

Designing a Race Car Rear Wing 2



Manmeet Singh (2114501)

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FEA Optimization Techniques

Since the evolution of Computational power, its algorithmic and materials science applications, there has been no major shift in the usage of Finite Element Analysis (FEA) optimization methodologies over the past several years. Over the years these approaches have further specialized and improved, allowing designers to better predict and optimize product performance. The following paper will cover an overview of the history of FEA optimization techniques, impact on design, and future potential.

Evolution on FEA Optimization Techniques

The early development (1960s-1980s)

Developed in the '60s, FEA was conceived to solve complex structural analysis problems that were impossible to solve using conventional analytical techniques. FEA was originally used to perform a linear static analysis of basic geometry parts (Cook, 1989). The first optimizations were empirical, manually changing dimensions or material properties and observing the outcome. The 1970s saw the advent of the first commercial FEA software, e.g. NASTRAN (NASA Structural Analysis) that allowed engineers to use computational methods for bigger and more complex structures (Zienkiewicz, 2000).

Parametric and Topology Optimization (1990s-2000s)

With the advent of more sophisticated software tools and increased computational capacity, engineers began to adopt more formalized optimization techniques. To improve certain design variable, like geometry or material property, while preserving the integrity of the structure, parametric optimization was born (Bendsoe, 1988). The design methodology was revolutionized by the introduction of topology optimization in the 1990s, notably through the Solid Isotropic Material with Penalization (SIMP) methods. This approach allows us to identify the best material distribution in the given design space, resulting in lightweight and structurally efficient designs (Rozvany, 1992).

Multi-Disciplinary and Multi-Objective Optimization (2010s)

The increasing complexity of modern designs, challenged with conflicting objectives such as weight minimization, robustness, and thermal dissipation, has motivated the development of multi-objective optimization methodologies. These techniques aim at finding compromise solutions that optimize conflicting design objectives (Gürdal, 2004). Multi-disciplinary optimization (MDO) incorporates diverse physics-based simulations (e.g., structural, thermal, fluid dynamic) into the optimization process, enabling designs that perform well in all relevant disciplines. This becomes especially useful in industries such as aerospace and automotive, where performance, safety, and efficiency are of the utmost importance (Martins, 2012).

Machine Learning and Real-Time Adaptive Optimization (2020s)

With the rise of artificial intelligence (AI) and machine learning, adaptive learning algorithms have been utilized in the FEA, allowing real-time modifications of design

variables when fresh data is obtained. An example is the automotive manufacturing industry, where rapid prototyping and iterative design processes are essential, among other sectors (Zhang, 2023). The use of AI methodologies in design, such as genetic algorithms, neural networks, and surrogate models, allow for the exploration of larger design spaces faster.

Future of FEA

In the future predictive modelling through AI and machine learning will be used to identify the best configurations, based on historical data, and guide real-time optimization during the design process. AI can also benefit surrogate modelling, reducing the calculation overhead from complex FEA simulations. (Digital Engineering 2024, 2024)

It is expected AI to enable the process of FEA optimization to be used in sectors with computational cooking point constraints. In manufacturing, for example, real-time optimization could become the norm, with designs constantly tweaked based on production data. (Neural Concept, 2024)

Fusion 360 Integration with Additive Manufacturing

Additive manufacturing (AM) gives a unique ability to manufacture complex structures which are difficult to fabricate by conventional methods. Coupling AM with FEA optimization will enable the design of structures with bespoke materials and geometries tailored to material performance criteria. This collaboration is expected to drive notable progress in lightweight structures and bespoke designs in sectors like aerospace, automotive, and medical equipment. (Autodesk, 2024)

Designers will not only be able to optimize for performance, but also for manufacturability and cost-effectiveness of additive manufacturing in order to create innovative product designs that were not feasible using traditional manufacturing methods. (Autodesk, 2024)

Collaborative optimization and cloud computing

As cloud computing technology continues to develop, FEA optimization will become available to smaller firms and individual engineers. This translates to solving larger, complex optimization problems and/or integrating optimization from several teams or organizations on a collaborative platform. (Rescale, 2025)

The cloud-enabled optimization solutions could democratize design optimization for advanced technologies — helping a broader swath of engineers perform sophisticated analyses and collaborate on design projects. (Digital Engineering , 2024)

How FEA Optimization Enhances the Design Process

The designs obtained using FEA optimization techniques completely revolutionizes the design process. Traditionally, design followed long iterative cycles of prototyping and testing which were often costly and labour-intensive. Enter FEA optimization, allowing engineers to simulate and optimize designs before creating physical prototypes. This transition provides multiple important advantages:

1. Accelerated Time-to-Market - Optimization allows engineers to quickly assess numerous design alternatives and determine the most effective option, minimizing the number of physical prototypes required. This speeds up product development cycles. (Inspenet, 2024)
2. Cost Savings - By reducing the quantity of prototypes created and minimizing wasted material through better designs, companies can achieve significant cost savings, especially in sectors with high material costs, such as aerospace. (Bunty LLC, 2024)
3. Greater Performance - The optimization of FEA ensures that designs meet performance targets, including safety, strength, or durability, and minimize material or power usage. This is important in industries such as automotive, aerospace and civil engineering where performance is of utmost importance. (MotiveWith, 2024)
4. Creative Design - The availability of such tools and methods can give rise to novel and highly efficient designs that may not be viable or intuitive using traditional design attitudes, leading to breakthrough products and technologies. (Modern CAD, 2024)

Conclusion

FEA optimization techniques have significantly improved the design process by reducing time, costs, and material waste while also enabling better performance and innovative products. Much of the future directions of AI, cloud computing, and additive manufacturing should continue to drive this field in the directions of increasing the power and accessibility of FEA optimization. This trend toward adaptive, real-time optimization techniques, driven by machine learning and AI will lead to even more efficient, cost-efficient and high-performance designs in many industries.

