

APPENDIX GA36d

Assessment Level 7

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Executive Summary

This report critically evaluates optimisation strategies for the aerodynamic bodywork of a Sports 2000-style race car in the UWTSD workshop, compliant with SRCC Duratec Championship 2025 regulations. This study addresses AHEP4 outcomes M1, M3, and M5 by examining traditional CFD/FE methodologies (such as adjoint shape optimisation and topology) in conjunction with AI-driven surrogates (including PINNs and NSGA-II). It proposes a hybrid workflow comprising parametric CAD, RANS $k-\omega$ SST simulations (5–8 million cells), and LHS-DOE utilising Kriging, aiming for a 10–15% reduction in drag coefficient through modifications to the nose rake, engine cover camber, and splitter, while maintaining a downforce balance with a 50% rear bias. evaluation.

Technical limits, including RANS separation errors of 10–20% and surrogate extrapolation RMSE exceeding 5%, are counterbalanced by practical constraints such as workshop tolerances of ± 2 mm and prototyping costs ranging from £200 to £500, as well as SRCC regulations stipulating a height of 90 cm and an underbody deviation of no more than 2.5 cm. Robustness through sensitivity analysis and validation (coast-down, tunnel) guarantees less than 3% performance variance.

Proposals improve safety stability, impact structures, environmental efficiency (8–15% fuel savings), and commercial viability (0.5–1 second lap reductions, employability), providing innovative, regulatory-compliant concepts for student-led motorsport.

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1. Introduction

In motorsport engineering, aerodynamic optimisation is crucial for enhancing lap times in tightly regulated classes like the SRCC Sports 2000 Duratec Championship, which governs open-cockpit, rear-engine prototypes using a standard 2.0L Ford Duratec engine. These cars, similar to the Sports 2000-style prototype available in the UWTSD workshop, feature strict dimensional limits on bodywork width, height, overhangs, and open cockpit design to ensure safety and competitive balance. Aerodynamic performance directly influences drag, downforce, and balance, whereas existing body shapes often result from iterative evolution rather than systematic optimisation.

This assessment targets body aerodynamics optimisation for such a vehicle, where gains must comply with championship regulations while addressing AHEP4 learning outcomes. The primary aim is to propose and critically evaluate strategies that minimise drag coefficient while maintaining or improving downforce, using modern tools like CFD-based parametric optimisation.

The primary objectives involve evaluating optimisation methods from traditional finite element and computational fluid dynamics to artificial intelligence-driven strategies. Establishing targets, variables, and methodologies. Examining technical and practical constraints, considering broader implications for safety, the environment, and stakeholders, and drawing up findings. This methodical approach illustrates engineering design complexity within regulatory limitations.

2. Literature review: Optimisation tools

2.1 Definition and types of optimisations

Optimisation in engineering design is the systematic process of selecting the best possible solution from a set of feasible alternatives, based on clearly defined performance measures such as minimum drag, maximum stiffness, or lowest mass. It relies on design variables (parameters that can be changed, like wing angle or panel thickness), constraints and one or more objective functions that quantify performance. In motorsport aerodynamics, for example, typical objectives include minimising drag, maximising downforce, or improving the lift-to-drag ratio, while respecting dimensional and safety rules (Martins & Ning, 2022).

There are several main types of optimisations relevant to body and chassis design. Single-objective optimisation focuses on a singular performance metric, such as minimising drag, while multi-objective optimisation considers competing objectives like drag, downforce, and mass, frequently resulting in a Pareto front of trade-off solutions. Definitive optimisation assumes fixed inputs, while robust or reliability-based optimisation accounts for uncertainties in parameters like ride height or manufacturing tolerances. Methods are categorized as gradient-based, efficient for smooth problems with few variables, or gradient-free, such as evolutionary algorithms and particle swarm optimization, which are better for complex, highly non-linear problems like aerodynamic shape optimization but require greater computational effort (AI-Solutions, n.d.; Hottois, et al., 2023).

2.2 Conventional optimisation in FE/CFD packages

Conventional optimisation in finite element (FE) and computational fluid dynamics (CFD) packages integrates simulation solvers directly with optimisation algorithms to iteratively improve designs. For aerodynamics, shape optimisation modifies surface geometry to minimise drag or maximise downforce, typically using parametric representations like free-form deformation (FFD) or spline-based methods to control design variables efficiently. These are linked to CFD solvers running Reynolds-averaged Navier-Stokes simulations, with adjoint methods providing gradient information to guide rapid convergence on optimal shapes, as demonstrated in race car wing designs (Beck, et al., 2025).

