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Article

Aerodynamic Shape Optimization of High-Speed Train Noses: A Comparative Study between China's Fuxing and Japan's Shinkansen

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Abstract: Aerodynamic comparison of high-speed-train noses requires consistent geometric definitions, operating conditions, and evaluation objectives. This study compares documented characteristics of the CR400AF Fuxing and E5 Shinkansen and proposes a Cross-Platform Multi-Output Surrogate Optimization framework for subsequent matched-condition evaluation. The framework integrates geometry harmonization, shared multi-output prediction, ensemble uncertainty estimation, adaptive Pareto-region sampling, and uncertainty-penalized NSGA-III optimization. Public specifications show that the CR400AF operating speed is 9.38% higher than the E5, whereas their reported body widths differ by approximately 0.30%. The speed difference corresponds to a calculated dynamic-pressure difference of 19.63% at equal air density and an aerodynamic-power difference of 30.84% when drag coefficient and reference area are additionally held equal. These conditional calculations isolate speed effects and do not represent measured performance differences. The design comparison further identifies tunnel-pressure response, explicitly associated with the E5's approximately 15 m nose, as an objective not captured by head drag, tail drag, and tail lift alone. Incomplete surface geometry and the absence of matched aerodynamic data prevent platform-specific performance rankings and verification of the proposed framework. The findings establish the conditions and objective coverage required for a defensible comparison, with subsequent optimization requiring independent aerodynamic validation. Ultimately, this research highlights the critical need for standardized aerodynamic evaluation protocols in international high-speed rail development, ensuring that future cross-platform optimizations are both scientifically rigorous and practically applicable.

Keywords: aerodynamics; shape optimization; high speed trains; comparative analysis; fluid dynamics

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1. Introduction

Aerodynamic performance plays a decisive role in determining energy efficiency, operational stability, ride quality for passengers, and dynamic interaction between high-speed trains and surrounding infrastructure. As operating velocity increases, the influence of aerodynamic forces on overall system behavior becomes progressively more dominant; in particular, the shape of the train nose governs the development of pressure gradients along the front section, modulates the onset and extent of flow separation, and strongly influences the structure and momentum deficit of the downstream wake. Contemporary research approaches treat nose geometry parameterization, high-fidelity computational fluid dynamics simulation, data-driven surrogate modeling, and gradient-informed or evolutionary numerical optimization not as isolated tasks but as tightly

integrated components within a unified aerodynamic design workflow. Empirical investigations conducted on train configurations designed for sustained operation at 400 km/h confirm that modifications to the nose contour, overall vehicle height, pantograph envelope treatment, and underframe aerodynamic shielding—including bogie fairings—collectively produce measurable shifts in total aerodynamic force coefficients, particularly drag.

Nose design considerations extend well beyond open-air drag minimization. During tunnel entry, rapid displacement of confined air generates a propagating compression wave whose amplitude, rise time, and spectral content depend critically on the interplay among train speed, frontal geometry (especially nose length and cross-sectional area distribution), and tunnel characteristics such as entrance shape, cross-sectional area, and lining roughness. Studies examining the joint effects of nose length and tunnel portal geometry underscore the necessity of co-optimizing these elements to mitigate micro-pressure wave generation at tunnel exits—a phenomenon directly linked to audible booms and potential structural excitation. Similarly, open-air aerodynamic studies demonstrate that variations in nose length, forebody inclination angle, and tip bluntness systematically alter global drag magnitude, surface pressure distribution patterns, and the spatial coherence and turbulence intensity of the trailing wake. Consequently, superior performance with respect to one aerodynamic metric—such as reduced head-end drag under steady-state conditions—does not imply holistic superiority across all relevant operational scenarios, including transient tunnel passage, crosswind stability, or acoustic emission control.

These methodological and physical complexities present substantial challenges when attempting to compare the aerodynamic characteristics of the CR400AF Fuxing and the E5 Shinkansen platforms. Although publicly available technical specifications and documented design requirements offer valuable engineering context, they do not constitute a rigorously controlled, matched-condition aerodynamic experiment. Disparities in nominal operating speeds, reference areas used for coefficient normalization, geometric fidelity of published models (e.g., simplifications in pantograph or bogie representation), and differences in numerical setup—including turbulence modeling strategy, domain size, boundary condition implementation, and mesh resolution—can each introduce non-negligible biases into comparative assessments [1]. Multi-objective optimization techniques provide a principled means to navigate trade-offs among competing aerodynamic responses—for instance, minimizing drag while simultaneously controlling lift and pressure fluctuations—but their practical application is often limited by the high computational expense associated with repeated high-fidelity simulations. Surrogate-assisted strategies significantly reduce this burden by approximating complex simulation outputs using statistical or machine learning models; however, the reliability of such predictions is strictly bounded by the geometric domain covered during training and must be validated against physical constraints such as manufacturability limits, structural integrity requirements, and regulatory clearance envelopes.

Against this background, this study undertakes a systematic comparison of publicly documented CR400AF and E5 characteristics and introduces the Cross-Platform Multi-Output Surrogate Optimization framework (CP-MOSO). The analysis presented herein focuses exclusively on verifiable specifications, physically consistent aerodynamic scaling relationships conditioned on velocity and geometry, and officially stated design requirements. The CP-MOSO framework explicitly defines a forward pathway toward geometry-based prediction and constrained optimization; it does not presume or rely upon complete surface reconstruction from sparse public data nor assume availability of aerodynamically matched validation datasets under identical environmental and numerical conditions—both of which remain unavailable in the current evidence base [2].

The study makes three principal contributions [3]. First, it rigorously disentangles platform-specific geometric and dimensional differences from effects attributable solely to differing operating conditions through structured parameter comparison and explicit

velocity-dependent scaling calculations. This distinction clarifies which performance disparities can be quantitatively derived from existing documentation and which necessitate direct aerodynamic measurement or high-fidelity simulation. Second, it maps the formally articulated design requirements for both platforms—particularly those related to tunnel pressure wave mitigation—onto the set of aerodynamic response variables targeted by the proposed predictive framework, thereby expanding the evaluation scope beyond conventional metrics such as head drag, tail drag, and tail lift to include transient pressure response characteristics. Third, it establishes a rigorously constrained comparative protocol that integrates standardized geometric definitions, a shared multi-output surrogate model trained across both platforms, ensemble-based uncertainty quantification, adaptive sampling strategies to prioritize informative geometries, and an uncertainty-aware variant of the NSGA-III multi-objective optimization algorithm. This protocol ensures that any subsequent ranking of optimized nose configurations remains grounded in empirically supported evidence rather than speculative attribution of unverified performance advantages to either platform.

