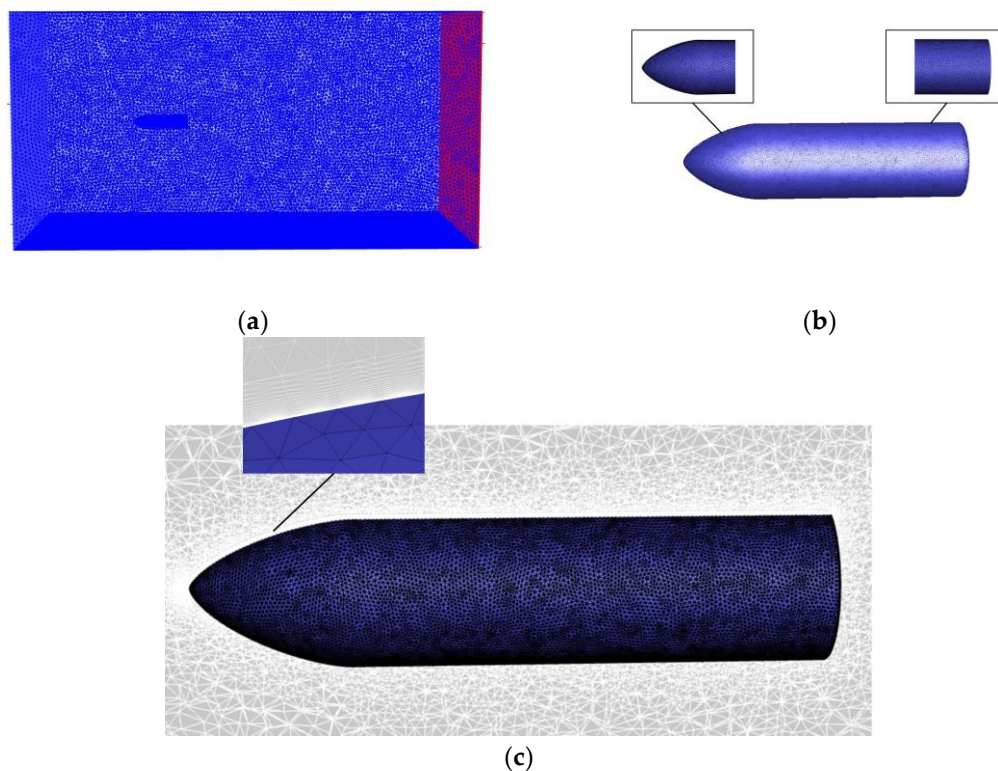
### 2.3. Computational Domain, Boundary Conditions and Physical Properties

To reduce boundary interference on the flow around the AUV and the development of the wake, a three-dimensional rectangular external flow computational domain is established. The coordinate origin is located at the AUV nose, with the  $x$ -axis aligned with the incoming flow direction, the  $y$ -axis vertical, and the  $z$  axis lateral. The inlet boundary is positioned  $1.875L$  upstream of the nose, the outlet boundary is placed  $5L$  downstream of the flat stern, and the radial far-field boundary is approximately  $1.875L$  from the hull surface. This domain size is selected as a compromise between wake capturing capability and computational cost, while reducing the sensitivity of the low-pressure wake behind the flat stern to the outlet boundary [24,30]. The same outer computational control volume and boundary locations were retained for the baseline, low drag test, and trade-off test configurations at all three grid levels. The outer control volume boundaries were not used to partition the drag; the pressure and viscous components were obtained exclusively from traction integration over the complete wetted hull surface.

The upstream boundary is specified as a velocity inlet with a uniform free-stream velocity of  $U = 2.0$  m/s. The downstream boundary is specified as a pressure outlet. The top, bottom, and lateral boundaries are defined as symmetry boundaries, and the AUV surface is treated as a no-slip wall. The working fluid is fresh water at  $25^\circ\text{C}$  and is treated as incompressible on the quantitative basis established in Section 2.2, with density  $\rho = 998.2$  kg/m<sup>3</sup> and kinematic viscosity  $\nu = 1.003 \times 10^{-6}$  m<sup>2</sup>/s. The computational domain layout and boundary assignments are shown in Figure 2, while the surface, near wall, and local-refinement meshes used for the target hull simulations are illustrated in Figure 3.



**Figure 2.** Computational domain and boundary conditions used for the external-flow simulations. The inlet is located  $1.875L$  upstream of the nose, the outlet is located  $5L$  downstream of the vehicle, and the hull surface is treated as a no-slip wall.



**Figure 3.** The mesh setup for the blunt-nosed AUV includes: (a) the three-dimensional external flow field computational domain and the relative position of the AUV within the computational domain; (b) the distribution of grids on the hull surface and the localized refined regions at the bow and stern; (c) the near-hull flow field mesh and the localized refined region near the hull.

All target hull simulations are performed under the single operating condition summarized in Table 2. For  $U = 2.0$  m/s,  $L = 0.8$  m, and fresh water at  $25$  °C with  $\rho = 998.2$  kg/m<sup>3</sup> and  $\nu = 1.003 \times 10^{-6}$  m<sup>2</sup>/s, the length-based Reynolds number is  $Re_L = UL/\nu \approx 1.60 \times 10^6$ . The simulations represent a fully submerged bare hull in uniform inflow, sufficiently remote from the free surface and seabed for surface wave, blockage, and bottom-boundary effects to be neglected. Because gravity, cavitation, and a free surface are not included, absolute hydrostatic depth is not an input to the numerical model. The conclusions therefore apply to the idealized deep submergence external-flow condition rather than to a specified operational depth [1,2,24,25,30].

**Table 2.** CFD computational setup.

| Item                        | Setting                                  |
|-----------------------------|------------------------------------------|
| Governing equations         | 3D incompressible RANS                   |
| Turbulence model            | SST k- $\omega$                          |
| Fluid                       | Fresh water at $25$ °C                   |
| Density                     | $998.2$ kg/m <sup>3</sup>                |
| Kinematic viscosity         | $1.003 \times 10^{-6}$ m <sup>2</sup> /s |
| Inlet velocity              | $2.0$ m/s                                |
| Outlet                      | Pressure outlet                          |
| Wall condition              | No slip wall                             |
| Far-field boundary          | Symmetry                                 |
| Reference area              | Maximum cross-sectional area $\pi R^2$   |
| Target near-wall resolution | $y^+ \leq 1$                             |

## 2.4. Numerical Validation and Mesh-Sensitivity Diagnosis

This study employs a three-level numerical credibility chain. The first level comprises two complementary benchmark assessments. The DARPA SUBOFF AFF-1 case evaluates the integrated-resistance procedure for a streamlined axisymmetric underwater body [7,31,32], whereas the sharp-edged axisymmetric blunt-base experiment of Mariotti and Buresti evaluates the mean pressure deficit and recirculating near wake produced by fixed separation at a flat base [33,34]. The second level is the pre-optimization production grid selection for the target flat-ended AUV, which establishes a unified mesh strategy for the parametric CFD database. The third level is the coarse/medium/fine-grid reassessment of the previously selected CFD evaluated test configurations, which examines whether the ranking of the previously selected low-drag CFD test configuration and the previously selected trade-off CFD test configuration remains stable under refinement. These levels address different numerical questions and are not interpreted as interchangeable or as universal validation of all wake quantities.

### 2.4.1. SUBOFF Benchmark Validation

For the SUBOFF benchmark validation, the AFF-1 unappended bare hull has axisymmetric geometric characteristics under zero angle of attack and uniform inflow. Therefore, a two-dimensional axisymmetric meridional-plane model is used. This is not a planar half-model simplification, but a physically motivated dimensional reduction based on the axisymmetric governing formulation. For zero-angle-of-attack bare-hull drag prediction, this approach preserves the main mechanisms directly related to drag, including axial pressure recovery, boundary-layer development, wall shear, wake pressure drag, and surface pressure integration.

The SUBOFF validation conditions are defined by a model hull length of  $L = 4.356$  m and a uniform incoming-flow velocity of  $U = 2.0$  m/s. The reference area follows the wetted-surface-area convention of  $5.98$  m<sup>2</sup> used in the public benchmark dataset. The computed total drag coefficient is  $C_D = 0.003149$ , which differs by approximately 1.58% from the public EFD/LES benchmark range of 0.00310–0.00320. This result indicates that the RANS/SST  $k-\omega$  model, near-wall mesh treatment, and drag-integration procedure adopted in this study can reasonably predict the resistance of typical axisymmetric underwater bodies of revolution within the present validation range.

The SUBOFF validation should be interpreted as the first level of numerical-method validation rather than as direct proof of complete reliability for the three-dimensional wake prediction of the target low- $L/D$  flat-ended AUV. SUBOFF AFF-1 and the present AUV differ in slenderness ratio, stern geometry, and wake structure. A two-dimensional axisymmetric model cannot capture non-axisymmetric wake features, body interference effects, or fully three-dimensional unsteady separation. Therefore, the three dimensional mesh-sensitivity diagnosis of the target AUV and the fine-grid reassessment of key candidate configurations are the direct numerical evidence supporting the final design conclusions. The validated SUBOFF solution is subsequently reused in Section 4.1 only as a dimensionless tapered-body reference for comparing the upper meridian pressure distribution and centerline mean wake velocity; it is not treated as a geometrically matched stern control configuration.

### 2.4.2. Complementary Sharp-Edged Blunt-Base Benchmark

To complement the streamlined SUBOFF assessment, the smooth axisymmetric blunt-based experiment of Mariotti and Buresti [33] was reproduced because its sharp circular base imposes fixed separation and generates the base-pressure deficit that is absent from the tapered SUBOFF stern. The experimental body had  $D/L = 0.175$  and was tested in air at  $Re_D = 9.6 \times 10^4$ . A geometrically similar model with  $D = 0.100$  m and  $L =$

0.5714 m was therefore simulated at  $U = 14.023$  m/s using air with  $\rho = 1.225$  kg/m<sup>3</sup> and  $\mu = 1.7894 \times 10^{-5}$  kg/m s, giving  $Re_D = 9.6 \times 10^4$  and  $Re_L$  approximately  $5.49 \times 10^5$ . The Mach number was approximately 0.041; hence compressibility effects were negligible. Although the working fluid differs from that used for the target AUV, this case tests an incompressible, single-phase, dimensionless separation problem. Under geometric and Reynolds-number similarity, the normalized mean-pressure and recirculation quantities are governed by the same nondimensional equations; the case is therefore appropriate for assessing the blunt-base component of the numerical method, but not free-surface, cavitation, transition, or water-specific operational effects [33,35,36].

The same three dimensional steady RANS/SST  $k-\omega$  formulation and smooth no slip wall treatment were retained. Three systematically refined meshes contained 4.128, 5.358, and 7.100 million cells. The total drag coefficient changed from 0.2902 to 0.2850 from the coarse to the fine grid, a spread of 1.83%, while  $Lr/D$  remained between 0.971 and 0.984, with a maximum pairwise spread of 1.24%. All meshes satisfied  $\text{Max } y^+ < 0.52$ . Because the sequence did not exhibit a demonstrably asymptotic response for every quantity, these results are reported as a mesh-sensitivity envelope rather than as a formal grid-convergence index estimate [30,35–39].

For a definition-consistent pressure comparison, the numerical mean base-pressure coefficient was area-averaged only over  $r/D \leq 0.4$ , matching the experimental pressure-tap coverage. The fine-grid clipped area was  $5.0211 \times 10^{-3}$  m<sup>2</sup>, within 0.108% of the analytical disk area, confirming the extraction region. The resulting value,  $\overline{C_{p,b}} (r/D \leq 0.4) = -0.1403$ , is compared with the measured smooth-model value of  $-0.160$  in Table 3 [33]. The corresponding relative difference in pressure-deficit magnitude is 12.32%. Thus, the calculation reproduces the negative mean base pressure and its order of magnitude, but underpredicts the central-base suction. This discrepancy is retained as a quantitative model-form/configuration limitation of steady RANS for an intrinsically unsteady separated wake, rather than being concealed by a claim of exact agreement. Possible contributors include unresolved wake unsteadiness, differences in the separating boundary layer state, and omission of the experimental support-induced asymmetry [33,34]. The measured recirculation length was inferred from fluctuation maxima, whereas the present  $Lr$  was obtained from the downstream zero crossing of centerline mean axial velocity; consequently,  $Lr/D$  is reported as a grid-robustness diagnostic, and no formal experimental error is assigned to it [33,34].

**Table 3.** Direct quantitative comparison.

| Quantity                                       | Experiment [33]                             | Fine-Grid CFD                       | Difference/Interpretation                    |
|------------------------------------------------|---------------------------------------------|-------------------------------------|----------------------------------------------|
| Mean base-pressure coefficient, $r/D \leq 0.4$ | −0.160                                      | −0.1403                             | 12.32% lower pressure-deficit magnitude      |
| $Lr/D$                                         | Indirectly inferred from fluctuation maxima | 0.971 (mean-velocity zero crossing) | No formal error assigned; definitions differ |

#### 2.4.3. Target-AUV Production-Grid Selection for the 53 Sample Database

A three-dimensional coarse/medium/fine-grid sensitivity assessment was first performed for the baseline target AUV to define a common production mesh for the subsequent 53-sample CFD database. This step was completed before surrogate-model training and candidate-region screening. Its purpose was to establish a consistent mesh for comparative sampling rather than to demonstrate grid independence for every sampled configuration. The two previously selected CFD test configurations were subsequently

reassessed on three grids and were not used retrospectively to justify the production grid selection.

The three mesh configurations use the same geometry, computational-domain dimensions, boundary conditions, turbulence model, material properties, reference area, residual criteria, drag monitoring method, and drag integration surfaces. Only the global mesh scale, hull surface mesh size, and first-layer mesh height are varied. The target linear refinement ratio is 1.30. For a three-dimensional unstructured mesh, the equivalent grid scale of mesh level  $i$  is defined as

$$h_i = \left( \frac{V_\Omega}{N_i} \right)^{\frac{1}{3}} \quad (14)$$

where  $V_\Omega$  is the computational domain volume and  $N_i$  is the actual number of cells in mesh level  $i$ . In the present notation,  $i = 1, 2$ , and  $3$  denote the fine, medium, and coarse grids, respectively. Because the same computational domain is used for all three grids,  $V_\Omega$  cancels when the adjacent refinement ratios are evaluated. The refinement ratios are therefore defined as

$$\begin{cases} r_{21} = \frac{h_2}{h_1} = \left( \frac{N_1}{N_2} \right)^{\frac{1}{3}} \\ r_{32} = \frac{h_3}{h_2} = \left( \frac{N_2}{N_3} \right)^{\frac{1}{3}} \end{cases} \quad (15)$$

Using the actual cell counts reported in Table 4, the resulting fine-to-medium and medium-to-coarse refinement ratios are  $r_{21} = 1.3058$  and  $r_{32} = 1.2772$ , respectively. Both values are close to the target ratio of 1.30 and therefore support an approximately systematic refinement sequence. The resulting mesh settings and near-wall quality metrics are summarized in Table 4.

