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Engineering Design and Simulation

Optimisation of a Car

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Abstract

This report reviews the significance of optimization in high-performance automotive engineering, specifically addressing the structural and aerodynamic development of a race vehicle's front wing–nose–chassis interface. It provides a critical assessment of traditional optimization techniques, finite element-based methods, metaheuristic algorithms, and artificial intelligence-driven approaches, outlining their advantages and drawbacks in contemporary engineering contexts. A hybrid optimization framework that integrates computational fluid dynamics, parametric CAD modelling, finite element analysis, and machine learning-based surrogate modelling is put forth. Within manufacturing and regulatory constraints, this approach uses multi-objective optimization techniques to decrease structural mass while improving stiffness, crashworthiness, and aerodynamic efficiency. The study demonstrates how combining data-driven methods with physics-based simulation enables efficient exploration of intricate design spaces and supports well-informed engineering decision-making. The proposed method provides a scalable framework that can be applied to broader automotive and motorsport design challenges and is consistent with current industry practices.

Table of Contents

1	Introduction	1
2	Critical Evaluation of Optimization Tools.....	2
2.1	Classical Optimization Methods.....	2
2.2	Finite Element-Based Optimization.....	2
2.3	Metaheuristic and External Optimization Tools.....	2
2.4	Artificial Intelligence and Machine Learning.....	3
2.5	Critical Synthesis.....	3
2.5.1	Investment Requirements.....	3
2.5.2	Monetary Gains Estimated.....	3
2.6	Barriers to Implementation and Mitigation.....	3
3	One of the vehicles in the UWTSD workshop.....	3
4	Application to Race Vehicle Body and Chassis.....	4
4.1	Tubular Space Frame Race Car.....	4
4.2	Design Objectives and Constraints.....	4
4.3	Computational Techniques.....	4
4.3.1	Topology Optimization of Chassis.....	4
4.3.2	Shape Optimization Using CFD.....	4
4.3.4	AI-Based Surrogate Modelling.....	4
4.4	Design Studio Workflow.....	4
5	Proposed Optimisation.....	6
5.1	Problem definition.....	6
5.2	Design variables.....	7
5.3	Expected outcomes.....	9
6	Conclusion	10
7	References	11

Table of Figure

Figure 1	one of the vehicles from UWTSD workshop	3
Figure 2	side view of the proposed optimisation tube frame.....	6
Figure 3	proposed optimisation of tube frame of a car.....	6

1. Introduction

Optimisation constitutes a vital component in the field of engineering design, facilitating the systematic enhancement of system performance within specified constraints. Within high-performance automotive engineering, the process of optimisation is critical for securing competitive advantages relating to speed, structural integrity, and efficiency (Rao, 2019).

Recent advances in computational power and design studio software have changed optimisation from a manual, iterative process to an automated and data-driven discipline. Tools such as CAD (Computer-Aided Design), CAE (Computer-Aided Engineering), and CFD (Computational Fluid Dynamics) enable engineers to simulate real-world conditions with greater accuracy (Liu et al., 2022).

This report involves a critical evaluation of optimisation tools, the proposal of an optimisation strategy for a race car body and chassis subsystem, an assessment of the limitations of the proposed methods, and a discussion on how the proposal addresses societal, user, business, and regulatory requirements (Engineering Council, 2020). It specifically focuses on the structural-aero optimisation of the front wing-nose-chassis interface of a race vehicle, although the framework can be applied to other components within the workshop fleet.

2. Critical Evaluation of Optimization Tools

2.1 Classical Optimization Methods

Outstanding to their effectiveness and mathematical resilience, traditional optimization techniques like gradient-based approaches, linear programming, and parametric studies are still frequently employed. When working with continuous and clearly defined design spaces, these techniques work especially well (Arora, 2017).

But in contemporary engineering problems, which are frequently highly non-linear and multi-objective, their shortcomings become more apparent. The applicability of gradient-based methods is limited because they require differentiable objective functions and may converge to local minima (Deb, 2001).