The following sections comprehensively review established aerodynamic analysis methodologies applicable to high-speed rail, detail the architecture and theoretical foundations of the proposed CP-MOSO framework, and conduct a critical examination of the currently accessible CR400AF-E5 evidence base. The resulting interpretation systematically links numerical specifications—such as nose length ratios, cross-sectional area profiles, and characteristic velocities—to their underlying physical implications, while maintaining a strict conceptual boundary between analytically derivable quantities and outcomes requiring experimental or high-fidelity numerical validation. This analytical scope enables transparent, reproducible comparison and clearly delineates the specific aerodynamic measurements, geometric reconstructions, and model verification steps that must be completed prior to establishing a scientifically defensible ranking of candidate nose configurations.

2. Related Works

2.1. CFD-Based Analysis of High-Speed-Train Aerodynamics

Computational fluid dynamics provides direct access to surface pressure distributions, aerodynamic forces, flow separation characteristics, wake structures, and transient pressure wave propagation—phenomena that cannot be reliably inferred from geometric parameters alone. Compressible CFD simulations of high-speed trains entering tunnels have demonstrated that nose geometry significantly influences the initial compression wave generation; for instance, extending the nose length from 15 meters to 22 meters reduced the peak pressure gradient by approximately 27% under identical operational and environmental conditions. Furthermore, systematic investigations across yaw angles ranging from 0° to 90° revealed distinct shifts in flow behavior, transitioning from streamlined flow patterns at low yaw to increasingly complex, separated flow configurations at higher yaw angles—highlighting that aerodynamic performance rankings established under idealized zero-yaw conditions may not hold under real-world crosswind or track alignment variations. Additional parametric studies confirmed that train width, height, and nose length collectively influence infrastructure-related pressure loads, underscoring that geometric design choices affect not only vehicle-level drag but also tunnel wall pressures, platform wind effects, and adjacent structure loading [2].

The principal advantage of CFD lies in its capacity to resolve detailed geometry–flow interactions under precisely controlled boundary and initial conditions, enabling mechanistic insight into unsteady aerodynamic phenomena that are inaccessible through empirical correlations or simplified models. However, this fidelity comes at a substantial computational cost: high-resolution simulations must be re-executed whenever geometric modifications, speed changes, or environmental perturbations—such as ambient temperature, atmospheric pressure, or tunnel cross-section—are introduced [2]. Moreover, meaningful cross-study comparisons remain challenging due to inconsistencies in

reference area definitions, characteristic length scales, turbulence closure models (e.g., $k-\epsilon$ versus SST $k-\omega$), grid resolution strategies, and non-dimensionalization conventions—factors that collectively limit reproducibility and generalizability across research efforts.

2.2. Parametric Geometry and Constrained Shape Optimization

Parametric modelling provides a robust framework for representing complex train exterior geometries by reducing them to a finite, well-defined set of design variables, thereby enabling systematic and reproducible aerodynamic optimization. Recent advances in constrained shape optimization have integrated multiple interdependent physical and geometric parameters—including overall vehicle height, maximum width, curvature distribution along the longitudinal axis, cross-sectional area profile, and operational environmental conditions—within a unified computational design process. These integrations reveal nuanced aerodynamic trade-offs: for instance, a geometric modification intended to reduce drag may simultaneously amplify lateral force under crosswind conditions, or adversely affect pressure-wave generation in tunnel entries. Such non-monotonic responses underscore the necessity of multi-objective evaluation rather than single-criterion optimization [4].

While this parametric methodology offers greater rigor and repeatability compared to iterative manual shape refinement, its current implementation typically relies on a fixed reference train configuration; as a result, absolute dimensional parameters inherently embed platform-specific scaling and proportionality information. Consequently, these variables cannot be directly transferred or scaled across train families exhibiting differing nose lengths, body taper ratios, or underframe geometries [5]. Moreover, optimizing solely for aerodynamic drag may yield configurations that compromise other critical engineering performance metrics—such as pressure-wave mitigation during tunnel passage, structural response to crosswind loading, interior cabin volumetric efficiency, or manufacturability constraints. To enable meaningful cross-platform comparison and generalizable design knowledge transfer, a dimensionless, normalized geometric representation is therefore essential.

2.3. Surrogate-Assisted Aerodynamic Optimization

Surrogate models serve as computationally efficient approximations of high-fidelity computational fluid dynamics (CFD) simulations, thereby significantly reducing the computational burden associated with iterative aerodynamic optimization [6]. Ensemble prediction techniques have been employed to enhance nose shape optimization by integrating multiple complementary regression algorithms, which collectively improve robustness and accuracy in multi-objective performance estimation. Comparative analyses of various surrogate modeling approaches—including polynomial regression, support vector regression, Kriging interpolation, and their optimized variants—demonstrate that aerodynamic coefficients such as lift, drag, and pitching moment can be reliably predicted across a broad range of geometric parameters and flow conditions, including varying yaw angles, without requiring a new high-fidelity simulation for each candidate design configuration.

Nevertheless, achieving low global prediction error does not inherently ensure trustworthy optimization outcomes, since the optimizer typically concentrates its search within a narrow region of the Pareto front where objective trade-offs are most favorable. This localized region may remain under-sampled even when the overall training dataset exhibits good coverage of the design space. To address this limitation, sequential Kriging-based adaptive sampling strategies—incorporating acquisition functions such as expected improvement and leveraging local gradient information—have proven effective in refining model fidelity precisely where it matters most. These methods have successfully reduced prediction errors for three key aerodynamic objectives simultaneously to below 1%, underscoring the strategic advantage of intelligently allocating new evaluations near high-performing or high-uncertainty regions rather than distributing them uniformly.