**Table 4.** Baseline three-grid mesh settings and near-wall quality metrics used for production-grid selection.

| Mesh      | Cells ( $10^6$ ) | Actual r          | Global Size | Surface Size | First Layer (m)       | Layers | Growth | Mean y+ | Max y+ |
|-----------|------------------|-------------------|-------------|--------------|-----------------------|--------|--------|---------|--------|
| G1 Fine   | 6.933958         | -                 | 0.0339      | 0.00339      | $1.00 \times 10^{-5}$ | 30     | 1.15   | 0.4272  | 0.5953 |
| G2 Medium | 3.114564         | $r_{21} = 1.3058$ | 0.0500      | 0.00500      | $1.30 \times 10^{-5}$ | 30     | 1.15   | 0.5551  | 0.7756 |
| G3 Coarse | 1.495075         | $r_{32} = 1.2772$ | 0.0695      | 0.00695      | $1.69 \times 10^{-5}$ | 30     | 1.15   | 0.7199  | 1.0116 |

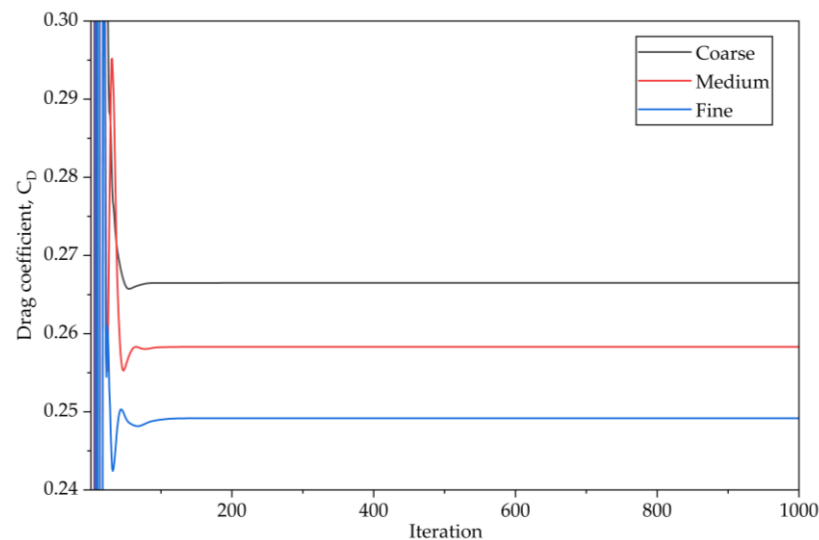
The corresponding drag coefficient monitoring statistics and decomposed force components are summarized in Table 5. Here,  $C_{D,avg}$  is the arithmetic mean over the final 300 iterations,  $C_{D,last}$  is the terminal iteration value, and  $C_{D,fluct}$  is the peak-to-peak range over the same 300 iteration window normalized by  $C_{D,avg}$ . Reporting these quantities together verifies that the mean used for the grid comparison is drawn from a stable monitoring plateau and is not controlled by an anomalous final iteration.  $D_T$ ,  $D_p$ , and  $D_v$  are the mean total, pressure, and viscous drag forces integrated over the complete wetted surface, with  $D_T = D_p + D_v$ . The force columns therefore provide a component-level closure check and the baseline decomposition subsequently extended in Section 3.7. The average drag coefficients for the fine, medium, and coarse meshes are 0.2492, 0.2583, and 0.2665, respectively. As the mesh is refined,  $C_D$  decreases monotonically, indicating that the integral drag of the target AUV is sensitive to spatial discretization. The fine-to-medium difference is approximately 3.66%, and the medium-to-coarse difference is approximately 3.17%. Therefore, the medium mesh should not be interpreted as an absolutely mesh-independent mesh for absolute drag prediction, but rather as a unified production mesh that balances computational cost and trend identification. On the same computing platform and under identical solver and parallel settings, a representative target AUV case

required approximately 40 min on the medium grid and 70 min on the fine grid. The medium grid therefore reduced the per case wall clock time by approximately 43% relative to the fine grid, a material saving for the 53-sample production database.

**Table 5.** Baseline three-grid drag-coefficient monitoring statistics and force decomposition.

| Mesh      | $C_{D,avg}$ | $C_{D,last}$ | $C_{D,fluct}$ (%) | $D_T$ (N) | $D_p$ (N) | $D_v$ (N) |
|-----------|-------------|--------------|-------------------|-----------|-----------|-----------|
| G1 Fine   | 0.249175827 | 0.249175787  | 0.000226          | 15.6201   | 11.9111   | 3.7090    |
| G2 Medium | 0.258303674 | 0.258303981  | 0.000678          | 16.1923   | 12.4555   | 3.7367    |
| G3 Coarse | 0.266489626 | 0.266489655  | 0.000176          | 16.7054   | 12.9371   | 3.7683    |

To confirm that the drag statistics are not affected by initial transients, Figure 4 presents the complete 1–1000 iteration  $C_D$  monitoring histories for the baseline configuration on the three grid levels. All three histories reach stable plateaus after the initial adjustment. The final-window statistics reported in Table 5, rather than a separate magnified inset, quantify the residual monitoring variation and show that the grid-to-grid differences reflect stable spatial discretization responses rather than iterative non-convergence.



**Figure 4.** Drag-coefficient monitoring histories for the baseline configuration on the coarse, medium, and fine grids over iterations 1–1000. Final-window monitoring statistics are reported in Table 5.

A Richardson diagnostic further shows that although the grid response is monotonic, the medium–fine difference is not smaller than the coarse–medium difference. Therefore, the standard asymptotic convergence condition is not strictly satisfied, and the apparent order obtained by mechanical application of the Richardson formula is not physically meaningful. Consequently, the production grid selection results are used as a mesh sensitivity diagnosis rather than as a strict GCI uncertainty statement. The medium grid is therefore adopted for all 53 production grid parametric CFD samples because it provides internally consistent relative drag responses at the quantified wall clock cost. In conjunction with the approximately systematic refinement sequence, low- $y^+$  near-wall resolution, stable drag monitoring plateau, and preservation of the principal cross-grid ordering documented in Section 3.5, this evidence supports the medium grid as an adequate common production mesh for the present comparative screening task; it is not interpreted as proof of mesh-independent absolute drag. Final absolute drag values and configuration-specific physical comparisons are therefore based primarily on the fine

grid reassessment of the representative configurations. The refinement ratios, adjacent grid differences, asymptotic-range diagnosis, and resulting production grid decision are summarized in Table 6.

**Table 6.** Summary of the baseline mesh-sensitivity diagnosis and production-grid selection.

| Diagnostic Item                                                                 | Value                               | Interpretation                                                                                                                                               |
|---------------------------------------------------------------------------------|-------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------|
| $r_{21}, r_{32}, r$                                                             | 1.3058, 1.2772, 1.2915              | Actual refinement ratios are close to the target value 1.30.                                                                                                 |
| $\delta_{21} = \frac{ C_{D,medium} - C_{D,fine} }{C_{D,fine}} \times 100\%$     | 3.66%                               | The medium grid is suitable for production search, but not for final absolute drag claims.                                                                   |
| $\delta_{32} = \frac{ C_{D,coarse} - C_{D,medium} }{C_{D,medium}} \times 100\%$ | 3.17%                               | Monotonic mesh sensitivity exists.                                                                                                                           |
| p diagnostic from Richardson formula                                            | −0.426                              | The grid family is monotonic but not in the standard asymptotic Richardson range.                                                                            |
| Production grid decision                                                        | Use medium grid for all CFD samples | Use as a consistent screening mesh for GPR/NSGA-II; representative CFD-evaluated test configurations undergo configuration-specific three-grid reassessment. |

### 2.5. Two-Stage CFD Sampling and Surrogate-Assisted Search

Forty initial designs were generated over  $1.0 \leq N \leq 3.0$  and  $150 \leq L_{nose} \leq 350$  mm to provide broad coverage of the two-dimensional design space. An initial GPR model was then used to guide targeted enrichment in two decision-relevant portions of the domain. Twelve additional production-grid CFD samples were evaluated: three in the low-drag boundary neighborhood and nine in the Pareto knee neighborhood. The baseline configuration,  $N = 1.5$  and  $L_{nose} = 200$  mm, was subsequently added, giving the final 53-sample GPR training database. This two-stage procedure follows the established use of adaptive sampling for computationally expensive surrogate-assisted design problems [9–12,40].

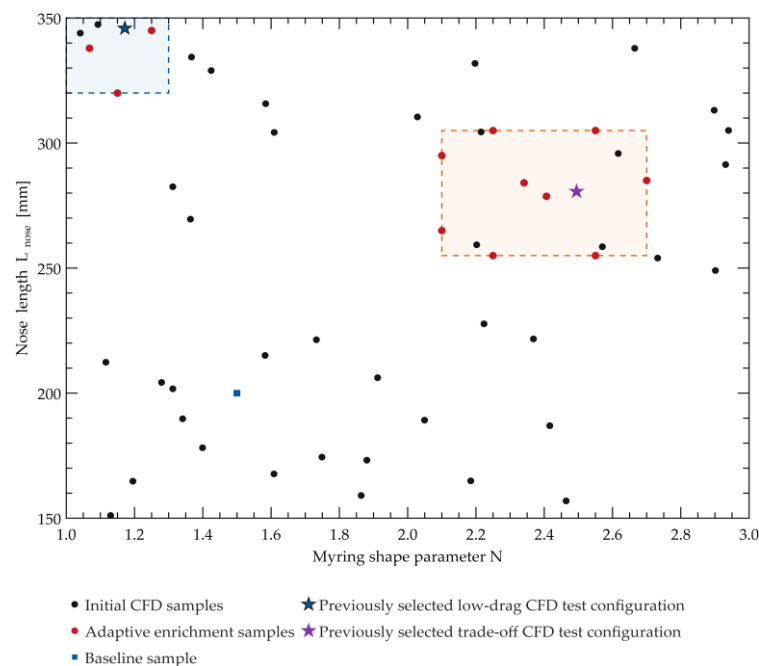
The two sampling neighborhoods were specified during the adaptive-enrichment stage, before examination of the strict LOOCV residuals. The low-drag neighborhood,  $1.0 \leq N \leq 1.3$  and  $320 \leq L_{nose} \leq 350$  mm, contains five CFD samples, comprising two initial and three adaptive samples. The Pareto knee neighborhood,  $2.1 \leq N \leq 2.7$  and  $255 \leq L_{nose} \leq 305$  mm, contains 13 samples, comprising four initial and nine adaptive samples. Their union defines the predefined 18-sample decision region used for the regional strict LOOCV diagnostics.

These coordinate bounds are operational sample-membership definitions rather than performance-based design criteria. They were not derived from thresholds on  $C_D$ , internal volume, pressure gradient, or wake metrics, and are therefore not interpreted as continuously valid optimum windows. The GPR model was used to guide sampling and identify screening locations, whereas final drag values and nondominance status were determined from direct CFD. Two previously screened coordinates were evaluated separately by production grid CFD and terminal three-grid reassessment; they are retained as CFD test configurations rather than as members of the 53-sample GPR training database, or as final optimized designs. The sampling stages and the distinct roles of the CFD evaluations are summarized in Table 7.

**Table 7.** Sampling stages and roles of the CFD evaluations.

| Sample Group                                | Region                                               | Purpose                                                                              |
|---------------------------------------------|------------------------------------------------------|--------------------------------------------------------------------------------------|
| Initial designs (n = 40)                    | $1.0 \leq N \leq 3.0, 150 \leq L_{nose} \leq 350$ mm | Broad design-space coverage and initial GPR construction                             |
| Low-drag enrichment (n = 3)                 | $1.0 \leq N \leq 1.3, 320 \leq L_{nose} \leq 350$ mm | Increase sampling density near the low-drag boundary                                 |
| Pareto knee enrichment (n = 9)              | $2.1 \leq N \leq 2.7, 255 \leq L_{nose} \leq 305$ mm | Increase local resolution of the sampled drag volume trade-off                       |
| Baseline configuration (n = 1)              | $N = 1.5, L_{nose} = 200$ mm                         | Provide a common CFD reference                                                       |
| Previously selected CFD test configurations | Two previously screened design coordinates.          | Production-grid CFD back-substitution and subsequent three-grid and flow-field audit |

The first four rows constitute the 53-sample GPR training database. The two previously selected CFD test configurations were evaluated separately and are retained for model auditing and physical comparison; they are not final direct CFD Pareto-optimal designs. Figure 5 shows the spatial distribution of the 53 production-grid CFD samples, the predefined adaptive sampling neighborhoods, and the two separately evaluated CFD test configurations; the complete numerical database is provided in Table A1.



**Figure 5.** Distribution of the 53 production-grid CFD samples and the predefined adaptive sampling neighborhoods in the  $N$ - $L_{nose}$  design space. Black circles denote the 40 initial designs, red circles denote the 12 adaptive-enrichment designs, and the blue square denotes the baseline configuration. The blue and orange dashed rectangles indicate the predefined low-drag and Pareto knee sampling neighborhoods, respectively. The blue and purple stars identify the two previously selected CFD test configurations evaluated separately from the 53 sample training database. The rectangles define sample membership for targeted enrichment and regional diagnostics; they are not continuously valid optimum windows.

## 2.6. GPR Surrogate Model and LOOCV Assessment

The input vector is  $x = [N, L_{nose}]^T$ , and the model output is the total drag coefficient  $C_D$  obtained from CFD. The input variables and the CFD response are standardized be-

fore model fitting to reduce the influence of their different numerical scales. The GPR representation is written as

$$\hat{C}_D(x) = m(x) + Z(x) \quad (16)$$

where  $m(x)$  is the deterministic trend function and  $Z(x)$  is a zero-mean Gaussian random process. A pure-quadratic trend function and an automatic relevance-determination squared-exponential covariance kernel are employed, allowing the two design variables to possess different characteristic length scales [10–12,40].

Surrogate performance is assessed through strict leave-one-out cross-validation rather than through fitted responses at the training locations. For each omitted sample  $i$ , the input and output normalization parameters are recomputed using only the remaining  $n - 1$  samples. The GPR covariance parameters and characteristic length scales are then re-estimated from these  $n - 1$  samples, after which the drag coefficient of the omitted sample is predicted. Consequently, every reported LOOCV value is obtained from a model that has not been trained using the corresponding CFD response.

The signed out of fold prediction error for sample  $i$  is defined as

$$e_i = \hat{C}_{D,i}^{(-i)} - C_{D,i}, \quad (17)$$

where  $C_{D,i}$  is the direct CFD value and  $\hat{C}_{D,i}^{(-i)}$  is the prediction from the GPR model fitted without sample  $i$ . A positive value of  $e_i$  denotes an overprediction of drag, whereas a negative value denotes underprediction.