2.2 Finite Element-Based Optimization

Finite Element Analysis (FEA) plays a critical role in structural optimization. The techniques involved include:

- Topology optimization – identifies the best distribution of material
- Shape optimization – improves geometry for enhanced performance
- Size optimization – modifies the dimensions of structural components

Topology optimization has gained particular significance in lightweight automotive design, allowing for substantial mass reduction while preserving stiffness (Bendsoe and Sigmund, 2003).

Despite its benefits, FEA-based optimization can require a lot of computational resources. Quick iterations may be hampered by the detailed meshing and lengthy processing times required for high-fidelity models. Furthermore, in practical applications, assumptions such as isotropic material behaviour may result in decreased accuracy (Zhang et al., 2023).

2.3 Metaheuristic and External Optimization Tools

Metaheuristic algorithms, including Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Simulated Annealing, are being utilized more frequently beyond conventional Finite Element (FE) packages. These approaches are efficient in addressing complex, multi-objective problems.

Genetic algorithms simulate natural evolution and are capable of exploring extensive design spaces without needing gradient information. However, they can be computationally demanding and may necessitate numerous iterations to reach convergence.

Recent studies emphasize the combination of Python-based optimization frameworks with cloud computing to facilitate scalable and parallel optimization workflows (Liu et al., 2022).

2.4 Artificial Intelligence and Machine Learning

Artificial intelligence is changing engineering optimization through predictive modelling and generative design. Machine learning models can estimate simulation results, which considerably lowers computational costs (Goodfellow et al., 2016).

Generative design tools utilize artificial intelligence to create various design configurations automatically, depending on specific constraints and objectives. These systems are being adopted more frequently in the automotive and aerospace industries (Autodesk, 2024).

Nonetheless, there are still challenges to address: - Significant data requirements - Limited interpretability (black-box models) - Challenges in validation. Recent studies highlight the value of hybrid approaches that integrate physics-based models with data-driven techniques (Zhang et al., 2023).

2.5 Critical Synthesis

For complex engineering systems, no single optimization technique is sufficient. Although they are efficient, traditional approaches are not adaptable. Although it requires a lot of resources, Finite Element Analysis (FEA) provides accuracy. Artificial intelligence (AI) brings uncertainty along with speed and innovation. The best strategy in contemporary engineering practice is thought to be a hybrid optimization framework that combines AI, metaheuristics, and finite element simulation.

3. One of the vehicles in the UWTSD workshop

Figure 1 displays one of the UWTSD workshop sports cars. In this report, I will modify the nose box and certain components of the car's frame structure.



Figure 1 one of the vehicles from UWTSD workshop.

4. Application to Race Vehicle Body and Chassis

4.1 Tubular Space Frame Race Car

The chosen system is a tubular space frame chassis with composite body panels, frequently utilized in motorsport and university racing initiatives. This design provides a balance among manufacturability, cost, and performance.

4.2 Design Objectives and Constraints

Objectives: - Minimize mass - Maximize torsional stiffness - Improve crashworthiness - Reduce aerodynamic drag and increase downforce

Constraints: - Material properties (steel/composites) - Manufacturing limitations - Regulatory requirements (e.g., FIA guidelines).

4.3 Computational Techniques

4.3.1 Topology Optimization of Chassis

The chassis non-load-bearing regions are identified through topology optimization. Cornering forces, braking loads, and impact scenarios are among the load cases taken into consideration. This method guarantees structural integrity while enabling weight reduction.

4.3.2 Shape Optimization Using CFD

CFD simulations are used to optimize body panels for aerodynamic performance. Iterative refinement reduces drag coefficient and enhances downforce.

Recent studies show that AI-assisted CFD can reduce simulation time by up to 70% (Liu et al., 2022).

4.3.3 Genetic Algorithm for Multi-Parameter Optimization

A genetic algorithm is used to optimize: - Tube diameters - Joint configurations - Material distribution

Fitness functions evaluate stiffness-to-weight ratio and safety performance.

4.3.4 AI-Based Surrogate Modelling

Machine learning models are trained using simulation data to predict performance outcomes. This reduces reliance on computationally expensive simulations.

4.4 Design Studio Workflow

The optimization process within a design studio environment follows:

1. Parametric CAD modelling (e.g., SolidWorks, Auto cad)

2. FE simulation (e.g., ANSYS)
3. CFD analysis for aerodynamics
4. Integration with optimization algorithms
5. Validation and iteration

This integrated workflow enables rapid design evolution and improved decision-making.