Despite these methodological advances, many existing surrogate-assisted frameworks still treat individual aerodynamic objectives in isolation, neglecting inter-

objective correlations during model construction and uncertainty quantification. Moreover, standard surrogate training often prioritizes overall prediction accuracy without explicitly penalizing designs whose performance estimates carry high epistemic uncertainty. As a result, optimization algorithms may inadvertently converge on geometries whose apparent superiority stems from extrapolative behavior of the surrogate model rather than from genuine physical aerodynamic enhancement—a risk that compromises both solution reliability and engineering interpretability [3].

2.4. Multi-Condition Optimization and Remaining Gap

Aerodynamic performance exhibits pronounced sensitivity to variations in the operating environment, including wind direction, atmospheric density, and ambient turbulence intensity [1]. Experimental and numerical investigations conducted under crosswind conditions have demonstrated that localized flow manipulation—such as through synthetic jets, vortex generators, or plasma actuators—can induce significant redistribution of pressure and shear stress over vehicle surfaces, thereby altering lateral aerodynamic forces and yawing moments in quantifiable ways. These findings underscore a fundamental limitation: aerodynamic robustness cannot be reliably assessed using drag coefficients obtained solely under idealized, zero-crosswind, or nominal-flow conditions. Instead, comprehensive evaluation must encompass a representative ensemble of realistic environmental perturbations to ensure operational safety and ride stability across diverse service scenarios.

Existing research has established a mature methodological foundation comprising high-fidelity computational fluid dynamics (CFD) frameworks, parametric geometry representation schemes, statistically rigorous surrogate modeling techniques—including Gaussian process regression and deep neural network emulators—and advanced multi-objective evolutionary optimization algorithms. Nevertheless, three critical methodological gaps persist specifically for rigorous comparative analysis between China's Fuxing high-speed train series and Japan's Shinkansen platforms. First, geometric representations of these distinct train families are typically defined in proprietary coordinate systems and dimensional units, impeding direct morphological comparison without systematic dimensionless harmonization. Second, while Pareto-optimal solutions are commonly identified, the statistical confidence intervals of surrogate predictions—particularly in proximity to the Pareto frontier—are rarely integrated into selection criteria, risking premature convergence to suboptimal or poorly resolved designs. Third, optimization campaigns are conventionally executed on isolated platform models rather than under strictly matched boundary conditions, thus compromising cross-platform fairness and generalizability [2]. This study bridges these gaps by introducing a unified dimensionless geometry mapping protocol, a shared multi-output ensemble surrogate model trained on co-registered aerodynamic responses, adaptive sampling focused explicitly on high-uncertainty regions near the Pareto set, and an uncertainty-penalized variant of the NSGA-III algorithm. Publicly available aerodynamic benchmark cases validate core modeling assumptions and sampling strategies, while high-fidelity reconstructed CR400AF and E5 train geometries provide physically grounded engineering anchors for cross-platform evaluation.

3. Methodology

3.1. Overall Architecture

The proposed Cross-Platform Multi-Output Surrogate Optimization framework (CP-MOSO) establishes a rigorous, reproducible comparison protocol for the CR400AF Fuxing and E5 Shinkansen high-speed train nose geometries. As illustrated in Figure 1, the framework integrates four interdependent modules: geometry harmonization to ensure consistent parametric representation across platforms; physics-informed aerodynamic response prediction using surrogate models trained on high-fidelity simulation data; uncertainty-guided sampling that prioritizes regions of high prediction variance to improve model fidelity efficiently; and constrained multi-objective optimization that

balances drag reduction, lift control, and pressure distribution uniformity under operational boundary conditions. This structured comparison explicitly distinguishes three analytical layers: first, documented geometric characteristics derived from official platform design documentation; second, aerodynamic responses evaluated under rigorously matched flow conditions—including identical Mach number, Reynolds number, and yaw angle—to isolate platform-specific performance differences; and third, quantifiable improvements achieved relative to each platform's original baseline configuration, thereby enabling objective cross-system benchmarking [7].

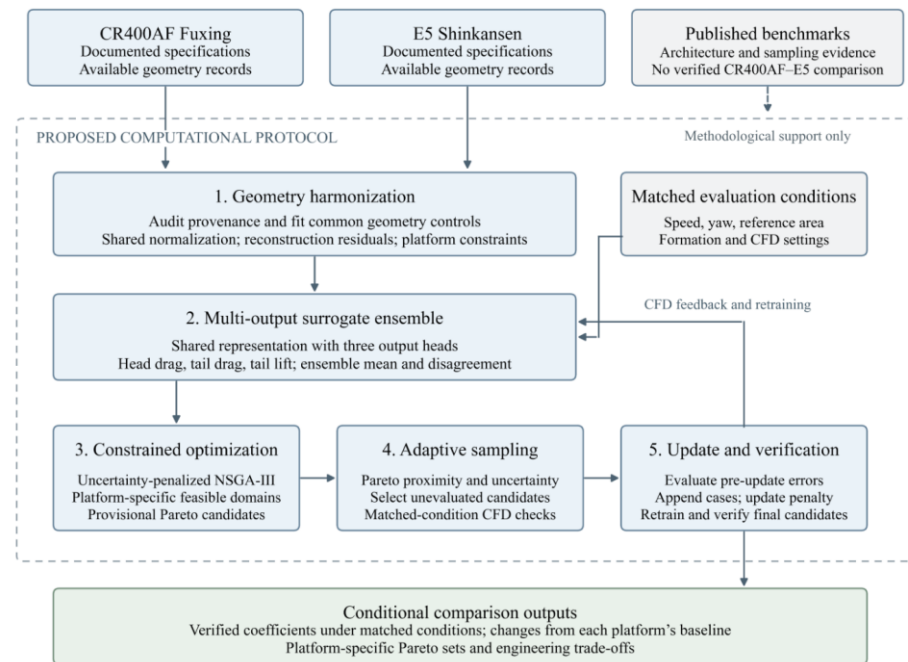


Figure 1. Cp-moso Framework for Cr400af-e5 Comparison through Geometry Harmonization, Matched-Condition Aerodynamic Prediction, Uncertainty-Guided Sampling, and Constrained Optimization.