The absolute predictive performance is quantified using the root mean square error, mean absolute error, maximum absolute error, mean signed bias, and mean absolute percentage error, as follows

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n e_i^2} \quad (18)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |e_i| \quad (19)$$

$$e_{\max} = \max_i |e_i| \quad (20)$$

$$\text{Bias} = \frac{1}{n} \sum_{i=1}^n e_i \quad (21)$$

$$MAPE = \frac{100\%}{n} \sum_{i=1}^n \left| \frac{e_i}{C_{D,i}} \right| \quad (22)$$

The cross-validated coefficient of determination is calculated as

$$Q^2 = 1 - \frac{\sum_{i=1}^n (C_{D,i} - \hat{C}_{D,i}^{(-i)})^2}{\sum_{i=1}^n (C_{D,i} - \bar{C}_D)^2} \quad (23)$$

where  $\bar{C}_D$  is the mean CFD drag coefficient of the evaluated subset.  $Q^2$  approaching unity indicates stronger cross-validated variance-explaining performance, whereas  $Q^2 < 0$  indicates that the out-of-fold predictions perform worse than the corresponding subset-mean predictor. Because the denominator depends on the response variance of the evaluated subset,  $Q^2$  can be sensitive when it is calculated for a small region with a narrow range of  $C_D$ . It is therefore interpreted together with MAE, RMSE, signed bias, MAPE, sample count, and the relative-error range, rather than in isolation.

To examine the internal calibration of the GPR predictive intervals, the standardized out-of-fold residual is defined as

$$z_i = \frac{\tilde{C}_{D,i}^{(-i)} - C_{D,i}}{s_i^{(-i)}} \quad (24)$$

where  $s_i^{(-i)}$  is the predictive standard deviation produced by the fold-specific GPR model. The proportions of samples satisfying  $|z_i| \leq 1$ ,  $|z_i| \leq 2$ , and  $|z_i| \leq 1.96$  are reported as internal interval-calibration diagnostics. These quantities remain conditional on the adopted covariance model and CFD database, and are not treated as independently calibrated probabilistic uncertainty bounds.

The diagnostics are first calculated over the complete 53-sample database and are then recomputed within the two predefined decision-relevant regions introduced in Section 2.5. The low-drag region is defined by  $1.0 \leq N \leq 1.3$  and  $320 \leq L_{nose} \leq 350$  mm, whereas the Pareto knee region is defined by  $2.1 \leq N \leq 2.7$  and  $255 \leq L_{nose} \leq 305$  mm. Metrics are reported separately for these two regions and for their 18-sample union. Because the region boundaries originate from the adaptive sampling strategy, they are not selected retrospectively on the basis of the LOOCV errors.

Mean signed bias is included specifically to identify systematic drag underprediction or overprediction within the candidate neighborhoods. However, neither global nor local LOOCV constitutes independent physical validation, and local cross-validation does not demonstrate reliable extrapolation beyond the sampled design space. The GPR model is used only for candidate-region screening. Database-wide drag values and nondominance status are determined from the common production-grid direct CFD dataset. The subsequent three-grid reassessment and hydrodynamic analyses are used only for configuration-specific numerical and physical interpretation [41].

## 2.7. Surrogate-Assisted Screening and Direct CFD Compromise-Set Definition

The drag volume screening problem was formulated by minimizing the GPR-predicted drag coefficient  $C_D(N, L_{nose})$  and maximizing the analytically evaluated internal volume  $V(N, L_{nose})$ . For implementation in the NSGA-II minimization framework, the second objective was expressed as  $-V$ . When a single illustrative screening representative was required, the two objectives were first min–max-normalized within the candidate set under consideration as

$$\tilde{C}_{D,i} = \frac{C_{D,i} - C_{D,\min}}{C_{D,\max} - C_{D,\min}}, \tilde{V}_i = \frac{V_i - V_{\min}}{V_{\max} - V_{\min}} \quad (25)$$

The corresponding normalized ideal point is  $(\tilde{C}_D, \tilde{V}) = (0, 1)$ . The weighted distance of candidate  $i$  from this ideal point was defined as

$$d_i = \left[ w_d \tilde{C}_{D,i}^2 + w_v (1 - \tilde{V}_i)^2 \right]^{1/2}, w_d \geq 0, w_v \geq 0, w_d + w_v = 1 \quad (26)$$

Here,  $w_d$  and  $w_v$  denote the drag and volume-retention weights, respectively. The illustrative equal-weight selection used  $w_d = w_v = 0.5$ , and the candidate with the minimum  $d_i$  was selected. For the surrogate screening candidate, the normalization extrema were evaluated over the nondominated points on the surrogate mean response front. For the illustrative direct CFD representative, the extrema were recomputed using only the locally nondominated production-grid CFD samples. The weights were used only for representative selection after nondominance had been established; they did not enter the dominance test and therefore did not alter the membership of either direct CFD nondominated set. The surrogate-selected location remains a screening candidate and is not assumed to remain nondominated after direct CFD reassessment.

Because the surrogate model exhibits limited global cross-validated predictive skill, final compromise-set membership was determined independently of the production grid CFD data. Nondominance was evaluated at two levels. First, a global audit was per-

formed over all 53 production-grid CFD samples. Second, a local audit was performed within the predefined 13 sample Pareto knee sampling neighborhood.

For a comparison set  $S$ , design  $j$  dominates design  $i$  if

$$C_{D,j} \leq C_{D,i}, V_j \geq V_i \quad (27)$$

with at least one strict inequality. The direct CFD nondominated set is therefore

$$P_{\text{CFD}}(S) = \{i \in S : \nexists j \in S \text{ such that } C_{D,j} \leq C_{D,i}, V_j \geq V_i, \text{ with at least one strict inequality}\} \quad (28)$$

The global audit uses all 53 production grid CFD samples, whereas the local audit uses only the 13 samples within the predefined Pareto knee sampling neighbourhood. Both sets are discrete; neither defines a continuously resolved Pareto front or a rectangular optimum window.

When a single illustrative representative is required within the local direct CFD nondominated set, the normalization and weighted ideal point distance defined above are applied only to the seven directly evaluated nondominated samples. Under  $w_d = w_v = 0.5$ , I26 gives the minimum normalized distance and is therefore retained as the illustrative local representative. This designation is conditional on the local sample population, min-max normalization, and prescribed objective weights; I26 is not interpreted as a unique, database-wide, or universally optimal design.

### 2.8. Paired Direct CFD Finite-Change Assessment

Local parameter coupling was assessed exclusively using four existing production-grid CFD designs that form a  $2 \times 2$  paired comparison: A06 ( $N = 2.25$ ,  $L_{\text{nose}} = 255$  mm), A08 (2.55, 255 mm), A07 (2.25, 305 mm), and A09 (2.55, 305 mm). These samples allow one design variable to be changed while holding the other at one of two directly sampled levels.

For a response  $Y \in \{C_D, V\}$ , the signed finite change associated with increasing  $N$  from 2.25 to 2.55 at fixed nose length  $L$  was defined as

$$\Delta_Y^{(N)}(L_{\text{nose}}) = \frac{Y(2.55, L_{\text{nose}}) - Y(2.25, L_{\text{nose}})}{Y(2.25, L_{\text{nose}})} \times 100\% \quad (29)$$

The signed finite change associated with increasing  $L_{\text{nose}}$  from 255 to 305 mm at fixed  $N$  was defined as

$$\Delta_Y^{(L_{\text{nose}})}(N) = \frac{Y(N, 305) - Y(N, 255)}{Y(N, 255)} \times 100\% \quad (30)$$

The signed finite changes in  $N$  and  $L_{\text{nose}}$  are therefore defined by Equations (29) and (30), respectively. Drag coefficients were taken directly from the production-grid CFD database, whereas internal volumes were evaluated analytically using Equation (4). No surrogate predictions, fitted gradients, or interpolated response curves entered these comparisons. The resulting quantities are deterministic finite changes between existing sampled designs rather than derivatives, formal uncertainty bounds, or global sensitivity indices.

Because configuration-specific grid refinement studies were not available for A06–A09, the smaller drag changes are interpreted descriptively as production grid observations rather than as uncertainty-resolved directional effects.

## 3. Results

The results are organized according to an evidence hierarchy that separates surrogate screening from direct CFD inference. Section 3.1 reports global and local cross-validation diagnostics. Section 3.2 documents the nominal outputs of the revised surrogate-screening model. Section 3.3 audits the two previously selected CFD-evaluated test configurations. Sections 3.4–3.8 use these representative test config-

urations to assess mesh behavior and interpret the pressure-recovery mechanism. Section 3.9 establishes global and local direct CFD nondominated sets, while Section 3.10 reports paired finite changes from existing CFD samples. Final compromise-set membership is determined from direct CFD rather than from the continuous surrogate front.

### 3.1. Strict Fold-Wise Global and Decision-Region Surrogate Diagnostics

Strict fold-wise LOOCV was applied to the fixed GPR model class comprising a pure-quadratic mean and an ARD squared-exponential covariance function. In each fold, the omitted sample was excluded before input/output normalization and hyperparameter estimation. The resulting predictions are therefore strictly out of fold. Because only 53 computationally expensive CFD samples were available, the metrics are interpreted as internal predictive diagnostics rather than external validation.

Over the complete design space, the strict LOOCV MAE, RMSE, MAPE, and  $Q^2$  were 0.001577, 0.002756, 0.6049%, and 0.172840, respectively, indicating limited global predictive skill. The regional metrics were obtained by filtering the same 53 out-of-fold predictions using the sampling-neighborhood boundaries defined before residual inspection; no separate local GPR model or regional hyperparameter retuning was used. The combined 18-sample decision region gave an RMSE of 0.001399, a MAPE of 0.4673%, and  $Q^2 = 0.683314$ , with signed relative errors between  $-0.8817\%$  and  $+1.1247\%$ .

The five-sample low-drag neighborhood retained a negative  $Q^2 = -2.873257$ , despite comparatively small absolute errors. This result reflects the small sample count and narrow response variance, and is not interpreted as evidence of stand-alone local predictive skill. The model-based predictive intervals are likewise used only as internal calibration diagnostics conditional on the adopted covariance model and CFD database.

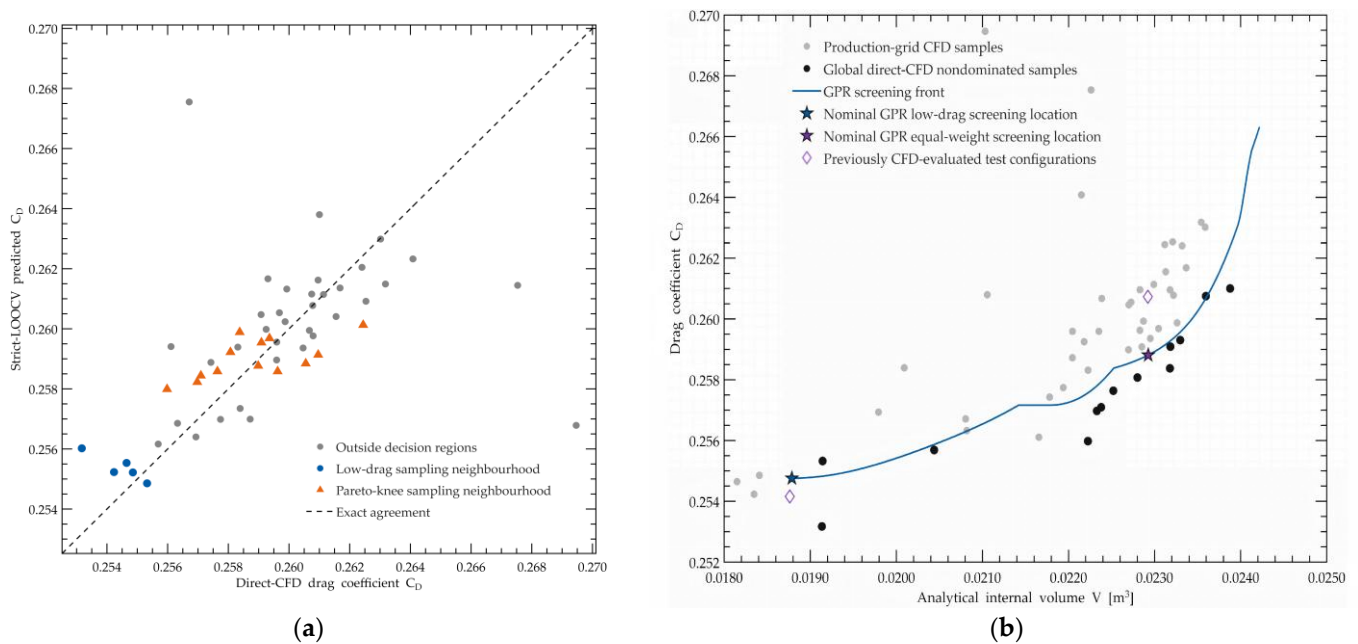
Figures 6 and 7 visualize the same out-of-fold predictions summarized in Table 8, and do not constitute independent validation datasets. Figure 6b further separates the final GPR screening trace from the globally nondominated direct CFD samples. The continuous GPR curve and nominal screening locations are retained only to document candidate-region screening; final Pareto membership is determined from the discrete production-grid CFD data.

**Table 8.** Strict fold-wise LOOCV diagnostics for the fixed 53-sample GPR model class, evaluated globally and within the predefined sampling neighborhoods.

| Validation Subset        | n  | MAE      | RMSE     | $e_{\max}$ | Mean Signed Bias | MAPE (%) | Relative-Error Range (%) | $Q^2$     |
|--------------------------|----|----------|----------|------------|------------------|----------|--------------------------|-----------|
| Global design space      | 53 | 0.001577 | 0.002756 | 0.012678   | +0.000036        | 0.6049   | −4.7051 to +4.2215       | 0.172840  |
| Low-drag region          | 5  | 0.001113 | 0.001432 | 0.002848   | +0.000926        | 0.4385   | −0.1830 to +1.1247       | −2.873257 |
| Pareto knee region       | 13 | 0.001239 | 0.001386 | 0.002314   | +0.000146        | 0.4784   | −0.8817 to +0.7849       | 0.348243  |
| Combined decision region | 18 | 0.001204 | 0.001399 | 0.002848   | +0.000363        | 0.4673   | −0.8817 to +1.1247       | 0.683314  |

Note: MAE, RMSE,  $e_{\max}$ , and mean signed bias are reported in  $C_D$  units, whereas MAPE and the signed relative error range are percentages. The pointwise error is  $e_i = \hat{C}_{D,i} - C_{D,i}^{\text{CFD}}$ ; positive values denote GPR overprediction.  $Q^2$  is calculated using the CFD-response variance within each evaluation subset.