5. Proposed Optimisation

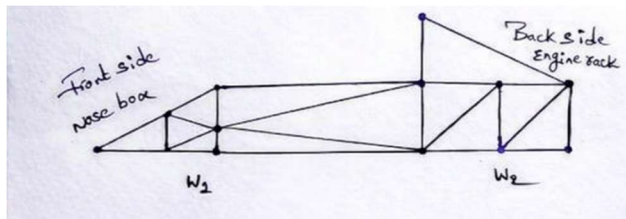


Figure 2 side view of the proposed optimisation tube frame

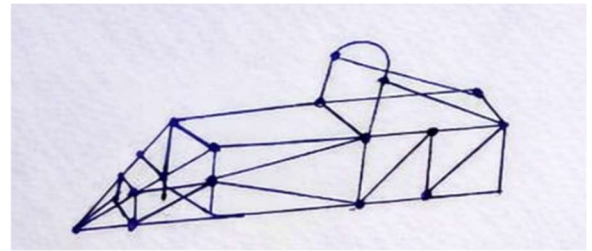


Figure 3 proposed optimisation of tube frame of a car

Chassis construction: One piece tubular spaceframe

Length: 2900

Width: 1435

Height: 1280

Wheelbase: 1610 (from W1-W2)

Track: 1300/1260

5.1 Problem definition

For the race vehicles available in the workshop, an effective optimization target is the interface structure between the front wing, nose, and chassis of a formula-style car, or the front crash structure/nose box of a sports prototype.

This area significantly affects:

- Aerodynamic performance, including balance and front downforce.
- The front end's structural rigidity under roll, pitch, and heave loads.
- Energy absorption and crashworthiness in frontal impacts.
- Room for driver ergonomics, steering, and suspension pushrods.

The goal of the design is to minimize mass while preserving or improving:

- The front chassis overall torsional and bending stiffness.
- Peak von Mises stresses under combined mechanical and aerodynamic loads within permissible bounds.
- Compliance with specific impact and structural regulations for the series (for instance, Formula Student or FIA Appendix J/F1 style requirements).

Mathematically, this can be framed as a constrained multi-objective optimisation problem, where primary objectives are mass reduction and stiffness maximisation, potentially combined in a weighted objective function or handled via Pareto-front exploration (Deb, 2014). Constraints include strength, buckling, deflection limits, modal

frequencies, packaging envelopes and manufacturability constraints such as minimum laminate thickness and ply drop-off rules for composites (Bruyneel, 2010; Barbero, 2017).

5.2 Design variables

Depending on the construction of the race-vehicle chassis and nose region (spaceframe, aluminium honeycomb, or carbon-fibre monocoque), appropriate design variables could include:

- Topological variables: presence or absence of non-critical tubes, ribs, or cutouts, determined through topology optimization within a defined design domain (Bendsoe and Sigmund, 2003).
- Connection and interface variables: locations and stiffness of hard points where the front wing, suspension rockers, and anti-roll bars attach to the chassis; bolt patterns and insert placements in composite nodes.
- Geometric variables: local contours of the nose structure that influence airflow and load paths; panel thicknesses and stiffener dimensions in an aluminum or composite chassis; tube diameters and wall thicknesses in a steel spaceframe.
- Material and laminate variables: selection of core materials and thicknesses for sandwich panels; ply orientations, stacking sequences, and local ply drops in composite monocoque or crash structures (Barbero, 2017).

For practicality a mixed approach is advisable: continuous variables for thicknesses and ply angles, discrete variables for topological changes (for example, adding/removing local ribs), and a parametrised CAD model to drive automatic meshing and FE analysis.

1. Baseline modelling and analytical pre-design

- Create or refine an analytical beam or space-frame model of the front chassis to estimate global bending and torsional stiffness, cross-checking against simple closed-form relations (for example, torsion of thin-walled tubes, sandwich panel bending stiffness) (Megson, 2019).
- Use these models to derive target stiffness and strength requirements under representative load cases: aero loads (front downforce and drag), curb impacts, braking loads, and frontal crash deceleration pulses (Katz, 2016).