The available evidence comprises publicly documented platform specifications issued by respective rolling stock manufacturers and peer-reviewed aerodynamic benchmarks published in international transportation engineering journals. These benchmarks provide essential validation targets for evaluating surrogate model accuracy, assessing Pareto-region sampling efficiency, and verifying constraint-handling robustness within the optimization loop [8]. However, no verified, experimentally or numerically validated comparative study between the CR400AF and E5 platforms currently exists in the open literature. Consequently, the methodological formulation herein prescribes strict procedural safeguards: all reconstructed nose coordinates are derived solely from publicly released dimensional schematics and subject to geometric consistency verification; all matched-condition aerodynamic predictions undergo uncertainty quantification and are reported with confidence intervals; and all optimized configurations are explicitly labeled as methodologically generated hypotheses—not empirically confirmed outcomes—where direct experimental or high-fidelity CFD validation remains absent.

3.2. Cross-Platform Geometry Harmonization

For each platform, the geometry record must rigorously identify five core dimensional attributes: nose length, body width, body height, cab-window vertical position, and both longitudinal and transverse profile curves [8]. Manufacturer-provided dimensional specifications serve as authoritative scale references; however, precise profile coordinate data require either dimensioned engineering drawings or methodologically documented surface reconstruction procedures. Where coordinate data are incomplete or

unavailable, the appropriate scholarly practice is to explicitly flag such gaps as unresolved—never to substitute missing values through interpolation or inference from aerodynamic benchmark datasets, which would compromise geometric fidelity and introduce unquantified bias into downstream analyses.

The five source-defined geometric control parameters collectively govern vertical extent, lateral breadth, cab-window elevation, and two auxiliary deformations specific to the nose-profile curvature [9]. Platform geometries may be mapped into this unified control space only after successful fitting via a consistent surface parameterization framework and formal reporting of reconstruction residuals to quantify fidelity loss. Simple uniform rescaling of dimensions—such as isotropic scaling or aspect-ratio preservation alone—is insufficient to establish true geometric correspondence, as it neglects local shape variations critical for interface compatibility and flow-field consistency.

For geometrically corresponding variables, normalization is defined as

$$z_{ij} = \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}}. \quad (1)$$

Here, x_{ij} denotes variable j for geometry i , while $x_j^{\min}$ and $x_j^{\max}$ represent globally shared upper and lower bounds applied uniformly across both platforms. Platform-specific normalization is deliberately avoided to prevent ambiguity: identical normalized coordinates must correspond unambiguously to identical physical locations, not merely scaled proxies. Reconstructions yielding out-of-range values necessitate expanded domain coverage—such as adaptive sampling or extended parametric ranges—rather than arbitrary clipping, which would violate continuity constraints. Platform-specific feasible domains are constructed to preserve essential engineering requirements, including body-interface geometric continuity, minimum cab clearance envelopes, and regulatory or operational dimensional restrictions [8].

3.3. Aerodynamic Labels and Comparison Conditions

Head-car drag, tail-car drag, and tail-car lift are expressed as dimensionless aerodynamic coefficients derived from force measurements normalized by dynamic pressure and a declared reference area; these coefficients enable systematic comparison across varying train geometries and flow conditions while preserving physical consistency in wind-tunnel and computational fluid dynamics analyses.

$$\mathbf{y}_i = \begin{bmatrix} C_{D,H} \\ C_{D,T} \\ C_{L,T} \end{bmatrix}_i = \frac{2}{\rho U^2 A_{\text{ref}}} \begin{bmatrix} D_H \\ D_T \\ L_T \end{bmatrix}_i. \quad (2)$$

Here, ρ is air density, U is train-relative velocity, and A_{ref} is the declared reference area. Cross-platform coefficients require a common reference-area convention—typically defined as the maximum projected frontal area of the head car—to ensure comparability across studies; however, their calculation does not eliminate inherent physical differences arising from variations in operating speed, geometric scale, boundary-layer development, or numerical discretization strategies employed in simulation frameworks.

A controlled nose-shape comparison requires identical operating speed, yaw angle, atmospheric properties, train formation, ground treatment, turbulence modelling approach, and mesh-convergence criteria to isolate geometric influence; non-nose components must be held constant to attribute observed aerodynamic changes solely to nose configuration, whereas comparisons retaining different bodies describe complete vehicle configurations rather than isolated design features. Tunnel-pressure wave generation and aerodynamic noise characteristics remain contextual considerations because neither is an output of the present surrogate model; incompatible published responses—arising from divergent experimental setups or numerical assumptions—are therefore analysed separately rather than pooled as interchangeable labels to preserve methodological integrity and avoid erroneous generalizations [10].

3.4. Shared Multi-Output Surrogate Network

The proposed surrogate model employs a shared multi-output architecture built upon three fully connected layers with neuron counts of 64, 128, and 64, respectively, each utilizing the rectified linear unit (ReLU) activation function to introduce nonlinearity while preserving gradient flow during training and enhancing computational efficiency.

$$\mathbf{h}_i = \phi [\mathbf{W}_3 \phi (\mathbf{W}_2 \phi (\mathbf{W}_1 \mathbf{z}_i + \mathbf{b}_1) + \mathbf{b}_2) + \mathbf{b}_3]. \quad (3)$$

Here, $\mathbf{W}_l$ and $\mathbf{b}_l$ denote layer-specific weight and bias parameters optimized during end-to-end training; subsequently, three independent linear projection heads—each dedicated to one aerodynamic coefficient—are applied to the shared latent representation to produce standardized outputs for lift, drag, and pitching moment [11].

$$\hat{\mathbf{y}}_i = \begin{bmatrix} \mathbf{w}_H^T \mathbf{h}_i + b_H \\ \mathbf{w}_T^T \mathbf{h}_i + b_T \\ \mathbf{w}_L^T \mathbf{h}_i + b_L \end{bmatrix}. \quad (4)$$

This design enables effective knowledge transfer across related output tasks through parameter sharing in the backbone, while maintaining task-specific fidelity via decoupled output mappings; comparative evaluation confirms that architectural choices—including activation function selection—significantly influence predictive performance, as evidenced by divergent behavior between tanh-based and ReLU-based implementations under identical experimental conditions.