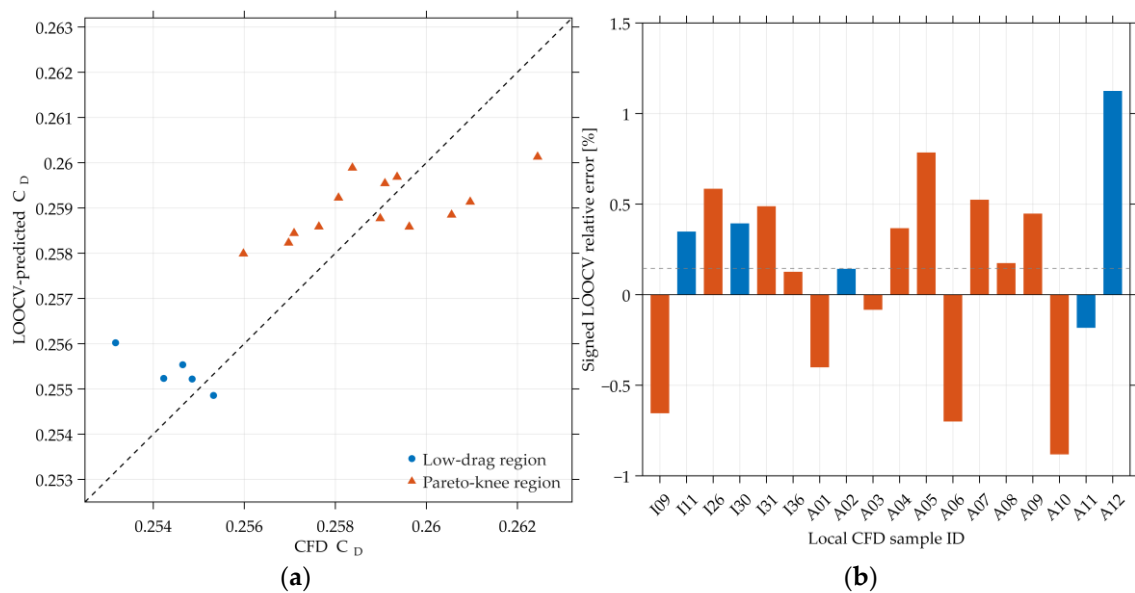
Figure 6 visualizes the strict out-of-fold predictions underlying Table 8 and separates the final surrogate-screening output from the discrete direct CFD evidence.



**Figure 6.** Strict fold-wise surrogate diagnostics and comparison with direct CFD evidence. **(a)** Strict-LOOCV predictions of  $C_D$  versus the corresponding production-grid CFD values for all 53 samples. Grey circles denote samples outside the predefined decision region, blue circles denote the five low-drag neighborhood samples, and orange triangles denote the 13 Pareto knee neighborhood samples; the dashed diagonal represents exact agreement. **(b)** Final GPR mean-response screening front and the production-grid direct CFD samples. Grey circles denote all 53 samples, black circles denote the globally nondominated direct CFD samples, and the blue curve denotes the GPR screening front. The stars identify the nominal GPR screening locations, whereas the open diamonds identify the production-grid CFD results at the two previously selected test configurations. The GPR curve and star locations are screening outputs rather than a continuously validated Pareto front.

Figure 6a shows that the largest strict LOOCV deviations occur predominantly outside the two predefined sampling neighborhoods, whereas the combined 18 sample decision region exhibits the more tightly bounded errors reported in Table 8. Because the panel displays the same out-of-fold predictions used to calculate those metrics, it is an internal diagnostic rather than an independent validation dataset. Figure 6b shows that the nominal GPR screening locations occur near CFD-populated portions of the objective space; however, proximity to the sampled points does not validate the continuous surrogate front between them. The final status of the screened configurations is therefore determined by the direct CFD dominance audit in Section 3.3, not by their position on the GPR curve.

Figure 7 resolves the parity and signed error structure of the same 18 strict out-of-fold predictions within the predefined decision region.



**Figure 7.** Strict fold-wise LOOCV diagnostics within the predefined 18-sample decision region. (a) Out-of-fold GPR predictions versus production-grid CFD values; the dashed diagonal denotes exact agreement. Blue circles identify the five low-drag sampling-neighbourhood samples, whereas orange triangles identify the 13 Pareto-knee sampling-neighbourhood samples. (b) Signed relative prediction errors; blue bars correspond to the low-drag sampling-neighbourhood samples, and orange bars correspond to the Pareto-knee sampling-neighbourhood samples. The solid horizontal line denotes zero error, and the grey dashed line denotes the mean signed relative error of the combined decision region. Positive errors indicate GPR overprediction. Both panels visualize the strict out-of-fold predictions reported in Table 8 and do not constitute independent physical validation.

Within the combined decision region, the signed strict LOOCV errors range from  $-0.8817\%$  to  $+1.1247\%$ , and the small positive mean bias indicates no persistent tendency to underpredict drag. The negative  $Q^2 = -2.873257$  for the five-sample low-drag neighborhood is interpreted together with its small absolute errors, because the statistic is strongly affected by the small subset size and narrow CFD response variance. These diagnostics support the use of the GPR model for candidate-region screening, but do not establish uniformly accurate interpolation at unsampled geometries. Final drag values and Pareto membership are therefore taken from direct CFD and the subsequent dominance audit.

### 3.2. Nominal Candidate Locations from the Revised Surrogate Screening Model

The revised GPR screening model, based on the verified 53-sample database and the explicitly fixed pure quadratic mean and ARD squared-exponential covariance function, identifies a nominal low-drag screening location at  $N = 1.1670$  and  $L_{nose} = 343.3819$  mm. Its predicted drag coefficient is  $C_{D,GPR} = 0.2548$ , and its analytical internal volume is  $V = 0.01879$  m<sup>3</sup>.

The equal weight ideal-point calculation on the surrogate mean-response front identifies a nominal trade-off screening location at  $N = 2.4800$  and  $L_{nose} = 278.0000$  mm, with  $C_{D,GPR} = 0.2588$  and  $V = 0.02293$  m<sup>3</sup>. The corresponding nominal screening coordinates and surrogate-predicted responses are summarized in Table 9.

These locations are reported to document the reproducible output of the revised surrogate-screening workflow. Direct CFD was not performed at these revised nominal coordinates, and they are therefore not used as final optimized configurations or as members of the direct CFD nondominated set. Their role is limited to identifying persistent low-drag and Pareto knee candidate neighborhoods.

Relative to the locations selected in the earlier screening run, the revised coordinates exhibit small shifts resulting from the explicitly fixed GPR model specification.

**Table 9.** Nominal candidate locations identified by the revised 53-sample GPR screening model.

| Screening Output                            | $N$      | $L_{nose}$ (mm) | GPR $C_D$  | Volume (m <sup>3</sup> ) | Status                                         |
|---------------------------------------------|----------|-----------------|------------|--------------------------|------------------------------------------------|
| Low-drag screening location                 | 1.166970 | 343.381917      | 0.25476222 | 0.01878553               | Screening only; no direct CFD                  |
| Equal-weight ideal-point screening location | 2.480000 | 278.000000      | 0.25881058 | 0.02292583               | Weight-dependent screening only; no direct CFD |

The listed locations are nominal outputs of the revised surrogate model. They have not been evaluated by direct CFD and are not treated as final optimal designs.

### 3.3. Production-Grid CFD Audit of the Previously Selected Test Configurations

Before the present audit, production-grid CFD back-substitution and terminal three-grid reassessment had been completed at two previously selected locations:  $N = 1.171728$ ,  $L_{nose} = 345.859592$  mm and  $N = 2.494532$ ,  $L_{nose} = 280.631954$  mm. Because these coordinates do not coincide with the nominal outputs of the revised GPR model, they are retained as a low-drag CFD test configuration and a trade-off CFD test configuration, respectively, rather than as final optimized designs.

The final 53-sample GPR model was reevaluated at these two fixed coordinates. Table 10 compares the revised GPR predictions with the corresponding production-grid CFD values and reports their dominance status within the complete 53-sample direct CFD database.

**Table 10.** Revised GPR predictions and production grid CFD audit of the two previously selected test configurations.

| CFD-Evaluated Configuration  | $N$      | $L_{nose}$ (mm) | Revised GPR $C_D$ | Production Grid CFD $C_D$ | Signed GPR CFD Discrepancy (%) | Direct CFD Dominance Status                  |
|------------------------------|----------|-----------------|-------------------|---------------------------|--------------------------------|----------------------------------------------|
| Low-drag test configuration  | 1.171728 | 345.859592      | 0.25476558        | 0.254159570               | +0.2384                        | Dominated by A12                             |
| Trade-off test configuration | 2.494532 | 280.631954      | 0.25881422        | 0.260731491               | −0.7353                        | Dominated by six existing direct CFD samples |

Note: The revised GPR values were obtained by evaluating the final 53 sample model at the two fixed test coordinates. The signed discrepancy is defined as  $E_{GPR} = (C_{D,GPR} - C_{D,CFD})/C_{D,CFD} \times 100\%$ , where positive and negative values denote GPR overprediction and underprediction, respectively. Direct CFD dominance is evaluated using lower  $C_D$  and higher  $V$  as the preferred objectives. The trade-off test configuration is dominated by I21, I26, I35, I36, I39, and A08.

The revised model slightly overpredicts the drag of the low-drag test configuration and underpredicts that of the trade-off test configuration, with signed discrepancies of +0.2384% and −0.7353%, respectively. These pointwise comparisons audit the model only at the two evaluated coordinates and do not validate the continuous GPR response surface. More importantly, the direct CFD dominance audit supersedes the earlier surrogate-based labels; the low-drag test configuration is dominated by A12, whereas the trade-off test configuration is dominated by six existing CFD samples. The two configurations are therefore retained only for traceability and for the subsequent mesh, force-decomposition, and flow-field comparisons.

### 3.4. Three-Grid Reassessment of Representative CFD-Evaluated Configurations

Because the drag differences among the baseline and the two CFD test configurations are relatively small, a common three-grid reassessment was performed using the same grid generation strategy. The three geometries are treated here as representative CFD evaluated configurations. The reassessment characterizes iterative stability, near-wall resolution, adjacent-grid sensitivity, and cross-grid ordering under a consistent numerical framework.

The three grid levels use identical computational-domain dimensions, boundary conditions, turbulence models, drag-integration surfaces, reference areas, and monitoring procedures. The fine, medium, and coarse grids are denoted by G1, G2, and G3, respectively. The monitoring quantities follow the definitions introduced with Table 5. For every grid and configuration,  $C_{D,avg}$  is evaluated over the final 300 iterations, while  $C_{D,last}$  and  $C_{D,fluct}$  are retained solely as iterative-stability diagnostics. The relative monitoring range is evaluated as

$$C_{D,fluct} = \frac{C_{D,max} - C_{D,min}}{C_{D,avg}} \times 100\% \quad (31)$$

and is not interpreted as spatial discretization uncertainty. The grid sizes, actual refinement ratios, and near-wall resolution of the three representative configurations are summarized in Table 11.

**Table 11.** Grid sizes, actual refinement ratios, and near-wall resolution for the baseline and the two representative CFD evaluated test configurations.

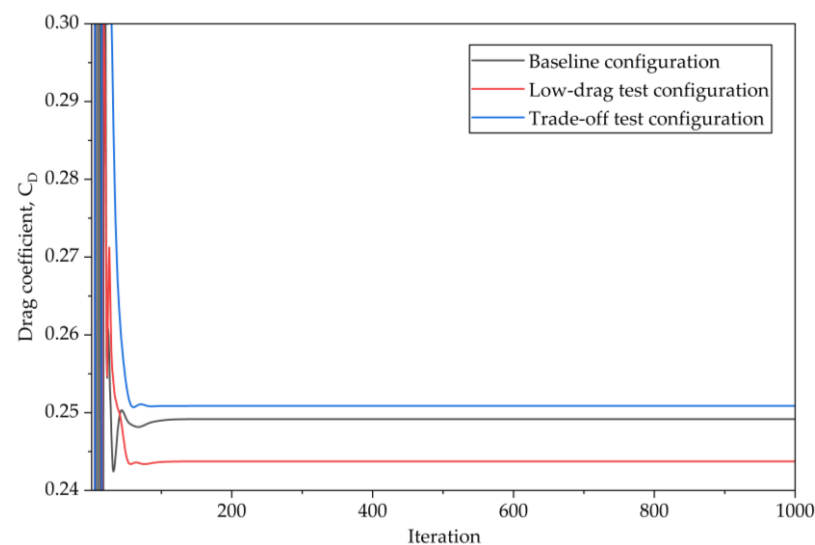
| Design                       | Mesh      | Cells (10 <sup>6</sup> ) | Actual r | Mean y+ | Max y+ | Near-Wall Assessment    |
|------------------------------|-----------|--------------------------|----------|---------|--------|-------------------------|
| Baseline                     | G1 Fine   | 6.933958                 | -        | 0.4272  | 0.5953 | Low-y+ resolved         |
| Baseline                     | G2 Medium | 3.114564                 | 1.3058   | 0.5551  | 0.7756 | Low-y+ resolved         |
| Baseline                     | G3 Coarse | 1.495075                 | 1.2772   | 0.7199  | 1.0116 | Local slight exceedance |
| Low-drag test configuration  | G1 Fine   | 6.933531                 | -        | 0.4324  | 0.6475 | Low-y+ resolved         |
| Low-drag test configuration  | G2 Medium | 3.055106                 | 1.3141   | 0.5610  | 0.8294 | Low-y+ resolved         |
| Low-drag test configuration  | G3 Coarse | 1.494701                 | 1.2691   | 0.7246  | 1.0552 | Local slight exceedance |
| Trade-off test configuration | G1 Fine   | 7.417207                 | -        | 0.4277  | 0.5883 | Low-y+ resolved         |
| Trade-off test configuration | G2 Medium | 3.288442                 | 1.3114   | 0.5552  | 0.7660 | Low-y+ resolved         |
| Trade-off test configuration | G3 Coarse | 1.603620                 | 1.2705   | 0.7205  | 0.9937 | Low-y+ resolved         |

As shown in Table 12, the drag coefficient fluctuations over the final 300 iterations are small for all three configurations and grid levels, indicating stable monitoring plateaus. For example, on the baseline coarse grid, the mean  $C_D$  over the final 300 iterations is 0.266489626, whereas the final-iteration value is 0.266489655. Their difference is approximately  $2.9 \times 10^{-8}$ . The monitoring results therefore indicate that the observed differences among the grid levels are not caused by an isolated final-iteration anomaly. This conclusion concerns iterative monitoring stability only, and does not establish grid independence.

Figure 8 presents the complete fine-grid  $C_D$  monitoring histories for the baseline, low-drag test, and trade-off test configurations. All three curves reach stable plateaus after the initial transient. The final-window statistics reported in Table 12 are used for the subsequent three-configuration fine-grid comparison.

**Table 12.** Drag-coefficient monitoring statistics for the baseline and the two representative CFD-evaluated configurations on the three grid levels.

| Design                       | Mesh      | $C_D$ avg.  | $C_D$ Last  | $C_D$ Fluct (%) |
|------------------------------|-----------|-------------|-------------|-----------------|
| Baseline                     | G1 Fine   | 0.249175827 | 0.249175787 | 0.000226        |
| Baseline                     | G2 Medium | 0.258303674 | 0.258303981 | 0.000678        |
| Baseline                     | G3 Coarse | 0.266489626 | 0.266489655 | 0.266490        |
| Low-drag test configuration  | G1 Fine   | 0.243734823 | 0.243734775 | 0.000071        |
| Low-drag test configuration  | G2 Medium | 0.254159570 | 0.254159902 | 0.000271        |
| Low-drag test configuration  | G3 Coarse | 0.261210960 | 0.261211288 | 0.000811        |
| Trade-off test configuration | G1 Fine   | 0.250870327 | 0.250870486 | 0.000141        |
| Trade-off test configuration | G2 Medium | 0.260731491 | 0.260731908 | 0.000591        |
| Trade-off test configuration | G3 Coarse | 0.266316173 | 0.266317365 | 0.000799        |

**Figure 8.** Fine-grid drag-coefficient monitoring histories for the baseline, low-drag test, and trade-off test configurations over iterations 1–1000. Final window monitoring statistics are reported in Table 12. The histories assess iterative stability rather than spatial grid independence.