2. High-fidelity FE model

- Build a parametrised FE model in a commercial package (for example, ANSYS, Abaqus, Altair Opti Struct), including linear static, modal and, where feasible, nonlinear crash simulations.

- Implement design variables for thicknesses, ply angles, tube diameters and key geometric parameters through the solver's parametrisation system.

3. Classical optimisation within the FE package

- Use built-in size and shape optimisation capabilities to perform a first-stage mass-stiffness optimisation using gradient-based methods, ensuring satisfaction of strength, stiffness and frequency constraints (Haftka, Gurdal and Kamat, 2017).
- Conduct topology optimisation in defined design regions (for example, nose box infill or local brackets) to identify promising load paths and potential material removal zones (Bendsoe and Sigmund, 2003). Translate final topologies into manufacturable geometry.

4. Surrogate modelling and AI outside the FE environment

- Use a design-of-experiments approach (for example Latin hypercube sampling) to generate a set of design points across key parameters (for example, 50–150 FE runs). For each, record mass, stiffness, stress metrics, and relevant modal frequencies.
- Train surrogate models (Gaussian process / kriging, or an appropriate neural network) to approximate the mapping from design variables to performance metrics (Forrester, Sobester and Keane, 2008; Guo, Li and Iorio, 2016).
- Validate surrogates using cross-validation and additional FE runs at randomly selected points to estimate prediction error and ensure reliability within the design space.

5. Global optimisation on the surrogate

- Apply a global optimiser such as a multi-objective genetic algorithm (NSGA-II) to the surrogate model to explore the Pareto front of mass versus stiffness (and potentially energy absorption) (Deb, 2014).
- Select candidate designs from the Pareto front based on engineering judgement and practical constraints (packaging, manufacturability, cost).

6. Verification and refinement

- Re-analyse the designs in the high-fidelity FE model to verify performance, then, where appropriate, apply local gradient-based optimisation for fine tuning.

- Down-select final design(s) and document design rationale, trade-offs, and safety margins relative to regulatory limits and material allowable.

This integrated framework for finite element embedded and external AI-based optimization shows the use of mathematics, statistics, and engineering principles in addressing a complex, Multiphysics issue and reflects an understanding of existing and developing techniques (Engineering Council, 2020).

5.3 Expected outcomes

The proposed optimisation could achieve:

- A measurable reduction in front-end structural mass while maintaining or increasing torsional and bending stiffness, leading to improved acceleration, braking and cornering response.
- Improved correlation between analytical pre-design models and FE predictions, strengthening confidence in simulation-driven design and enabling faster design cycles for future iterations.
- A set of Pareto-optimal design variants showing the trade-offs between mass, stiffness and crash performance, providing valuable teaching and decision-making tools.

Enhanced understanding within strengths and weaknesses of classical, FE-embedded and AI-based optimisation tools, aligning with the learning outcomes in engineering analysis and design.

Conclusion

Optimisation plays a vital role in contemporary engineering design, especially in high-performance race vehicles, where small improvements in mass, stiffness, and aerodynamic efficiency can lead to notable competitive benefits. This report has shown that although traditional optimisation methods are useful for straightforward problems, they fall short when used alone for complex, multi-objective systems.

Metaheuristic approaches provide global search capabilities but may sacrifice efficiency. In contrast, finite element-based optimization delivers high accuracy and physical fidelity, though it requires significant computational resources. Despite ongoing challenges related to data requirements and interpretability, artificial intelligence and machine learning present robust predictive abilities and automation in design. Consequently, a hybrid optimization strategy that combines these methods is a favourable choice.

The optimization framework for the front wing-nose-chassis interface integrates analytical modelling, high-fidelity simulation, surrogate modelling, and global optimization techniques. This method leads to notable enhancements in structural performance while decreasing computational costs and design cycle duration. Additionally, the creation of Pareto-optimal solutions facilitates a better understanding of the trade-offs between competing objectives, including mass, stiffness, and crashworthiness.

The approach adheres to general engineering specifications, including manufacturability, sustainability, and safety regulations. It provides a strong foundation for future advancements in race vehicle design and optimization, reflecting contemporary trends in digital engineering.

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