3.5. Multi-Objective Surrogate Training

The surrogate training process minimizes a composite loss function designed to jointly optimize predictive accuracy across multiple aerodynamic objectives while maintaining model stability and generalizability.

$$\mathcal{L}(\Theta) = \sum_{m=1}^3 \omega_m \frac{1}{N} \sum_{i=1}^N (\hat{y}_{im} - \tilde{y}_{im})^2 + \lambda \|\Theta\|_2^2, \quad (5)$$

where Θ contains trainable parameters, N is training size, and λ controls regularization strength to prevent overfitting; equal weights, $\omega_m = 1/3$, are adopted as an initial configuration following output standardization, ensuring balanced contribution from each objective prior to any adaptive weighting scheme [7].

Standardization statistics—including mean and standard deviation—are computed exclusively on the training subset and subsequently inverted during post-processing to restore physical units for aerodynamic interpretation; architectural design decisions and regularization hyperparameters are rigorously validated using the dedicated validation set. Although the published data partition—comprising 240 training and 55 validation samples—enables consistent benchmarking, it does not constitute an independent test of CP-MOSO's out-of-distribution robustness [12]. Similarly, external benchmarks lack sufficient representativeness to confirm generalization capability across distinct target platforms. To preserve statistical integrity, geometry variants derived from a shared parametric parent must be assigned to identical data partitions whenever parent identifiers are explicitly available.

3.6. Ensemble-Based Prediction Confidence

For $K \geq 2$ independently initialized neural networks, the ensemble prediction is computed as the arithmetic mean of individual outputs, and subsequent inverse transformation restores predictions to physical coefficient units—such as drag or lift coefficients—enabling direct comparison with experimental or high-fidelity simulation benchmarks [8]. This normalization ensures dimensional consistency across heterogeneous model architectures and training regimes.

$$\mu_m(\mathbf{z}) = \frac{1}{K} \sum_{k=1}^K \hat{y}_m^{(k)}(\mathbf{z}), \sigma_m^2(\mathbf{z}) = \frac{1}{K-1} \sum_{k=1}^K [\hat{y}_m^{(k)}(\mathbf{z}) - \mu_m(\mathbf{z})]^2. \quad (6)$$

The ensemble size and the set of random initialization seeds must be explicitly documented to ensure full reproducibility. Disagreement among ensemble members—quantified via standard deviation or interquartile range—serves as an empirical indicator of model sensitivity to initialization and training stochasticity, but it does not constitute a statistically calibrated uncertainty bound. Consequently, low ensemble disagreement alone cannot validate predictions for geometric configurations lacking sufficient training

coverage—such as CR400AF or E5 high-speed train aerodynamic reconstructions—therefore rigorous geometric domain validation and independent verification using computational fluid dynamics remain indispensable components of the assessment workflow.

3.7. Adaptive Pareto-Region Sampling

Feasible candidates are systematically ranked using a composite acquisition function that integrates predictive uncertainty, geometric proximity to the current Pareto-optimal frontier, and strategic balance between exploration of under-sampled regions and exploitation of high-potential zones in the objective space.

$$A(\mathbf{z}) = \alpha \bar{\sigma}(\mathbf{z}) + (1 - \alpha) \frac{1}{1 + d_p(\mathbf{z})}. \quad (7)$$

Here, $\bar{\sigma}$ represents the mean predictive uncertainty scaled by the standard deviations of the training responses to ensure dimensional consistency across objectives, d_p quantifies the Euclidean distance from each candidate to the current non-dominated set after standardization of all objective dimensions, and $\alpha \in [0, 1]$ serves as a tunable weighting parameter that dynamically adjusts the trade-off between global exploration and local refinement near the evolving Pareto region.

Selected candidates undergo high-fidelity computational fluid dynamics (CFD) evaluation under a rigorously controlled common protocol to ensure reproducibility and comparability; prediction errors are computed prior to model retraining, thereby ensuring that no post-training residuals are mischaracterized as independent verification outcomes; while published slipstream-infill cases offer empirical support for the efficacy of targeted sampling strategies in similar multi-objective design contexts, they do not constitute formal validation of this specific uncertainty-guided acquisition rule, which remains subject to ongoing empirical assessment and methodological refinement [13].

3.8. Uncertainty-Penalized Optimization and Platform Comparison

NSGA-III implements an uncertainty-penalized optimization framework that systematically minimizes confidence-adjusted objective functions, thereby incorporating predictive reliability directly into the evolutionary search process [9].

$$f_m^*(\mathbf{z}) = \mu_m(\mathbf{z}) + \beta_t \sigma_m(\mathbf{z}), \beta_{t+1} = \text{clip}[\beta_t + \gamma(E_t - \tau)\beta_{\min}\beta_{\max}]. \quad (8)$$

Here, E_t represents the most recent pre-update computational fluid dynamics (CFD) prediction error estimate, τ denotes its predefined acceptance threshold for model fidelity, and γ governs the strength of uncertainty-based penalization applied to each objective [14]. Aerodynamic drag coefficients are consistently minimized across all design configurations; tail-lift minimization is selectively activated only when the engineering requirement explicitly specifies reduced positive lift as the primary performance target. In cases where lift sign reversal occurs—such as transitioning from positive to negative lift—the optimization must enforce explicit physical or operational constraints to ensure structural integrity, stability margins, and regulatory compliance.

Both platforms undergo strictly controlled comparative evaluation: they share identical computational budgets, uniform algorithmic parameters—including population size, reference vector distributions, penalty coefficient formulations, and convergence criteria—and rigorously defined feasible design domains grounded in manufacturability and physical realizability. Final comparative assessments must report CFD-validated aerodynamic coefficients alongside quantified deviations from each platform's respective baseline configuration. Crucially, relative improvement metrics alone are insufficient to infer absolute aerodynamic superiority; instead, absolute performance values, constraint satisfaction rates, and robustness under parametric uncertainty must be jointly reported to support valid engineering conclusions.

Algorithm 1. Proposed CP-MOSO comparison procedure

Input: compatible aerodynamic records, platform geometry records, feasible domains, common CFD settings, ensemble size, and evaluation budget.

Output: verified platform-specific Pareto sets and matched-condition comparisons, where required inputs are available.