In structural FE analysis for chassis or body, common approaches include size optimisation, shape optimisation, and topology optimisation. Packages like ANSYS or Siemens automate this workflow: define variables/constraints, evaluate via FE/CFD, update design via algorithms, and iterate until convergence. For motorsport, such methods have reduced drag by 20–30% in vehicle bodies while maintaining regulatory volumes (Neural Concept, 2026).

These techniques excel in handling physics-based constraints but require high-fidelity meshes and significant computational resources, making them suitable for mid-to-late design stages where geometry is mature (Zhang, et al., 2026).

2.3 AI and data-driven optimisation

AI and data-driven optimisation represent a paradigm shift from physics-based solvers alone, using machine learning (ML) to create surrogate models that predict performance from limited simulation data, dramatically accelerating design exploration. Neural networks are trained on CFD/FEA datasets to approximate flow fields, stresses, or coefficients, enabling thousands of rapid evaluations where full simulations would take days. In motorsport, for instance, Dallara uses AI-reduced order models (ROMs) for fluid-structure interaction on race car wings, cutting FSI cycle times from 15 minutes to near-instant while preserving accuracy (Suvanjumrat, et al., 2025; La Guardia & Battaglia, 2025).

Key techniques include physics-informed neural networks (PINNs), which embed governing equations into ML training for data-efficient predictions of turbulent flows or structural responses, and generative adversarial networks (GANs) for creating novel geometries. Reinforcement learning (RL) or Bayesian optimisation then navigates the design space, as seen in vehicle drag reduction studies where autoencoders map high-dimensional shapes to low-dimensional manifolds for Pareto-optimal aero designs. These methods have achieved 20–40% faster design cycles in automotive/aerospace, with CFMS demonstrating aerofoil performance gains via AI-augmented CFD (Style3D, 2026; Tran, et al., 2024).

While powerful for multi-objective problems with high-dimensional variables, AI approaches require quality training data, risk estimating errors outside the learned domain, and demand validation against physics-based simulations to ensure regulatory compliance in safety-critical applications like race car bodywork (Suvanjumrat, et al., 2025).

3. Proposed optimisation of the race car body

3.2 Choice of optimisation target and variables

The main optimisation objective for the Sports 2000 race car body is a multi-dimensional function aimed at reducing the drag coefficient (C_d) by a minimum of 10–15%, while preserving or enhancing the downforce coefficient (C_z) and aerodynamic equilibrium (targeting a rear bias of 45–55% at standard race velocities of 150–200 km/h), in compliance with SRCC regulatory conditions. This refers to the class's focus on competitive racing, wherein drag reduction correlates

with increased peak speeds and fuel efficiency, all while maintaining stability and sticking to the open-cockpit, 2-seater configuration and a maximum body height of 90 cm (excluding the rear wing) (Sports Racing Car Club , 2025).



Figure 1. UWTSD race car for SRCC race.

Design factors are chosen based on their practicality within workshop constraints and regulatory parameters, emphasising adjustable body panels. Essential variables encompass nose cone rake angle ($\pm 5^\circ$ from baseline), leading-edge radius (10–20 mm), engine cover camber height (maximum 90 cm overall), rear deck trailing-edge angle (0–10° downward), and front splitter extension (maximum 91.5 cm front of front axle). This design circumvents forbidden ground effects (underbody variation ≤ 2.5 cm, absence of skirts/fences) and guarantees compliance to the obligatory SRCC-RA2 rear wing, cockpit aperture ($\geq 80 \times 40$ cm rectangle), and sidepod symmetry. Constraints include manufacturing tolerances (± 2 mm), ride height changes (± 20 mm), and yaw angles ($\pm 5^\circ$), guaranteeing resilient designs (Sports Racing Car Club , 2025).

3.3 Computational and analytical techniques

The proposed optimisation employs a hybrid computational workflow combining parametric CAD modelling, high-fidelity CFD simulation, design of experiments (DOE), and surrogate-based optimisation, aligned with AHEP4 outcome M3 for selecting appropriate analytical techniques. This approach systematically explores the design space while respecting SRCC chassis/body constraints like maximum height (90 cm), underbody flatness (≤ 2.5 cm deviation), and open cockpit requirements.

CAD Parametrisation and Meshing (Samareh, 2004)

Geometry is parametrised in SolidWorks or Fusion 360 using 12–15 design variables via scripted features and equations, enabling rapid iteration without manual remodelling. Each variant generates a watertight STL exported to ANSYS Fluent or Open FOAM for meshing: a polyhedral volume mesh with prism layers ($y^+ \approx 1$ for RANS accuracy), ≈ 5 –8 million cells, targeting the Sports 2000 frontal area (≈ 1.2 m²) and wheel enclosures per regulations. Boundary conditions reflect race conditions: freestream velocity 40–55 m/s, static pressure outlet, no-slip walls, and rotating wheels ($\omega = 200$ rad/s) to capture interference drag.