### 3.5. Three-Grid Mesh-Sensitivity Diagnosis: Monotonic but Non-Asymptotic Behavior

The coarse-, medium-, and fine-grid results exhibit a monotonic decrease in  $C_D$  for each of the three representative configurations. However, in every sequence, the medium-to-fine change is larger than the coarse-to-medium change. The mechanical application of the three-grid Richardson relation consequently produces a negative apparent order  $p$ , indicating that the available grid families have not entered the standard asymptotic convergence range. A positive-order Richardson extrapolation and a formal Roache-type grid convergence index are therefore not reported.

Mesh sensitivity is instead described using the absolute adjacent-grid relative differences,

$$\delta_{21} = \left| \frac{C_{D,G2} - C_{D,G1}}{C_{D,G1}} \right| \times 100\%, \quad \delta_{32} = \left| \frac{C_{D,G3} - C_{D,G2}}{C_{D,G2}} \right| \times 100\% \quad (32)$$

An observed adjacent-grid sensitivity indicator is defined as

$$U_{\text{mesh,sens}} = \max(\delta_{21}, \delta_{32}) \quad (33)$$

The resulting  $U_{\text{mesh,sens}}$  values are 3.66% for the baseline, 4.28% for the low-drag test configuration, and 3.93% for the trade-off test configuration. These quantities represent the maximum observed adjacent grid change within each available grid family. They are

not probabilistic uncertainty bounds, formal GCI values, or evidence of grid-independent absolute drag.

The principal numerical evidence is therefore the direction of the cross-grid ordering. Relative to the baseline, the low-drag test configuration has lower drag on the coarse, medium, and fine grids by 1.98%, 1.60%, and 2.18%, respectively. Relative to the low-drag test configuration, the trade-off test configuration has higher drag by 1.95%, 2.59%, and 2.93%, respectively. These two ordering directions are consistent across the three evaluated grid levels, although the percentage differences are not formally uncertainty-resolved. By contrast, the trade-off-to-baseline difference changes from  $-0.06\%$  on the coarse grid to  $+0.94\%$  on the medium grid and  $+0.68\%$  on the fine grid. No grid-level-independent drag ordering is therefore claimed between the baseline and trade-off test configurations. The adjacent-grid sensitivity indicators and asymptotic-range diagnoses for the three representative configurations are summarized in Table 13.

**Table 13.** Adjacent-grid sensitivity indicators and asymptotic-range diagnosis for the three representative CFD-evaluated configurations.

| Design                       | $r_{21}$ | $r_{32}$ | $\delta_{21}$ (%) | $\delta_{32}$ (%) | $U_{\text{mesh,sens}}$ (%) | Apparent p Diagnostic | Convergence Judgment      |
|------------------------------|----------|----------|-------------------|-------------------|----------------------------|-----------------------|---------------------------|
| Baseline                     | 1.3058   | 1.2772   | 3.66              | 3.17              | 3.66                       | −0.426                | Monotonic, non-asymptotic |
| Low-drag test configuration  | 1.3141   | 1.2691   | 4.28              | 2.77              | 4.28                       | −1.528                | Monotonic, non-asymptotic |
| Trade-off test configuration | 1.3114   | 1.2705   | 3.93              | 2.14              | 3.93                       | −2.226                | Monotonic, non-asymptotic |

Note:  $r_{21}$  and  $r_{32}$  are the actual fine-to-medium and medium-to-coarse refinement ratios, respectively.  $\delta_{21}$  and  $\delta_{32}$  denote the corresponding absolute adjacent grid-relative changes.  $U_{\text{mesh,sens}}$  is the maximum observed adjacent grid change and is not a formal GCI or probabilistic numerical-uncertainty estimate. The negative apparent p values indicate that none of the three grid sequences has entered the standard Richardson asymptotic range.

### 3.6. Fine-Grid Drag Volume Comparison of the Representative Configurations

The G1 results provide a common fine-grid reporting level for translating the cross-grid ordering established in Section 3.5 into effective towing-power and gross-volume differences. The associated drag differences remain smaller than the observed adjacent-grid sensitivity indicators, and are therefore interpreted as configuration-level comparisons rather than formally uncertainty-resolved improvements.

At  $U = 2.0$  m/s, the fine-grid drag forces correspond to effective bare-hull towing powers;  $P_{\text{tow}} = D_T U$ , of 31.24, 30.56, and 31.45 W for the baseline, low-drag test, and trade-off test configurations, respectively. Table 14 summarizes the pairwise power-volume differences. Relative to the low-drag test configuration, the trade-off test configuration provides 4.16 L (+22.17%) more gross internal volume at 0.89 W (+2.93%) greater effective towing power. Because the baseline–trade-off drag ordering reverses with grid refinement, that comparison is not interpreted as mesh-robust. Direct CFD nondominance is assessed separately in Section 3.9.

**Table 14.** Fine-grid effective towing-power and gross-volume differences among the representative CFD-evaluated configurations.

| Comparison                                                   | $\Delta P_{\text{tow}}$ (W)<br>(Relative Change (%)) | $\Delta V$ (L)<br>(Relative Change (%)) | Cross-Grid Interpretation                                                                                                        |
|--------------------------------------------------------------|------------------------------------------------------|-----------------------------------------|----------------------------------------------------------------------------------------------------------------------------------|
| Low drag test configuration vs. baseline                     | −0.68<br>(−2.18%)                                    | −3.46<br>(−15.59%)                      | Lower drag on all three evaluated grids; the difference is not formally uncertainty-resolved.                                    |
| Trade-off test configuration vs. baseline                    | +0.21<br>(+0.68%)                                    | +0.70<br>(+3.13%)                       | Drag ordering reverses across the three grids; the principal difference is increased internal volume at a comparable drag level. |
| Trade-off test configuration vs. low-drag test configuration | +0.89<br>(+2.93%)                                    | +4.16<br>(+22.17%)                      | Higher drag on all three evaluated grids while providing substantially greater internal volume.                                  |

Note: At  $U = 2.0$  m/s,  $\Delta P_{\text{tow}} = \Delta D_T U$ . Here,  $P_{\text{tow}}$  denotes the effective power required to overcome computed bare-hull resistance and excludes propulsor, drivetrain, electrical conversion, auxiliary load, and battery losses. The reported  $\Delta V$  denotes gross geometric internal volume rather than usable payload volume.

### 3.7. Cross-Grid Drag Decomposition of the Representative Configurations

The total wall force was decomposed into pressure and viscous contributions for the baseline, low-drag test, and trade-off test configurations on all three grid levels. As summarized in Table 15, pressure drag is the largest component of the absolute total drag in all nine configuration-grid combinations, accounting for 75.88–79.20% of  $D_T$ . On the fine grid, the pressure-drag fraction ranges from 75.88% to 77.84%. These values establish pressure-dominated drag composition for the three evaluated configurations, but do not by themselves show that the differences between configurations are caused primarily by pressure drag.

Applying the adjacent-grid relative-change definition separately to  $D_p$  and  $D_v$  gives maximum changes in  $D_p$  of 4.57%, 5.36%, and 5.08% for the baseline, low-drag test, and trade-off test configurations, respectively. The corresponding maximum changes in  $D_v$  are 0.85%, 0.46%, and 0.65%. The pressure fraction varies by 1.19, 1.36, and 1.18 percentage points across the three-grid sequences. Both force components decrease monotonically with refinement, but the pressure-force sequences have not been demonstrated to lie within a formal asymptotic convergence range. The cross-grid results therefore support the persistence of pressure-dominated drag composition, rather than the grid independence of the individual force components.

Component differences must be distinguished from component fractions. On the fine grid, the low-drag test configuration reduces total drag relative to the baseline by 0.3411 N. Of this difference, only 0.0183 N is associated with a reduction in pressure drag, whereas 0.3228 N is associated with a reduction in viscous drag. On the medium and coarse grids, the pressure drag of the low-drag test configuration is slightly higher than that of the baseline, while its viscous drag remains lower by 0.3350 N and 0.3622 N, respectively. The consistently lower total drag of this test configuration is therefore associated primarily with its lower viscous contribution across the three evaluated grids. The pressure fields and axial  $C_p$  curves remain useful for interpreting configuration-dependent pressure redistribution, but they do not demonstrate that pressure-drag reduction alone causes the observed total-drag ordering.

The trade-off test configuration has a more rounded forebody and retains greater internal volume than the low-drag test configuration. Its force decomposition and pressure field are retained as a contrasting CFD-evaluated case for interpreting configuration-dependent drag composition and pressure redistribution.

**Table 15.** Cross-grid decomposition of total drag into pressure and viscous components for the three representative CFD-evaluated configurations.

| Design                       | Mesh      | $D_T$ (N) | $D_p$ (N) | $D_v$ (N) | $\eta_p = D_p/D_T$ (%) |
|------------------------------|-----------|-----------|-----------|-----------|------------------------|
| Baseline                     | G1 Fine   | 15.6201   | 11.9111   | 3.7090    | 76.26                  |
| Baseline                     | G2 Medium | 16.1923   | 12.4555   | 3.7367    | 76.92                  |
| Baseline                     | G3 Coarse | 16.7054   | 12.9371   | 3.7683    | 77.44                  |
| Low-drag test configuration  | G1 Fine   | 15.2790   | 11.8928   | 3.3862    | 77.84                  |
| Low-drag test configuration  | G2 Medium | 15.9325   | 12.5308   | 3.4017    | 78.65                  |
| Low-drag test configuration  | G3 Coarse | 16.3745   | 12.9684   | 3.4061    | 79.20                  |
| Trade-off test configuration | G1 Fine   | 15.7263   | 11.9331   | 3.7932    | 75.88                  |
| Trade-off test configuration | G2 Medium | 16.3445   | 12.5393   | 3.8052    | 76.72                  |
| Trade-off test configuration | G3 Coarse | 16.6946   | 12.8646   | 3.8301    | 77.06                  |

Note: G1, G2, and G3 denote the fine, medium, and coarse grids, respectively. The pressure drag fraction is  $\eta_p = D_p/D_T$ , and the complementary viscous fraction is  $\eta_v = 1 - \eta_p$ . The pressure fraction describes the composition of the absolute total drag; it does not by itself determine which component is primarily responsible for the drag difference between two configurations. Minor discrepancies in reconstructed sums arise from rounding the reported force components. The corresponding fine-grid static-pressure and velocity-magnitude fields are compared qualitatively in Figure 9.

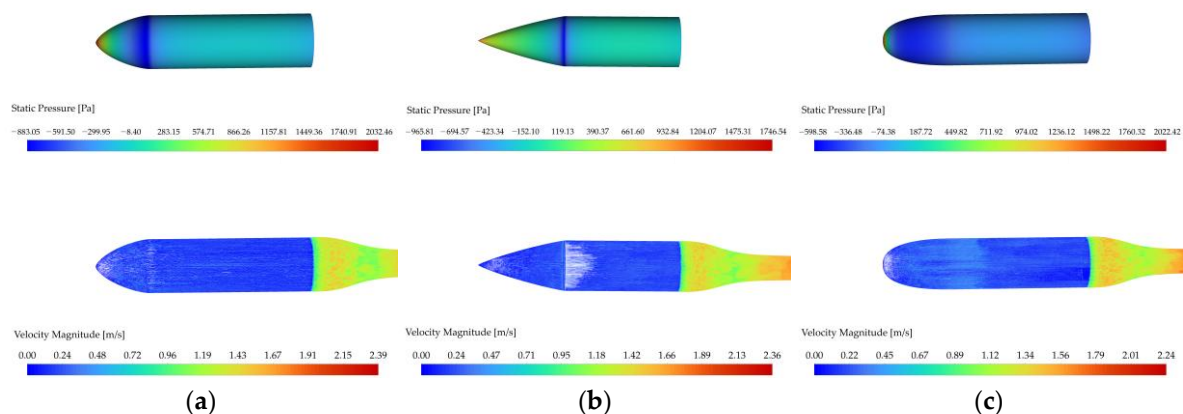
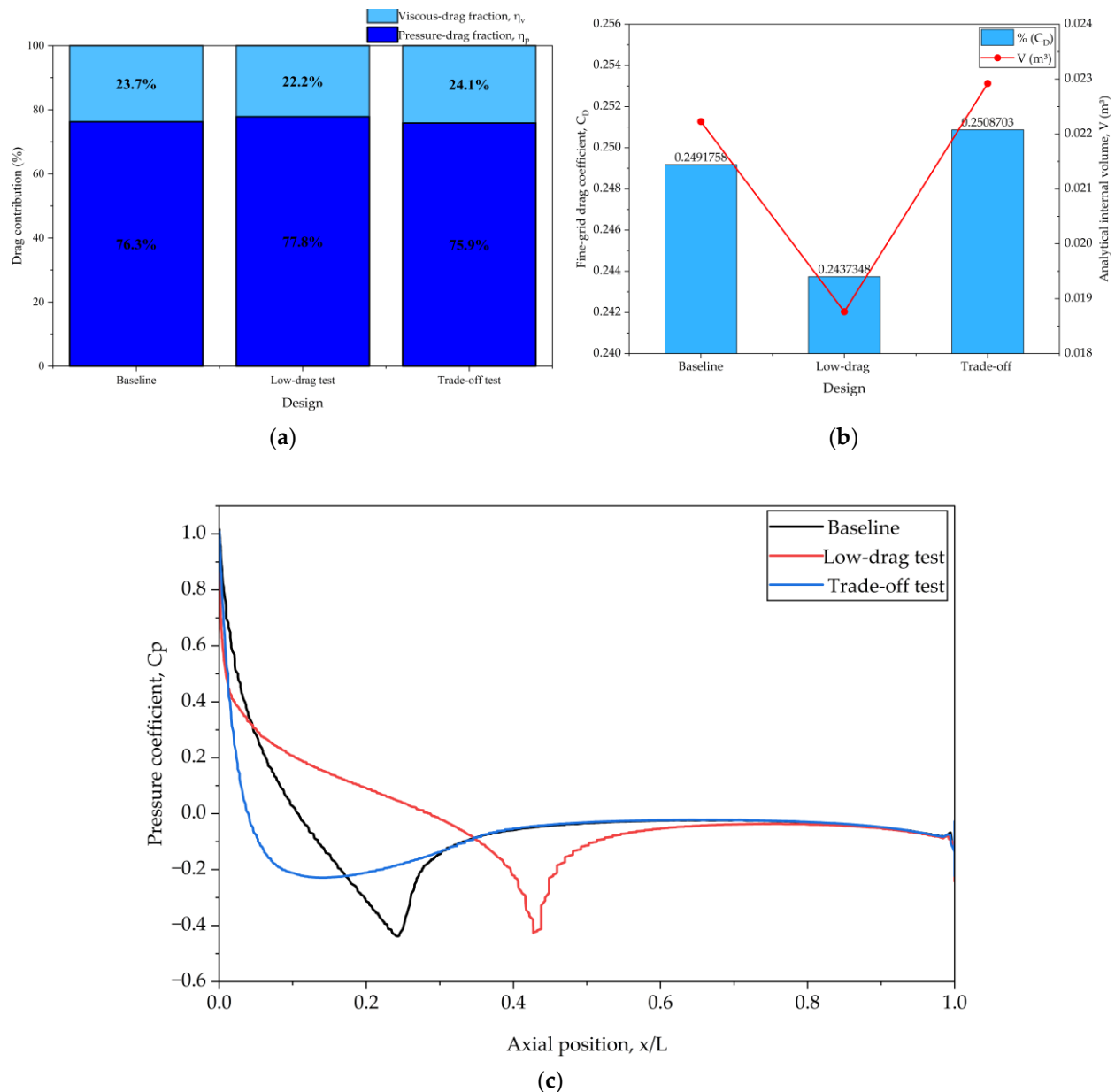
**Figure 9.** Fine-grid qualitative comparison of the static-pressure and velocity-magnitude fields for the three representative CFD-evaluated configurations: (a) baseline; (b) low-drag test configuration; and (c) trade-off test configuration. The fields illustrate configuration-dependent pressure redistribution and near-hull flow development.