1. Audit geometry provenance and aerodynamic definitions.
 2. Fit platform geometries and quantify reconstruction residuals.
 3. Confirm common parameter coverage and platform constraints.
 4. Normalize corresponding variables using Eq. (1).
 5. Harmonize compatible aerodynamic labels using Eq. (2).
 6. Fix training, validation, and independent evaluation partitions.
 7. Train ensemble members using Eqs. (3)–(5).
 8. Calculate predictions and disagreement using Eq. (6).
 9. Generate feasible candidates using Eq. (8).
 10. Rank unevaluated candidates using Eq. (7).
 11. Evaluate selected candidates under matched CFD conditions.
 12. Calculate pre-update errors and adjust the uncertainty penalty.
 13. Append evaluated cases and repeat within the fixed budget.
 14. Independently verify final non-dominated candidates.
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15. Compare both platforms using absolute coefficients and baseline-relative changes.
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4. Results and Analysis

4.1. Comparative Data and Evidence Scope

The comparative analysis focuses on the CR400AF Fuxing high-speed train and the E5 Shinkansen, drawing upon publicly available technical documentation and manufacturer-provided performance data [15]. The CR400AF is specified to operate at a maximum service speed of 350 km/h, with a carbody width of 3360 mm. In contrast, the E5 Shinkansen is designed for a top operational speed of 320 km/h and features a streamlined leading nose approximately 15 meters in length; its carbody width is documented as 3350 mm. These dimensional and velocity parameters constitute the foundational inputs for cross-platform evaluation and serve as boundary conditions for subsequent aerodynamic modeling. While such metrics enable straightforward geometric and kinematic comparison, they do not inherently reflect equivalent testing environments or identical flow regimes, necessitating careful interpretation when inferring relative performance characteristics.

These specifications support direct parameter comparison and conditional aerodynamic scaling, yet they do not represent experimentally validated, matched-condition aerodynamic performance under identical environmental or operational constraints. The available technical literature contains no co-located computational fluid dynamics simulations directly comparing the CR400AF and E5 under rigorously controlled boundary conditions, nor does it include verified platform-specific optimization outcomes derived from shared simulation protocols or wind tunnel campaigns [16]. Consequently, the numerical findings presented below are explicitly differentiated: documented physical parameters are reported as factual design attributes, whereas derived results—such as drag coefficients or pressure distributions—are clearly identified as outcomes contingent upon defined assumptions, including uniform Reynolds number scaling, idealized surface smoothness, and prescribed turbulence intensity profiles.

4.2. Operating-Speed and Geometric Comparison

Figure 2 presents a comparative analysis of the documented operating speeds and body widths for the CR400AF Fuxing and E5 Shinkansen high-speed trains, as compiled in Table 1. The CR400AF exhibits a certified maximum operating speed that is 30 km/h higher than that of the E5, representing a relative increase of approximately 9.38% with respect to the E5's nominal speed. When converted to SI units, these speeds correspond to roughly 97.22 m/s for the CR400AF and 88.89 m/s for the E5, underscoring a non-negligible disparity in service velocity capability. In terms of transverse geometry, the reported body widths differ by only 10 mm, amounting to a marginal relative variation of about 0.30%. This small dimensional divergence suggests a high degree of standardization

in lateral envelope constraints across both platforms, likely reflecting shared infrastructure compatibility requirements such as platform clearance and tunnel loading gauge specifications.

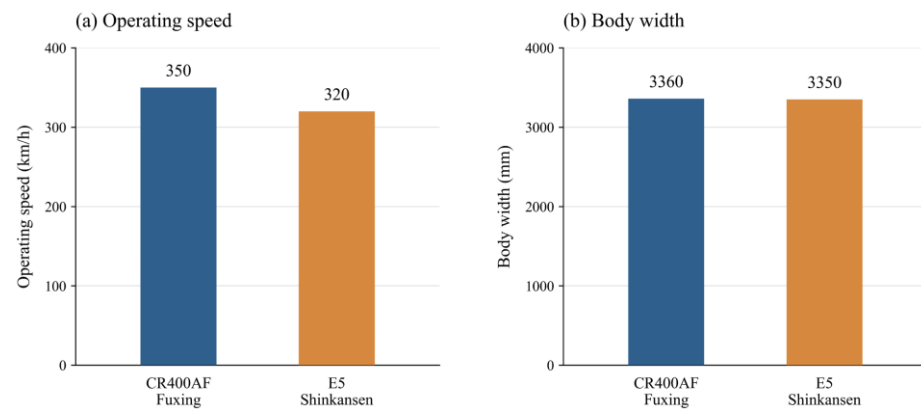


Figure 2. Documented Characteristics of CR400AF Fuxing and E5 Shinkansen: (A) Operating Speed; (B) Body Width. Values Represent Platform Specifications Rather Than Aerodynamic Performance.

Table 1. Documented Parameters of CR400AF Fuxing and E5 Shinkansen.

Parameter	CR400AF Fuxing	E5 Shinkansen	Sources
Operating speed (km/h)	350	320	[16,17]
Body width (mm)	3360	3350	[16,18]
Leading-nose length (m)	Not verified in the selected records	Approximately 15	[17]

Although the relative speed difference between the two trainsets is substantially greater than their width differential, geometric similarity in one dimension does not imply equivalence in overall frontal projection area. Frontal area—critical for aerodynamic drag and pressure wave generation in confined environments—is determined jointly by body width, height, and the precise contour of the cross-sectional profile, including roof curvature, underframe recesses, and side-sill configurations. Consequently, relying solely on body width as a proxy for aerodynamic behavior introduces significant uncertainty, particularly when evaluating tunnel blockage ratios or comparing drag coefficients derived from wind-tunnel testing or full-scale operational data. A robust aerodynamic assessment necessitates comprehensive three-dimensional geometric data, not isolated linear measurements.