CFD Simulation Setup (Beck, et al., 2025)

Steady-state RANS simulations use the $k-\omega$ SST turbulence model, validated for separated flows around open-wheel prototypes (error $< 5\%$ vs wind tunnel), solving incompressible Navier-Stokes equations on 32–64 CPU cores (≈ 2 –4 hours per case). Outputs include C_d , C_z front/rear, pitching moment (C_m), and centre of pressure (CoP), post-processed for L/D ratio and balance. Aero maps versus ride height (100–150 mm) and yaw ($\pm 5^\circ$) ensure yaw-stability compliance, with grid independence verified via $GCI < 3\%$ on C_d .

Design of Experiments and Surrogate Modelling (Samareh, 2004)

A Latin Hypercube Sampling (LHS) DOE generates 80–120 geometries spanning variable bounds, evaluated via CFD to build a Kriging surrogate model mapping inputs (C_d , C_z , C_m), reducing full simulations by 90% with RMSE < 3 –5%. The multi-objective genetic algorithm (NSGA-II, 100 generations, population 100) navigates the Pareto front, prioritising $C_d < \text{baseline} - 0.05$ at $C_z \geq \text{baseline}$, with penalty functions enforcing regulatory hard constraints.

This technique balances fidelity, cost, and originality, delivering a projected 8–12% Cd reduction directly applicable to UWTSO workshop constraints (University of Bristol, 2026).

4. Critical evaluation of the proposal

4.1 Technical limitations of the methods

While effective, the CFD-based optimisation workflow faces inherent technical limitations stemming from modelling approximations and computational paradigms. RANS simulations with $k-\omega$ SST provide good mean flow predictions but struggle with unsteady separated flows common in open-cockpit race cars, such as vortex shedding from sidepods or wheel wakes, leading to 10–20% errors in rear downforce and pitching moment compared to LES or experimental data. The turbulence model's reliance on Boussinesq eddy viscosity neglects non-linear Reynolds stress anisotropy in strong separation regions, potentially overpredicting diffuser effectiveness under SRCC flat-underbody rules (Rincón, et al., 2023).

Surrogate models like Kriging offer speed but suffer from interpolation bias and poor extrapolation beyond the DOE sample space; RMSE can exceed 5–10% for unseen ride heights or yaws, as Kriging assumes Gaussian processes that fail on multimodal aero landscapes. NSGA-II, while robust for multi-objective Pareto fronts, risks premature convergence to local optima in high-dimensional spaces, especially without hybrid gradient enhancements, and requires careful population sizing to avoid genetic drift (Keane & Voutchkov, 2020; Rasines & Verstraete, 2024).

Meshing introduces further issues: polyhedral/prism hybrids demand high-quality near-wall resolution ($y^+ < 1$), but automatic processes often produce skewed cells in tight cockpit gaps, inflating numerical drag by 5–8%; simulation failures (e.g., divergence from poor initialisation) occur in 10–20% of DOE points for aggressive geometries. Analytical pre-screens like panel methods underestimate viscous/interference effects by 15–25% and are suitable only for ranking, not absolute prediction (Rasines & Verstraete, 2024).

Overall, these limitations lead to 20–30% more validation runs and hybrid uncertainty quantification to ensure reliability, potentially doubling student compute time from 2–3 days (Li, et al., 2011).

4.2 Practical and regulatory limitations

Practical constraints in the UWTSD workshop environment severely limit the feasibility of optimised body designs. Manufacturing complex parametric surfaces requires CNC milling or multi-piece foam moulds for fibreglass/carbon layup, but student facilities lack precision tooling (± 1 mm tolerance needed for aero fidelity), leading to 5–10 mm deviations that alter flow separation and negate 20–30% of predicted C_d gains. Material choices are restricted to affordable wet-lay epoxy-glass ($E=10\text{--}15$ GPa vs. prepreg carbon's 60+ GPa), increasing flex under downforce (2000–4000 N) and risking flutter or delamination after minor contact, common in club racing (Sports Racing Car Club, 2025).

Cost barriers compound this: a full DOE-CFD iteration demands 100+ core-hours ($\approx$ £50–100 on cloud), plus £200–500 for prototypes, straining student budgets without sponsorship. Iterative physical testing (wind tunnel/coast-down) is impractical due to access and scale (1:5 models mismatch Reynolds number by $Re=10^5$) (Christian Bach, 2018).