Figure 10 consolidates the fine-grid drag fractions, drag volume comparison, and axial pressure distributions of the three representative configurations. The force-component results are interpreted quantitatively in Section 3.7, whereas the configuration-dependent pressure-recovery behavior is examined in Section 3.8.



**Figure 10.** Fine-grid hydrodynamic comparison of the baseline, low-drag test, and trade-off configurations. (a) Pressure and viscous drag fractions,  $\eta_p = D_p/D_T$  and  $\eta_v = D_v/D_T$ , determined by integrating the wall tractions over the complete wetted surface. (b) Fine-grid total drag coefficient  $C_D$  and analytically calculated gross internal volume  $V$ , illustrating the drag volume contrast among the three evaluated geometries. (c) Axial pressure coefficient distributions  $C_p$  along the normalized coordinate  $x/L$ ; the increase in  $C_p$  following each local forebody minimum indicates pressure recovery toward the forebody-mid-body junction. Panel (a) describes the composition of the absolute total drag, whereas panel (c) characterizes configuration-dependent pressure redistribution. Neither quantity alone identifies the component responsible for the total-drag differences between configurations, which is assessed from the integrated force differences reported in Table 15.

### 3.8. Axial Pressure Recovery Characteristics of the Representative Configurations

The fine grid axial pressure coefficient  $C_p$  is examined to characterize pressure redistribution among the three representative CFD-evaluated configurations. For a low- $L/D$  flat-ended AUV, the axial pressure field includes nose stagnation, local acceleration, forebody pressure recovery, boundary layer development, and the truncated-stern wake.

The resulting  $C_p$  distribution therefore provides a configuration-specific description of where suction and pressure recovery occur along the hull.

The baseline configuration has the shortest nose among the three cases. Its acceleration and subsequent pressure recovery are therefore concentrated over a shorter axial distance, producing a comparatively localized pressure minimum and recovery region.

The low drag test configuration combines a small  $N$  with a nose length close to the upper design boundary. Its longer, sharper forebody redistributes acceleration and pressure recovery over a greater axial distance. Among the three representative configurations, it has the lowest  $C_D$  on all evaluated grid levels, but it also has 15.59% less internal volume than the baseline. Table 15 further shows that its lower total drag is associated primarily with a reduced viscous contribution, while its integrated pressure force remains close to that of the baseline and changes relative ordering across the grid levels. The  $C_p$  curve should therefore be interpreted as evidence of pressure redistribution rather than proof that pressure drag reduction alone produces the lower total drag.

The trade-off test configuration has a longer nose than the baseline and a larger  $N$  than the low-drag test configuration. Its axial pressure distribution lies qualitatively between the other two cases over substantial portions of the hull, while its analytical internal volume exceeds that of both the baseline and low-drag configurations. Its fine-grid drag is higher than that of the low-drag test configuration and comparable to the baseline within the present mesh-sensitivity limits. These pressure-recovery characteristics are interpreted as configuration-specific physical evidence of the evaluated geometry.

The three pressure distributions collectively illustrate the coupled influence of  $N$ ,  $L_{nose}$ , forebody pressure redistribution, viscous contribution, stern wake development, and internal volume retention. Because the detailed flow fields were evaluated only for these three geometries, they provide mechanism-level interpretation rather than criteria for direct CFD nondominance. Sample-level nondominance is evaluated separately from the production grid CFD database in Section 3.9.

### 3.9. Global and Local Direct CFD Nondominated Sets

Direct CFD nondominance was evaluated independently of the continuous GPR surface. Over the complete 53-sample production grid CFD database, 13 designs are globally nondominated, as reported in Table A2. This global set represents the database-wide discrete drag volume trade-off.

Within the predefined 13-sample Pareto knee sampling neighborhood, seven samples are locally nondominated: A05, I31, A07, A04, A09, I26 and A08. These samples are listed in Table 16. All seven are also members of the global 53 sample nondominated set. The local analysis therefore does not replace or contradict the global audit; it resolves the trade-off structure within the CFD populated neighborhood targeted by adaptive sampling.

The seven point local set is non-rectangular. It demonstrates that no independently favorable interval of  $N$  or  $L_{nose}$  can represent the directly evaluated drag volume trade-off. The predefined rectangular sampling envelope specifies which samples enter the local comparison, but does not imply that every unsampled geometry inside the rectangle is favorable.

The previously selected trade-off test configuration is shown separately in Figure 11 because production-grid and three-grid CFD results are available at that geometry. It is not included in constructing the original 13 sample set. A separate audit shows that it is dominated after production grid CFD reassessment, and is therefore not treated as a direct CFD Pareto solution.

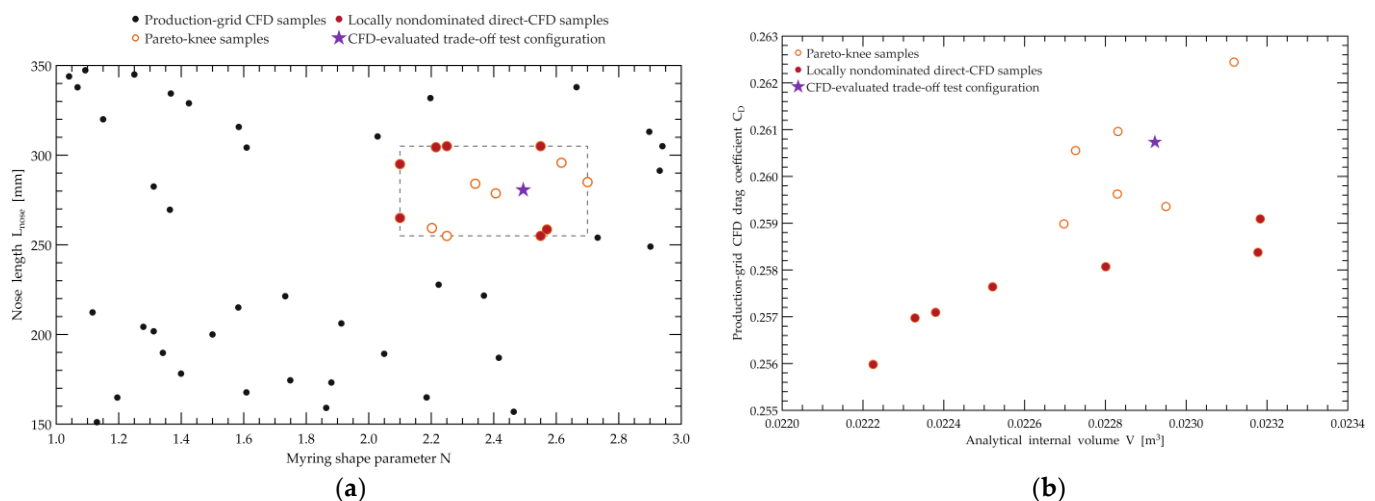
Within the local seven-point set, the equal-weight normalized ideal-point criterion defined in Section 2.7 identifies I26 as one illustrative representative. However, this se-

lection is conditional on the local sample set, normalization and weights. No single database-wide or universally optimal design is claimed.

**Table 16.** Locally nondominated production grid CFD samples within the predefined 13-sample Pareto knee sampling neighborhood.

| Sample | $N$      | $L_{nose}$ (mm) | Direct CFD $C_D$ | $V$ (m <sup>3</sup> ) |
|--------|----------|-----------------|------------------|-----------------------|
| A05    | 2.100000 | 295.000000      | 0.255980540      | 0.022225078           |
| I31    | 2.215090 | 304.448954      | 0.256974480      | 0.022328612           |
| A07    | 2.250000 | 305.000000      | 0.257094090      | 0.022379617           |
| A04    | 2.100000 | 265.000000      | 0.257639240      | 0.022520773           |
| A09    | 2.550000 | 305.000000      | 0.258069330      | 0.022800934           |
| I26    | 2.570352 | 258.539217      | 0.258376230      | 0.023177415           |
| A08    | 2.550000 | 255.000000      | 0.259090360      | 0.023183198           |

Note: Nondominance was evaluated only among the 13 production-grid CFD samples in the predefined Pareto knee sampling neighborhood. The listed samples define a discrete local compromise set rather than a continuously resolved Pareto front. All seven are also globally nondominated within the complete 53-sample database. Under the equal-weight normalized ideal point criterion defined in Section 2.7 and applied only to this local set, I26 is an illustrative representative; this designation is conditional and does not imply a unique global optimum.



**Figure 11.** Direct CFD-supported characterization of the Pareto knee sampling neighborhood. (a) Distribution of the 53 production grid CFD samples in the  $N$ - $L_{nose}$  design space. Orange open circles identify the 13 samples in the predefined Pareto knee sampling neighborhood, red-filled circles identify the seven locally nondominated direct CFD samples listed in Table 16, and the purple star denotes the previously selected CFD-evaluated trade-off test configuration. The dashed grey rectangle indicates the predefined sampling envelope  $2.1 \leq N \leq 2.7$  and  $255 \leq L_{nose} \leq 305$  mm, and is not an optimum window. (b) Production-grid CFD drag coefficient as a function of analytical internal volume for the same 13 samples. Red symbols denote the locally nondominated direct CFD set. No continuous direct CFD Pareto front is inferred between the sampled designs.

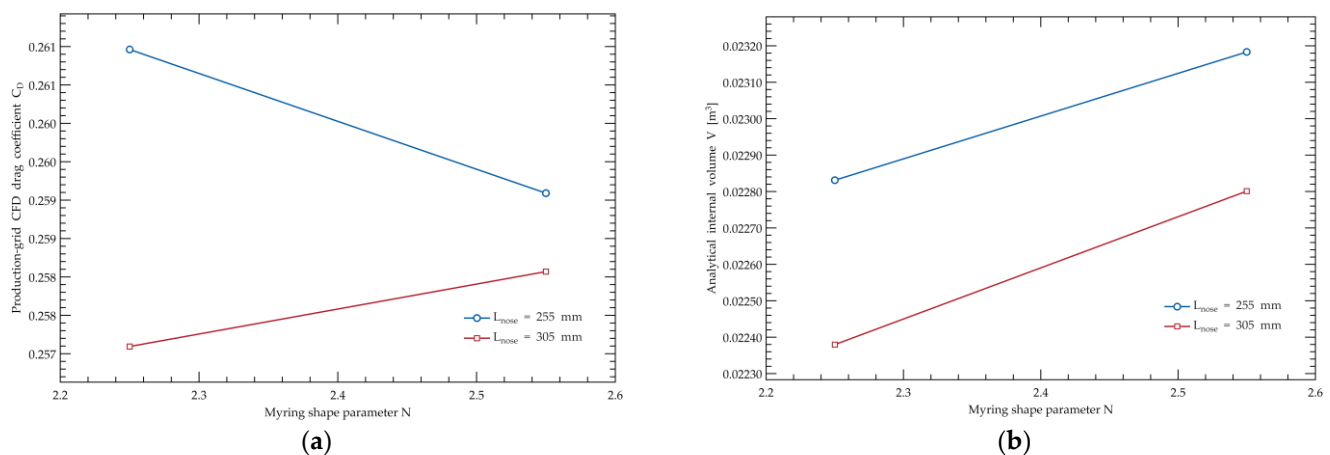
### 3.10. Paired Direct CFD Finite Changes and Local Parameter Coupling

Table 17 shows that increasing  $N$  decreases  $C_D$  at  $L_{nose} = 255$  mm but increases  $C_D$  at  $L_{nose} = 305$  mm, whereas analytical volume increases at both sampled nose lengths. Increasing  $L_{nose}$  reduces both  $C_D$  and  $V$  at the two sampled  $N$  values, with a weaker drag response at  $N = 2.55$ . These paired finite changes, visualized in Figure 12, provide sample-level evidence of local  $N$ - $L_{nose}$  coupling but are not differential sensitivities.

**Table 17.** Signed finite changes in the production grid CFD drag coefficient and analytical internal volume for the four paired designs.

| Changed Variable        | Fixed Coordinate    | Sample Pair | $\Delta C_D$ | $\Delta V$ | Observed Response                                          |
|-------------------------|---------------------|-------------|--------------|------------|------------------------------------------------------------|
| N: 2.25→2.55            | $L_{nose} = 255$ mm | A06→A08     | −0.71694%    | +1.54286%  | Larger N is associated with lower drag and greater volume  |
| N: 2.25→2.55            | $L_{nose} = 305$ mm | A07→A09     | +0.37933%    | +1.88260%  | Larger N is associated with higher drag and greater volume |
| $L_{nose}$ : 255→305 mm | N = 2.25            | A06→A07     | −1.48191%    | −1.97684%  | Longer nose is associated with lower drag and lower volume |
| $L_{nose}$ : 255→305 mm | N = 2.55            | A08→A09     | −0.39408%    | −1.64888%  | The sampled drag benefit of added nose length is weaker    |

Note: Drag changes were calculated from production grid CFD values, whereas volume changes were evaluated analytically using Equation (4). The reported quantities are paired finite changes and are not formal uncertainty bounds, derivatives, or global sensitivity indices.

**Figure 12.** Paired comparison of four existing production grid CFD samples. (a) Drag coefficient  $C_D$ ; (b) analytical internal volume  $V$ , at  $N = 2.25$  and  $2.55$  for  $L_{nose} = 255$  and  $305$  mm. The segments connect sampled coordinates only, and are not fitted or interpolated response curves.