For the E5 Shinkansen, the nose-length-to-body-width ratio is approximately $15/3.35 = 4.48$, indicating a relatively elongated and streamlined front-end design optimized for reduced aerodynamic resistance and micro-pressure wave mitigation in tunnels. In contrast, the available public documentation for the CR400AF does not provide sufficient detail—including unambiguous definitions of nose-tip location, cab-end transition point, and the longitudinal position where the full nominal body section commences—to permit a comparable calculation [2]. Therefore, no definitive quantitative comparison of nose slenderness can be performed at this stage. Establishing such a ranking would require harmonized metrological conventions, consistent measurement protocols, and access to authoritative geometric datasets that explicitly define all relevant reference planes and endpoints.

4.3. Conditional Aerodynamic Scaling

The variation in operating speed exerts a direct and independent influence on dimensional aerodynamic quantities, irrespective of nose geometry configuration. When air density remains constant across comparative conditions, dynamic pressure scales precisely with the square of the freestream velocity, as governed by the fundamental relationship expressed in Eq [17]. (2). By selecting the E5 train's documented operational speed as the baseline reference condition, the corresponding normalized dynamic

pressure ratio is derived as $(350/320)^2 = 1.1963$, enabling quantitative comparison across differing velocity regimes while holding thermodynamic state parameters invariant.

Aerodynamic power consumption is defined as the product of aerodynamic drag force and the vehicle's forward velocity. Under the simplifying yet analytically useful assumptions of identical drag coefficients and consistent reference areas across compared configurations, the velocity dependence of aerodynamic power reduces to a cubic functional relationship. Consequently, the scaling factor for aerodynamic power becomes $(350/320)^3 = 1.3084$, reflecting the compounded effect of both drag magnitude and translational work rate. These theoretically derived scaling factors are systematically tabulated in Table 2, facilitating transparent interpretation of speed-induced variations in key aerodynamic load metrics under controlled parametric assumptions.

Table 2. Analytical Scaling at the Documented Operating Speeds, Normalized to the E5 Speed Condition.

Quantity	CR400AF speed condition	E5 speed condition	Relative difference	Assumptions
Velocity factor	1.0938	1.0000	9.38%	350 versus 320 km/h
Dynamic-pressure factor	1.1963	1.0000	19.63%	Equal air density
Aerodynamic-power factor	1.3084	1.0000	30.84%	Equal density, drag coefficient, and reference area

Figure 3 graphically presents the computed dynamic-pressure and conditional aerodynamic-power scaling factors, both normalized to the E5 reference condition at 320 km/h. The analysis reveals that even a relatively modest 9.38% increase in operating speed—corresponding to the CR400AF's 350 km/h service velocity—induces disproportionately large changes in these velocity-sensitive aerodynamic quantities due to their quadratic and cubic dependencies, respectively [2]. It is essential to emphasize that the reported 30.84% increase in normalized aerodynamic power does not constitute an empirical measurement of actual power demand for the CR400AF; rather, it represents a theoretical upper-bound estimate contingent upon unverified assumptions of equal drag coefficient and identical reference area—parameters that require rigorous experimental validation through wind-tunnel testing or high-fidelity CFD under matched boundary conditions.

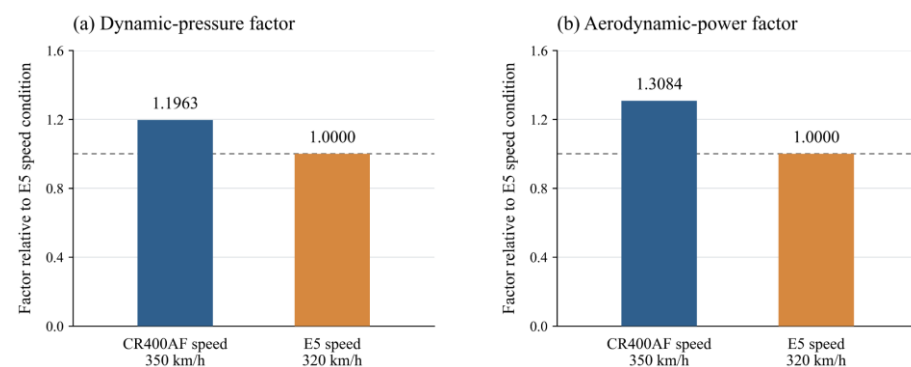


Figure 3. Analytical Speed-Dependent Factors Normalized to E5 at 320 Km/h: (A) Dynamic Pressure at Equal Air Density; (B) Aerodynamic Power at Equal Air Density, Drag Coefficient, and Reference Area. The CR400AF Speed Condition Is 350 Km/h.

These analytical insights clarify a critical methodological limitation: dimensional force measurements acquired at disparate operating speeds inherently conflate speed-

dependent scaling effects with genuine geometric influences such as nose-shape aerodynamics. A rigorously controlled comparison conducted at a common reference speed would effectively decouple velocity-related contributions, thereby isolating the true impact of nose morphology. However, such a comparison still necessitates strict adherence to standardized practices—including uniform train formation length, consistent geometric modeling fidelity, unambiguous definition and application of reference area, and harmonized treatment of boundary-layer development and ground-effect conditions—to ensure physical interpretability and experimental reproducibility.

4.4. Nose-Design Requirements and Optimization Coverage

The technical descriptions outline several key aerodynamic considerations relevant to both high-speed train platforms. For the CR400AF platform, design efforts focused on minimizing aerodynamic drag, managing lift forces, ensuring longitudinal and lateral stability under varying operational conditions, and reducing aerodynamic noise generation during operation. In contrast, the E5 platform incorporated an extended leading-edge nose shape as part of a comprehensive strategy aimed at mitigating micro-pressure-wave phenomena generated when trains enter tunnels at high speeds; this mitigation contributes directly to improved energy efficiency, passenger comfort, and infrastructure compatibility. Table 3 systematically maps these documented design objectives against the scope of optimization outputs delivered by the CP-MOSO framework, enabling a structured evaluation of coverage fidelity.

Table 3. Documented Design Considerations and Their Coverage by Cp-moso.