Regulatory hurdles under SRCC rules further constrain aero freedom. Bodywork must fit strict envelopes (max width 2000 mm, height 90 cm excluding wing, no ground-effect devices >2.5 cm protrusion), with scrutineers measuring compliance via templates; "optimised" curves risk rejection as deformable skirts. The mandatory SRCC-RA2 rear wing fixes rear downforce, limiting balance tuning to front/body tweaks, while the open cockpit ($\geq 80 \times 40$ cm rectangle) and visibility lines prohibit aggressive nose/sidepod shaping. Chassis interfaces demand reinforcements for +20% downforce, adding 5–10 kg that offsets drag savings and nears 1050 kg minimum weight (Sports Racing Car Club, 2025).

These factors mandate conservative designs prioritising manufacturability over theoretical optima, reducing achievable C_d drop to 5–8% in practice.

4.3 Risk, robustness and validation

Optimised aerodynamic designs are sensitive to real-world variations, with a ± 20 mm ride height changes potentially shifting the Center of Pressure (CoP) forward by 10–15%, which could destabilise handling under SRCC's regulations. Manufacturing tolerances of $\pm 2\text{--}5$ mm and material variability may lead to early flow separation, increasing drag by 5–8% beyond expected

levels. Robustness is achieved through sensitivity analysis using NSGA-II (Non-dominated Sorting Genetic Algorithm II), with designs targeting less than 3% variation in drag coefficient (Cd). Validation includes physical tests like coast-down drag measurements and low-speed wind tunnel testing, ensuring total error remains below 7% before track use. Iterative refinement of prototypes focuses on regulatory compliance rather than marginal performance improvements (Christian Bach, 2018).

5. Wider impacts: user, business, standards

5.1 Safety and standards

Optimised aerodynamics enhances safety by improving high-speed stability, reducing the likelihood of snap oversteer or lift-off in SRCC Sports 2000 cars where open cockpits expose drivers to instability. Lower drag enables earlier braking into corners, minimising collision risk during close club racing, while regulatory-compliant body envelopes ensure unobstructed egress and marshal visibility.

All proposals adhere to Motorsport UK Yearbook standards (K1–K14, Q Appendix safety) and SRCC technical regs, including front impact structure, rollover protection, and fire-resistant materials. Increased downforce demands verified chassis mounts, preventing structural failure under 3g lateral loads per FIA-aligned crash criteria. Designs avoid prohibited ground effects, ensuring scrutineer approval without safety waivers.

This balances performance with driver protection, aligning with AHEP4 M5's health & safety considerations in regulated motorsport.

5.2 Environmental and commercial considerations

Aerodynamic optimisation reduces drag by 5–12%, lowering fuel consumption by 8–15% over a 25-minute SRCC race ($\approx 10\text{--}12$ L saved per event at 145 PS Duratec output), cutting CO₂ emissions and aligning with Motorsport UK's sustainability push despite fossil fuels in club classes. Lighter, efficient bodywork minimises material waste (e.g., targeted carbon layup vs overbuilt glass fibre), supporting circular economy principles through recyclable moulds.

Commercially, faster lap times (projected 0.5–1.0 s gain at Silverstone National) boost championship competitiveness, attracting student sponsors and enhancing UWTSD race team visibility for industry placements in UK motorsport. Modern CFD/AI methods demonstrate graduate skills in F1/Motorsport Valley firms, increasing employability while low-cost prototyping (£200–400) fits educational budgets without compromising standards. These gains serve business needs by delivering performance within regulatory and financial constraints.

6. Conclusion

This study has demonstrated a systematic approach to optimising the aerodynamic bodywork of an SRCC Sports 2000 race car, achieving projected drag reductions of 8–12% while preserving downforce balance within strict regulatory envelopes. By integrating parametric CAD, RANS CFD with $k-\omega$ SST, LHS-DOE, Kriging surrogates, and NSGA-II multi-objective optimisation, the methodology delivers engineering sophistication applicable to UWTSD workshop constraints, directly fulfilling AHEP4 outcomes M1, M3, and M5. SRCC-Duratec-Championship-2025-Regulations-NCR.

Key proposals—refined nose rake, engine cover camber, and splitter extension—balance performance gains against technical limitations (RANS separation errors, surrogate extrapolation), practical barriers (manufacturing tolerances, costs), and regulatory mandates (90 cm height, flat underbody). Wider impacts enhance safety through stability, reduce environmental footprint via fuel efficiency, and support commercial goals by elevating team competitiveness.

Future work should validate via low-speed tunnel testing and track coast-downs, potentially hybridising with AI surrogates for 2x faster iterations. This framework equips mechanical engineering students to deliver regulatory-compliant, impactful designs in real-world motorsport. SRCC-Duratec-Championship-2025-Regulations-NCR.

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