## 4. Discussion

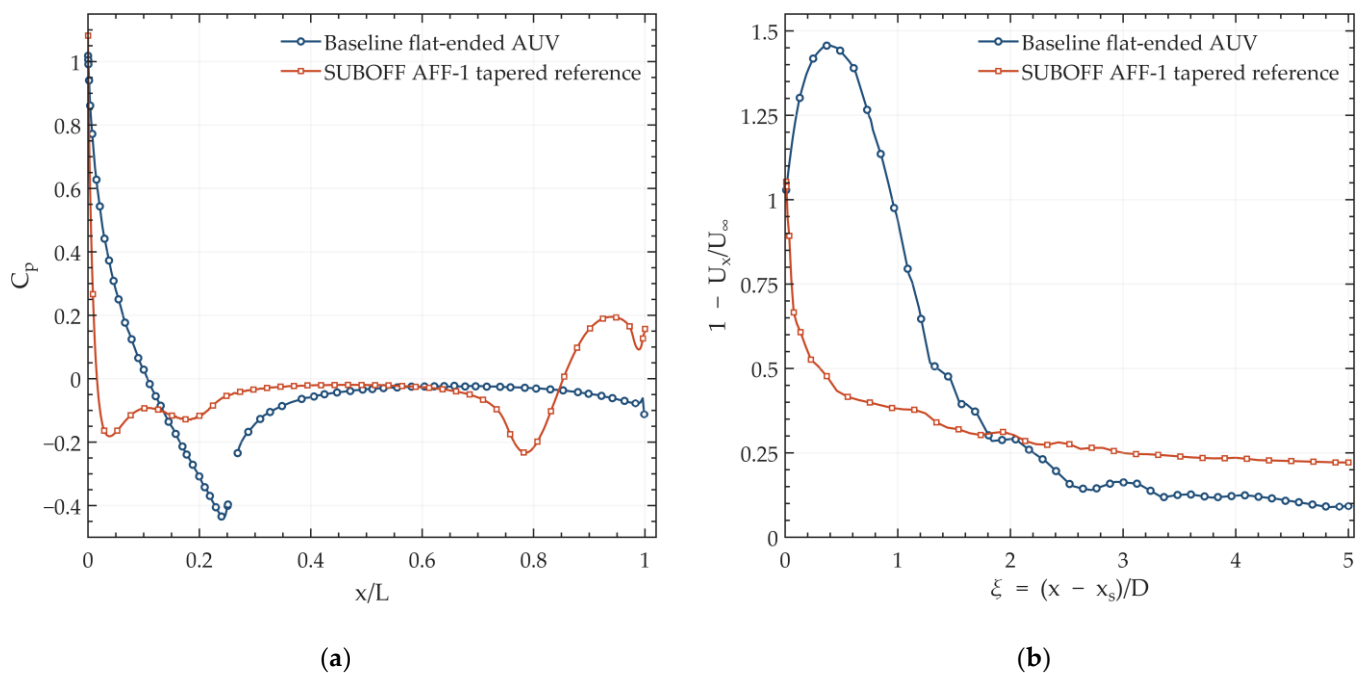
### 4.1. Difference from Classical Slender-Body Design

The classical slender-body design favors a large length-to-diameter ratio, gradual axial area variation, and a continuously tapered stern to reduce adverse pressure gradients, delay separation, and limit wake losses [3–6]. These principles remain appropriate for conventional streamlined underwater vehicles. Their direct transfer to the present ( $L/D = 4.0$ ) high-volume, flat-ended AUV is nevertheless incomplete because the flat aft end provides no convergent pressure-recovery section. Its hydrodynamic response therefore combines forebody-controlled pressure redistribution with fixed aft-edge separation, a base-pressure deficit, and a recirculating near wake.

Figure 13 and Table 18 provide a dimensionless configuration-level comparison between the baseline flat-ended AUV and the validated DARPA SUBOFF AFF-1 tapered reference. The baseline reaches  $C_{p,min} = -0.4357$  at  $x/L = 0.2405$ , whereas the SUBOFF minimum is  $-0.2336$  at  $x/L = 0.7858$ . At the common near-stern station  $x/L = 0.99$ , the baseline pressure remains negative,  $C_p = -0.0762$ , while the SUBOFF pressure has recovered to  $C_p = +0.0924$ . The centerline wake difference is similarly pronounced: the

minimum normalized axial velocity is  $-0.4568$  for the baseline and  $-0.0529$  for SUBOFF, and the corresponding first downstream zero crossings occur at  $x_i = 0.9504$  and  $0.0161$ , respectively, where  $x_i = (x - x_s)/D$ . The baseline velocity deficit is larger at  $x_i = 0.5$  and  $1$ , but becomes lower than the SUBOFF deficit beyond approximately  $x_i = 1.80$ ; at  $x_i = 5$ , the deficits are  $0.0922$  and  $0.2216$ , respectively. The baseline therefore exhibits a stronger but comparatively compact centerline recirculation signature, whereas the SUBOFF reference exhibits weaker near-stern reversal but a more persistent downstream centerline deficit.

These differences sharpen the departure from classical tapered-body expectations without contradicting slender-body theory. They show that the present flat-ended, low- $L/D$  configuration retains a negative near-stern pressure state and develops a substantially stronger near-wake reverse-flow region than the tapered reference. However, SUBOFF is not a stern-only controlled counterpart: the two configurations also differ in  $L/D$ , forebody geometry, overall axial-area distribution, and modeling dimensionality. The comparison is therefore interpreted as evidence of contrasting configuration-level pressure recovery and centerline wake signatures, not as causal isolation of the flat stern. The within-family drag volume and force component differences among the baseline and two previously evaluated test configurations are examined separately in Section 4.2.



**Figure 13.** Dimensionless upper-meridian pressure and centerline wake comparison between the baseline flat-ended AUV and the DARPA SUBOFF AFF-1 tapered reference. (a) Upper-meridian pressure coefficient  $C_p$  as a function of  $x/L$ ; the two baseline wall-zone data blocks are plotted separately. (b) Centerline axial-velocity deficit  $1 - U_x/U_\infty$  as a function of  $\xi = (x - x_s)/D$ . Symbols denote the supplied CFD samples, and line segments are used only as visual guides within continuous data blocks.

For quantitative comparison, Table 18 summarizes the pressure extrema, near-stern pressure coefficient, centerline reverse-flow indicators, and downstream velocity deficits extracted from the two datasets.

**Table 18.** Dimensionless surface pressure and centerline wake metrics for the baseline flat-ended AUV and the DARPA SUBOFF AFF-1 tapered reference.

| Quantity                                     | Baseline Flat-Ended AUV | SUBOFF AFF-1 Tapered Reference |
|----------------------------------------------|-------------------------|--------------------------------|
| $L/D$                                        | 4.0000                  | 8.5748                         |
| Maximum $C_p$                                | 1.0180                  | 1.0819                         |
| $x/L$ at maximum $C_p$                       | 0.0000                  | 0.0000                         |
| Minimum $C_p$                                | −0.4357                 | −0.2336                        |
| $x/L$ at minimum $C_p$                       | 0.2405                  | 0.7858                         |
| $C_p$ at $x/L = 0.99$                        | −0.0762                 | +0.0924                        |
| Minimum $U_x/U_\infty$                       | −0.4568                 | −0.0529                        |
| $\xi$ at minimum $U_x/U_\infty$              | 0.3992                  | 0.0100                         |
| First downstream $U_x = 0$ crossing, $\xi_0$ | 0.9504                  | 0.0161                         |
| $1 - U_x/U_\infty$ at $\xi = 0.5$            | 1.4369                  | 0.4262                         |
| $1 - U_x/U_\infty$ at $\xi = 1$              | 0.9381                  | 0.3809                         |
| $1 - U_x/U_\infty$ at $\xi = 2$              | 0.2907                  | 0.3057                         |
| $1 - U_x/U_\infty$ at $\xi = 5$              | 0.0922                  | 0.2216                         |

Note:  $\xi = (x - x_s)/D$ , where  $x_s$  is the stern-plane location and  $D$  is the maximum hull diameter;  $\xi = 0$  denotes the stern plane and  $\xi > 0$  denotes downstream locations. The centerline axial velocity deficit is  $1 - U_x/U_\infty$ . Values at common stations and the first downstream  $U_x$  crossing,  $\xi_0$ , were obtained by linear interpolation between adjacent supplied samples. The SUBOFF crossing lies within the first downstream sampling interval, and is interpreted as a near-stern sign-change estimate rather than a fully resolved recirculation length. The baseline  $C_p$  data contain an unsampled interval,  $0.251349 < x/L < 0.268743$ , across which no interpolation was performed. SUBOFF is used as a contextual tapered-body reference rather than a geometrically matched stern-only control.

#### 4.2. Pressure Recovery Mechanism in the Low- $L/D$ Blunt-Ended Configuration

The drag decomposition shows that pressure drag contributes approximately three quarters of the total drag for the representative configurations. This pressure drag dominance is consistent with the physical characteristics of a low-slenderness-ratio, flat-ended body. Classical resistance theory indicates that pressure distribution, separation behavior, and wake development are central contributors to the form drag of streamlined and bluff underwater bodies [3,4]. In the present configuration, the limited axial length requires acceleration and pressure recovery to occur over a short distance, while the flat stern constrains base-pressure recovery and produces a pronounced low-pressure wake. Within the target flat-ended AUV family, total drag is therefore governed jointly by forebody pressure redistribution, the adverse pressure gradient near the shoulder, flat-base pressure loss, and the resulting wake momentum deficit.

The axial  $C_p$  distributions show that the longer and sharper forebody of the low drag test configuration redistributes pressure recovery over a greater axial distance. This behavior is consistent with the classical expectation that gradual axial-area variation and an extended recovery path can moderate adverse pressure gradients and separation-related losses [3–6]. This pressure redistribution should not, however, be equated with a pressure drag-controlled reduction. As shown in Table 15, on the G1 grid,  $D_p$  is only 0.0183 N lower than that of the baseline, whereas 0.3228 N of the 0.3411 N total drag difference arises from  $D_v$ . On the G2 and G3 grids,  $D_p$  is slightly higher than the corresponding baseline value. The cross-grid evidence therefore associates the persistent total drag reduction primarily with the viscous component, while the pressure fields characterize configuration-dependent pressure recovery and flat-base wake loading. The latter interpretation is physically consistent with the fixed-separation and base pressure-deficit mechanisms documented for blunt-ended axisymmetric bodies [33,34].

The trade-off test configuration retains greater gross internal volume and exhibits an intermediate axial pressure distribution, but it is dominated in the complete 53-sample direct CFD audit (Section 3.9 and Table A2). It is therefore retained only as a representative CFD-evaluated configuration rather than as a final Pareto design. More generally, the engineering trade-off in a compact flat-ended AUV is governed by the combined effects of forebody pressure redistribution, viscous resistance, flat-base wake loss, and gross volume retention, rather than by a single drag component [1,2,4,16].

#### 4.3. Evidence Hierarchy and Limits of the Direct CFD-Supported Drag–Volume Trade-Off

The drag–volume trade-off is interpreted using three distinct levels of evidence: GPR-based candidate-region screening, sample-level direct CFD nondominance, and configuration-specific flow-field diagnostics. The GPR/NSGA-II results identify portions of the design space for further examination, but do not determine Pareto membership. Nondominance is evaluated from the production-grid CFD drag coefficient and analytical internal volume, with lower  $C_D$  and higher  $V$  preferred.

Thirteen samples are globally nondominated within the complete 53-sample database (Table A2), whereas seven samples are locally nondominated within the predefined 13 sample Pareto knee neighborhood (Table 16 and Figure 11). The seven local samples also belong to the global set, but the two classifications use different comparison populations. Both sets are discrete. The rectangular neighborhood was defined during adaptive sampling to determine sample membership; it was not derived from drag, volume, pressure gradient, or wake thresholds, and is not interpreted as a continuously valid optimum window.

The two previously selected CFD test configurations are retained for workflow auditing and physical comparison only. The low drag test configuration is dominated by A12, and the trade-off test configuration is dominated by I21, I26, I35, I36, I39, and A08. Neither is therefore identified as a final direct CFD Pareto optimum. Similarly, I26 is only an illustrative equal-weight representative of the local seven-point set and is conditional on the selected sample population, normalization, and objective weights.

The paired comparisons in Section 3.10 show that the sampled response to  $N$  changes with  $L_{nose}$ , providing evidence of local two-parameter coupling. However, the increments correspond to the available CFD sample spacing rather than differential perturbations, and only two levels of each variable are available. Moreover, detailed pressure and wake fields were evaluated only for the three representative configurations, not throughout the neighborhood. The present results therefore do not establish a continuous plateau, a unique local optimum, or an invariant pressure recovery or wake structure. Resolving those properties would require additional locally distributed CFD samples and configuration-specific numerical verification.

#### 4.4. Local Credibility and Limitations of Surrogate-Assisted Screening

Strict fold-wise LOOCV establishes a quantitative boundary on the predictive evidence provided by the GPR model. Over the complete 53-sample design space, the model gives an MAE of 0.001577, an RMSE of 0.002756, a MAPE of 0.6049%, and  $Q^2 = 0.172840$  (Table 8). The signed relative errors range from  $-4.7051\%$  to  $+4.2215\%$ . These results indicate limited global predictive skill and show that the GPR model should not be interpreted as a uniformly validated continuous surrogate over the complete parameter domain.

More relevant to the present screening objective is model behavior within the two predefined sampling neighborhoods, which were established during adaptive sampling before examination of the LOOCV residuals. For the combined 18-sample decision region, the MAE, RMSE, MAPE, and  $Q^2$  are 0.001204, 0.001399, 0.4673%, and 0.683314,

respectively (Table 8). The signed relative-error range is  $-0.8817\%$  to  $+1.1247\%$ , and the mean signed bias is  $+3.6280 \times 10^{-4}$ . All 18 CFD values fall within their corresponding model-based 95% LOOCV predictive intervals, with a maximum standardized residual of 1.2940. These intervals are used only as internal calibration diagnostics because they remain conditional on the adopted GPR covariance model and the available CFD database [9,10,12].

The five-sample low-drag subset retains  $Q^2 = -2.873257$  despite its small absolute errors because both the sample count and the CFD-response variance are limited. The resulting variance-normalized statistic is therefore highly sensitive, and is not treated as evidence of stand-alone local predictive skill [12]. At the two previously evaluated test coordinates, the revised signed GPR to CFD discrepancies are  $+0.2384\%$  and  $-0.7353\%$ , respectively (Table 10). Both values fall within the signed strict-LOOCV ranges of their corresponding sampling neighborhoods. However, the direct CFD audit shows that the low-drag and trade-off test configurations are both dominated. Accordingly, neither local  $Q^2$  nor pointwise GPR-CFD agreement is used to establish optimality.

The signed residuals in Figure 7 and the two Table 10 discrepancies occur on both sides of zero, providing no evidence of a persistent single signed drag bias across the two sampling neighborhoods. Figure 6b further shows that the revised nominal screening locations and the previously evaluated test coordinates lie near CFD-populated portions of objective space, rather than on an isolated extrapolated branch of the GPR screening front. These observations support the use of the GPR model for local candidate-region screening. They do not validate the continuous GPR front, establish the optimality of either previously evaluated test configuration, or alter the direct CFD dominance results.

This evidence hierarchy is consistent with the established use of surrogate models for candidate screening in computationally expensive engineering design [9–15,40]. In the present workflow, GPR/NSGA-II guides local screening, production-grid direct CFD determines drag and nondominance, and the three-grid and flow-field analyses provide configuration-specific interpretation. None of these steps independently validate a continuous surrogate Pareto front.