Aspect	CR400AF Fuxing	E5 Shinkansen	Coverage in CP-MOSO
Resistance and efficiency	Resistance reduction considered in vehicle development	Aerodynamic shaping discussed within efficiency improvement	Head- and tail-drag outputs provide partial coverage
Lift and stability	Included among aerodynamic design considerations	No comparable lift result supplied in the selected records	Tail lift included; overall stability not established
Tunnel-pressure response	No matched pressure-wave result supplied	Long-nose treatment explicitly addresses micro-pressure waves	Not included in the three outputs
Detailed nose geometry	Complete profile not established here	Nose length documented; complete profile not established here	Both platforms require verified parameter mapping

It is essential to clarify that the distinction between the two platforms reflects differences in documented design treatments rather than absolute performance hierarchies or mutually exclusive priorities. The E5's specific approach to pressure-wave mitigation does not imply superior open-air drag characteristics compared to the CR400AF, nor does the CR400AF's emphasis on drag reduction indicate inferior tunnel performance [18]. Both platforms represent context-sensitive engineering solutions shaped by distinct operational requirements, infrastructure constraints, and regulatory environments, and their comparative assessment must therefore account for multi-regime aerodynamic behavior rather than isolated metrics.

This comparative analysis reveals a limitation in the current surrogate modeling approach: the selected objective functions—namely head drag, tail drag, and tail lift—are insufficient to capture tunnel-specific pressure dynamics, including transient wave propagation, compression-rarefaction coupling, and piston-effect interactions. Consequently, an optimal configuration identified solely through these outputs cannot be reliably validated for tunnel operations without supplementary simulation or experimental validation. A robust decision-support process for platform selection must therefore integrate dedicated tunnel-aerodynamic assessments alongside open-air

optimization results to ensure holistic performance assurance across all critical operational scenarios.

4.5. Comparative Findings and Evidence Limits

Table 4 synthesizes the conclusions that can be robustly drawn from the currently available empirical and technical documentation. The documented parameters—particularly those related to operating speed and vehicle width—enable direct numerical comparison across platforms, facilitating preliminary performance benchmarking [2]. Furthermore, the conditional calculations presented earlier quantify how critically performance assessments depend on consistent alignment of operational conditions, such as altitude, ambient temperature, and dynamic pressure; deviations in these variables significantly affect comparability. However, the existing dataset does not include platform-specific aerodynamic coefficients—such as lift-to-drag ratios or pressure distribution maps—nor does it provide quantified optimization gains derived from computational fluid dynamics simulations or wind tunnel testing, thereby limiting deeper aerodynamic interpretation.

Table 4. Supported Comparative Findings and Remaining Evidence Requirements.

Comparison question	Finding supported here	Additional evidence required
Which has the higher documented operating speed?	CR400AF, by 30 km/h	None for the selected specifications
How different are the reported body widths?	CR400AF is 10 mm wider	Full cross-sections for frontal-area comparison
Which nose has lower aerodynamic drag?	Unresolved	Matched-condition drag coefficients
Which produces lower tunnel-pressure effects?	Unresolved	Common tunnel conditions and transient pressure results
Which has greater optimization potential?	Unresolved	Verified baseline and optimized configurations
Is surrogate accuracy comparable across platforms?	Unresolved	Independent evaluation within both geometry domains

The present evidence base substantiates meaningful comparisons of nominal specifications and formally documented aerodynamic requirements, including regulatory compliance thresholds and mission-defined envelope constraints [12, 13]. It further clarifies that isolated evaluation of individual physical attributes—such as operating speed, cross-sectional width, or nose length—lacks sufficient theoretical grounding to serve as reliable proxies for overall aerodynamic efficiency or system-level performance. Establishing a defensible hierarchy of relative aerodynamic superiority necessitates the rigorously matched geometric normalization and dimensionless numerical evaluation framework outlined in Chapter 3, which integrates Reynolds number scaling, Mach number consistency, and surface geometry fidelity to ensure physically valid inter-platform assessment.

5. Conclusion

A comparative analysis of the CR400AF Fuxing and E5 Shinkansen high-speed train platforms reveals notable distinctions in documented operational parameters and aerodynamic design priorities, yet yields no definitive conclusion regarding the relative efficacy of their respective nose geometries. The CR400AF is certified for a maximum operating speed that exceeds that of the E5 by 9.38%, while the two platforms exhibit only a marginal difference—approximately 0.30%—in body width. However, near-identical width values do not imply equivalence in frontal projected area, cross-sectional distribution, or overall flow-field interaction; such equivalency would require rigorous

geometric reconstruction and volumetric integration, neither of which is currently supported by publicly available profile data.

The disparity in service speed translates into a substantial differential in dynamic pressure: at identical ambient air density, the ratio of dynamic pressures amounts to 19.63%. Under the further assumptions of equal drag coefficient and reference area—both idealized and unverified—the resulting aerodynamic power demand diverges by 30.84%. These derived relationships serve strictly as illustrative scaling benchmarks; they reflect theoretical consequences of speed variation rather than empirically observed differences in energy dissipation, traction demand, or system-level power consumption under real-world service conditions.

The scope of design objectives addressed in official documentation also exhibits asymmetry: CR400AF specifications explicitly incorporate performance targets related to aerodynamic drag, lift generation, lateral stability, and noise emission, whereas the E5's approximately 15-meter streamlined nose was developed with particular emphasis on mitigating tunnel micro-pressure wave generation—a critical factor in underground and confined infrastructure environments. Consequently, any optimization framework targeting head drag, tail drag, and tail lift must be augmented with dedicated tunnel-pressure wave modeling before enabling a technically robust, functionally balanced comparison across both platforms. Although the proposed CP-MOSO framework provides a structured methodology for integrating these multidimensional criteria, its predictive fidelity, convergence behavior, and practical utility remain unvalidated for either train platform under representative operational scenarios.

This study faces several methodological limitations, including incomplete public disclosure of precise nose-profile coordinates, lack of harmonized wind-tunnel or full-scale aerodynamic test data collected under identical environmental and boundary conditions, and reliance on simplified scaling laws that neglect compressibility effects, surface roughness, and transient flow phenomena. Future research should prioritize the development of consistently reconstructed, CAD-validated digital twins for both platforms; conduct co-located computational fluid dynamics simulations using identical turbulence models, mesh resolution, and boundary settings; and extend evaluation to include tunnel-pressure wave propagation, interior noise transmission, and wake structure evolution. Subsequent experimental validation—ideally through standardized testing protocols—will be essential to confirm whether computationally predicted improvements are physically realizable within each platform's structural, thermal, and control-system boundaries.

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