#### 4.5. Numerical Significance and Engineering Implications

Because the grid sequences are monotonic but non-asymptotic, the observed adjacent-grid changes (3.66–4.28%) are treated as mesh-sensitivity indicators rather than uncertainty bounds. The low-drag test configuration remains lower in drag on all three grids, whereas the baseline and trade-off test configurations reverse order; hence, no mesh-robust ranking is assigned to the latter pair [30,35–39].

The power-volume exchange quantified in Table 14 is mission relevant only when internal accommodation is a binding design constraint [1,2,16]. Effective towing power represents the bare hull resistance requirement at the prescribed speed; installed propulsion power and endurance additionally depend on propulsive efficiency, usable onboard energy, non-propulsive loads, and operating conditions. Gross internal volume likewise does not equal net payload capacity because structural, buoyancy, and packaging allowances were not modeled. The observed exchange therefore does not establish the intrinsic superiority of either test configuration.

At the vehicle-system level, predictive models and operational constraints can be integrated into real-time marine vehicle guidance and operation [42]. The present CFD results provide upstream bare hull hydrodynamic evidence rather than mission-level performance predictions. Because both test configurations are dominated in the 53-sample direct CFD audit, mission-specific selection should instead be made from the directly evaluated nondominated set using explicit energy, payload, and objective weighting requirements.

#### 4.6. Applicability, Limitations, and Future Work

The conclusions of this study are conditional on three-dimensional steady RANS/SST  $k-\omega$  simulations of a deeply submerged, hydraulically smooth bare hull in uniform flow at zero incidence. They are further restricted to  $Re_L \approx 1.60 \times 10^6$ , the flat-ended  $L/D = 4.0$  geometry, and the sampled domain  $1.0 \leq N \leq 3.0$  and  $150 \leq L_{nose} \leq 350$  mm. GPR/NSGA-II was used only for candidate-region screening, whereas nondominance was determined from production-grid direct CFD drag coefficients and analytical gross internal volumes. Accordingly, the reported nondominated sets, drag decomposition, pressure recovery characteristics, and wake fields constitute configuration-specific mean-flow evidence within the sampled domain; they do not establish a continuous Pareto surface or a universally transferable optimum.

Steady RANS resolves the time-averaged hydrodynamic response, but does not establish instantaneous wake dynamics. In the complementary blunt base benchmark, the calculation reproduced the negative mean base pressure deficit, but underestimated its magnitude over the experimentally instrumented central region by 12.32%. This result is retained as a quantified model-form limitation for mean fixed-separation pressure rather than as validation of the unsteady wake [26–28,33–36]. The present calculations also exclude maneuvering and unsteady incidence, free-surface and seabed proximity, appendages and control surfaces, propulsor hull interaction, cavitation, laminar-to-turbulent transition, surface roughness, coating degradation, and biofouling. These effects may alter the local inflow, boundary-layer development, pressure recovery, separation, base wake structure, and installed propulsion loading [1,2,16,24,25,30]. The reported drag-volume ordering and sampling envelope bounds should therefore not be transferred unchanged to appended, self-propelled, maneuvering, or near-surface AUVs, or to hulls with different  $L/D$  ratios and stern treatments [4–6,16,20]. The SUBOFF comparison in Figure 13 and Table 18 is used only as a dimensionless configuration-level reference; isolating a stern-only causal effect would require a geometrically matched flat-ended/tapered-stern pair evaluated under identical numerical conditions.

Future work should extend the direct CFD design space to include  $L/D$ , afterbody geometry, Reynolds number, and operating attitude before introducing appendages, propulsion, and environmental proximity as controlled variables. Where quantitative wake or pressure attribution is required, configuration-specific grid assessments should be combined with unsteady wake resolved simulations and/or experimental measurements. Until such evidence is available, the transferable contribution of the present study is the evidence hierarchy surrogate screening followed by direct CFD dominance auditing and configuration-specific physical interpretation, rather than the numerical sampling envelopes or a universal optimum.

## 5. Conclusions

This study examined the drag-volume trade-off of a compact flat-ended AUV using a 53-sample production-grid CFD database, surrogate-assisted screening, direct CFD nondominance, three-grid reassessment, force decomposition, and paired finite changes. Four conclusions are drawn.

1. Strict fold-wise LOOCV showed that the GPR model is suitable for candidate-region screening but not for defining a globally validated continuous Pareto surface. The direct CFD audit identified 13 globally and 7 locally nondominated samples. Both previously selected CFD test configurations were dominated; the predefined rectangular regions are therefore sampling envelopes rather than optimum windows.
2. The three representative configurations exhibited monotonic but non-asymptotic grid sequences. The low-drag test configuration remained below the baseline on all

three grids, whereas the baseline and trade-off test configurations changed order. Pressure drag accounted for 75.88–79.20% of total drag, but the reduction in the low-drag configuration relative to the baseline was associated mainly with a lower viscous contribution. The axial pressure fields consequently describe configuration-dependent redistribution rather than proving pressure drag-controlled reduction.

3. The baseline retained negative pressure near its flat stern and exhibited a stronger, more compact centerline reverse-flow signature than the tapered SUBOFF reference. Because the two geometries are not matched, this comparison identifies configuration-level differences rather than a stern-only causal effect. At  $U = 2.0$  m/s, the trade-off test configuration provided 4.16 L more gross internal volume than the low-drag test configuration at 0.89 W greater effective bare hull towing power; these quantities do not directly represent installed propulsion power, endurance, or net payload capacity.
4. Paired production grid CFD samples showed that the sign of the  $C_D$  response to increasing  $N$  reverses between the two sampled nose lengths, whereas analytical volume increases in both pairs. Increasing  $L_{nose}$  reduces both drag and volume at the two sampled  $N$  values. These finite changes support local  $N$ - $L_{nose}$  coupling at the available sample resolution, but do not constitute differential sensitivities or establish a continuous plateau or unique optimum.

Overall, the transferable contribution is an evidence hierarchy that separates surrogate screening, sample-level direct CFD nondominance, numerical reassessment, and configuration-specific physical interpretation. The numerical conclusions remain conditional on the investigated steady, deeply submerged, smooth-wall, zero-incidence bare hull model.

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**Data Availability Statement:** The data supporting the findings of this study are provided within the article and its Appendices. Specifically, the CFD sample data used in this study are included in the Appendix A. Additional details can be made available from the corresponding author upon reasonable request.

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**Conflicts of Interest:** The authors declare no conflicts of interest.

## Abbreviations

The following abbreviations are used in this manuscript:

|      |                                 |
|------|---------------------------------|
| AUV  | Autonomous Underwater Vehicle   |
| CFD  | Computational Fluid Dynamics    |
| RANS | Reynolds-Averaged Navier–Stokes |
| SST  | Shear Stress Transport          |
| GPR  | Gaussian Process Regression     |

|         |                                            |
|---------|--------------------------------------------|
| NSGA-II | Non-dominated Sorting Genetic Algorithm II |
| LOOCV   | Leave-One-Out Cross-Validation             |
| RMSE    | Root Mean Square Error                     |
| MAE     | Mean Absolute Error                        |
| SUBOFF  | SUBOFF Benchmark Submarine Model           |
| DARPA   |                                            |
| AFF-1   | DARPA SUBOFF bare-hull configuration       |
| EFD     | Experimental Fluid Dynamics                |
| LES     | Large-Eddy Simulation                      |
| Re      | Reynolds Number                            |
| $C_D$   | Drag Coefficient                           |
| $C_p$   | Pressure Coefficient                       |
| $D_T$   | Total Drag                                 |
| $D_p$   | Pressure Drag                              |
| $D_v$   | Friction Drag                              |
| L/D     | Length-to-Diameter Ratio                   |

## Appendix A

**Table A1.** CFD sample data.

| $N$         | $L_{nose}$  | Direct CFD $C_D$ | $V$ (m <sup>3</sup> ) | Sample Group | Sample ID |
|-------------|-------------|------------------|-----------------------|--------------|-----------|
| 1.749080238 | 174.407647  | 0.26113496       | 0.022991225           | Initial      | I01       |
| 2.901428613 | 249.035382  | 0.26317775       | 0.023541793           | Initial      | I02       |
| 2.463987884 | 156.8777042 | 0.26100291       | 0.023876476           | Initial      | I03       |
| 2.197316968 | 331.8640804 | 0.25872169       | 0.022044348           | Initial      | I04       |
| 1.312037281 | 201.7559963 | 0.25742818       | 0.021780741           | Initial      | I05       |
| 1.311989041 | 282.5044569 | 0.25568868       | 0.020439011           | Initial      | I06       |
| 1.116167224 | 212.3422152 | 0.26079453       | 0.021056255           | Initial      | I07       |
| 2.732352292 | 254.0136042 | 0.26168233       | 0.023366872           | Initial      | I08       |
| 2.202230023 | 259.3420559 | 0.26055259       | 0.02272615            | Initial      | I09       |
| 2.416145156 | 186.9708911 | 0.26074866       | 0.023595727           | Initial      | I10       |
| 1.041168989 | 343.9169256 | 0.25464782       | 0.018148828           | Initial      | I11       |
| 2.939819704 | 305.0265647 | 0.26077932       | 0.023220255           | Initial      | I12       |
| 2.664885282 | 337.8997883 | 0.2604652        | 0.022700796           | Initial      | I13       |
| 1.424678221 | 328.9654701 | 0.258391         | 0.020091948           | Initial      | I14       |
| 1.363649934 | 269.5799958 | 0.25632561       | 0.020817875           | Initial      | I15       |
| 1.36680902  | 334.374847  | 0.25693361       | 0.019792913           | Initial      | I16       |
| 1.608484486 | 167.6985004 | 0.25992505       | 0.02287106            | Initial      | I17       |
| 2.049512863 | 189.1965725 | 0.26253465       | 0.023210399           | Initial      | I18       |
| 1.863890037 | 159.0454578 | 0.26240524       | 0.023319384           | Initial      | I19       |
| 1.58245828  | 215.0660662 | 0.25924809       | 0.022180331           | Initial      | I20       |
| 2.223705789 | 227.7354579 | 0.25968401       | 0.023045631           | Initial      | I21       |
| 1.278987721 | 204.2698064 | 0.25610991       | 0.021656271           | Initial      | I22       |
| 1.584289297 | 315.7475018 | 0.25671194       | 0.020803606           | Initial      | I23       |
| 1.732723687 | 221.3506653 | 0.26067163       | 0.022385467           | Initial      | I24       |
| 1.912139968 | 206.1869019 | 0.25907924       | 0.022852508           | Initial      | I25       |
| 2.570351923 | 258.5392166 | 0.25837623       | 0.023177415           | Initial      | I26       |
| 1.399347564 | 178.184845  | 0.2595938        | 0.022352728           | Initial      | I27       |
| 2.028468877 | 310.4393962 | 0.25774134       | 0.021937925           | Initial      | I28       |
| 2.184829138 | 164.9101287 | 0.26301971       | 0.023586825           | Initial      | I29       |

|             |             |            |             |          |     |
|-------------|-------------|------------|-------------|----------|-----|
| 1.092900825 | 347.3773873 | 0.25423121 | 0.018346833 | Initial  | I30 |
| 2.215089704 | 304.4489539 | 0.25697448 | 0.022328612 | Initial  | I31 |
| 1.341048247 | 189.7431363 | 0.2595933  | 0.02204587  | Initial  | I32 |
| 1.130103186 | 151.1044234 | 0.26753447 | 0.022261911 | Initial  | I33 |
| 2.897771075 | 313.0922857 | 0.26154882 | 0.02312898  | Initial  | I34 |
| 2.931264066 | 291.3714688 | 0.25930431 | 0.023298256 | Initial  | I35 |
| 2.616794696 | 295.8014336 | 0.25935647 | 0.022949734 | Initial  | I36 |
| 1.609227538 | 304.2540693 | 0.26946266 | 0.021031462 | Initial  | I37 |
| 1.195344228 | 164.8089303 | 0.2640826  | 0.022149805 | Initial  | I38 |
| 2.368466053 | 221.6931457 | 0.25987055 | 0.023261463 | Initial  | I39 |
| 1.880304987 | 173.1738119 | 0.26095849 | 0.023178763 | Initial  | I40 |
| 2.4065      | 278.7       | 0.25962422 | 0.022829431 | Adaptive | A01 |
| 1.0683      | 337.89      | 0.25485492 | 0.018409408 | Adaptive | A02 |
| 2.3408      | 284.09      | 0.25898581 | 0.02269735  | Adaptive | A03 |
| 2.1         | 265         | 0.25763924 | 0.022520773 | Adaptive | A04 |
| 2.1         | 295         | 0.25598054 | 0.022225078 | Adaptive | A05 |
| 2.25        | 255         | 0.26096129 | 0.022830948 | Adaptive | A06 |
| 2.25        | 305         | 0.25709409 | 0.022379617 | Adaptive | A07 |
| 2.55        | 255         | 0.25909036 | 0.023183198 | Adaptive | A08 |
| 2.55        | 305         | 0.25806933 | 0.022800934 | Adaptive | A09 |
| 2.7         | 285         | 0.26244355 | 0.023118369 | Adaptive | A10 |
| 1.15        | 320         | 0.25532391 | 0.01914258  | Adaptive | A11 |
| 1.25        | 345         | 0.25317285 | 0.019135163 | Adaptive | A12 |
| 1.5         | 200         | 0.25831445 | 0.022226278 | Baseline | B01 |

**Table A2.** Globally nondominated samples in the complete 53-sample production-grid CFD database.

| Sample | N           | $L_{nose}$  | Direct CFD $C_D$ | V (m <sup>3</sup> ) |
|--------|-------------|-------------|------------------|---------------------|
| I03    | 2.463987884 | 156.8777042 | 0.26100291       | 0.023876476         |
| I06    | 1.311989041 | 282.5044569 | 0.25568868       | 0.020439011         |
| I10    | 2.416145156 | 186.9708911 | 0.26074866       | 0.023595727         |
| I26    | 2.570351923 | 258.5392166 | 0.25837623       | 0.023177415         |
| I31    | 2.215089704 | 304.4489539 | 0.25697448       | 0.022328612         |
| I35    | 2.931264066 | 291.3714688 | 0.25930431       | 0.023298256         |
| A04    | 2.1         | 265         | 0.25763924       | 0.022520773         |
| A05    | 2.1         | 295         | 0.25598054       | 0.022225078         |
| A07    | 2.25        | 305         | 0.25709409       | 0.022379617         |
| A08    | 2.55        | 255         | 0.25909036       | 0.023183198         |
| A09    | 2.55        | 305         | 0.25806933       | 0.022800934         |
| A11    | 1.15        | 320         | 0.25532391       | 0.01914258          |
| A12    | 1.25        | 345         | 0.25317285       | 0.019135163         |

Global nondominance is evaluated over all 53 production-grid CFD samples. The table is reported to distinguish database-wide nondominance from the local seven-point compromise set in the predefined Pareto knee sampling neighborhood.

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