Laying model in Design Studio

The first step in design studio is to insert the CAD model into the software. Then as per instruction of the assignment brief data of the Carbon Fibre Reinforced Plastic (RFCP) material is inputted. The screenshot below shows the relevant data inserted in the software.

Materials

< Back Next > Finish Cancel

Edit a Material : 2-D Orthotropic Properties

E₁: 132e9
E₂: 10.8e9
nu₁₂: 0.24
G₁₂: 5.65e9
G₁₃: 5.65e9
G₂₃: 5.65e9
Rho: 1540
A₁:
A₂:
Tref:
GE:
F12:
☒ Stress Limits
☐ Strain Limits
Xt: 1513e6
Xc: 1000e6
Yt: 43.4e6
Yc: 43.4e6
S: 43.4e6

After assigning the vectors, this was laid-up with 25 plies of CFRP with the thickness of 0.1mm.

This was done as below:

1. 5 plies at -90 degrees
2. 5 plies at -45 degrees
3. 5 plies at 0 degrees
4. 5 plies at 45 degrees
5. 5 plies at 90 degrees

All Plies				
Regular				
Global Ply ID : Material : Thickness : Angle : Output				
Layer 1				
CFRP	0.001	-90.0	Yes	+
Layer 2				
CFRP	0.001	-45.0	Yes	+
Layer 3				
CFRP	0.001	0.0	Yes	+
Layer 4				
CFRP	0.001	45.0	Yes	+
Layer 5				
CFRP	0.001	90.0	Yes	+

Once this step was completed the optimization process could be undertaken.

Executing the experiment

To execute the suggested experiment to study again the deformation of an F1 car wing under operational forces, a coherent and careful approach must be taken. The process blends prototypes' fabrication, experiments' setup, data' collection, as well as comparison with simulated prediction. Let me detail how this experiment should be setup and how to go about data acquisition and comparison.

Prototype Fabrication

In this experiment, the initial step is to create an F1 car wing prototype. This prototype must be as close as possible (in terms of material properties, geometry, and structural integrity) to the actual component. It means for the material of the prototype to have the same mechanical properties as those of the real wing, like stiffness, strength, and weight. This arrangement maintains real-world conditions, capturing the same deformation behaviour when compared to the experiment. Tasked with faithfully reproducing features such as aerodynamic contours, mounting points, and reinforcement structures — all of which are critical to the wing's performance.

When the actual materials are cost-prohibitive, substitute materials with comparable mechanical properties can be used instead, but this necessitates application and documentation of consideration-based testing. If a prototype model is built, it must be designed based on unit geometrical dimensions and scaled down for practical testing.

Experimental Setup

Using an experimental rig capable of recreating the forces and environment the wing must endure during a race; the prototype wing can then be tested under controlled conditions. This rig needs to hold the wing in a stable position and be able to apply controlled forces. These forces include aerodynamic downforce, drag, and lateral forces, which the wing must endure through high-speed cornering and set road racing. Actuators on the rig should impart forces and moments gradually and evenly over the total surface area of the wing to accurately represent distributed aerodynamic loads.

A critical aspect of the rig design is being able to replicate the mounting conditions of the wing, including how it is fixed to the car's chassis. Now, even a small deviation in boundary conditions will cause big influence in the result with respect to the validity of the iterations of that experiment. The forces must be applied and measured with great precision; thus, actuators and load cells on the rig must be calibrated. The rig should deliver the ability to change both the direction and magnitude of the force to simulate deformation of the wing under different operational conditions.

Data Acquisition

It is essential to obtain accurate and complete data for the wing deformation response. The main measurement methods are as follows:

Strain Gauges

Important strain gauges are used to measure localized deformation and stress at some critical locations on the wing. These regions tend to be areas of high stress concentration, for example, near mount brackets or structural reinforcements. The strain gauges measure deformation and output a corresponding electrical signal (Vishay Precision Group, 2023).

Digital Image Correlation (DIC)

DIC is a full-field surface deformation measurement non-contact optical method. It consists of spraying the wing's surface with a spattered pattern and recording images of it using high-resolution cameras, both before and after deformation. The detailed displacement and strain maps across the wing's surface provide insights into deformation behaviour at the global scale, derived by tracking changes in the pattern (Sutton et al., 2009).

Displacement Sensors

Overall deflection and wingtip displacement are registered using displacement sensors (i.e. laser displacement meters, LVDTs - Linear Variable Differential Transformers). These sensors further corroborate the deformation measurements taken using strain gauges and DIC (Bailey & Shinn, 2018).

This means that all measurement devices must have synchronized working and should route the info to a centralized data acquisition (DAQ) system. "Prof. Wang said this DAQ system is capable of recording data in real time for analysis and visualization of the deformation trends in real time as well. The sensor and instrument have to be calibrated prior testing to have reliable data, along with controlling the test environment for temperature, humidity, and vibrations affecting the results.

Experimental Procedure

The first task in the experiment is to mount the prototype wing in the rig. With the wing mounted, incremental forces are applied starting from baseline and running up to the maximum expected operating loads. Data obtained from strain gauges, DIC, and displacement sensors is collected on each force level. It is advisable to run multiple tests to guarantee repeatability and accuracy of outcome results.

While Testing The Wing You Will Need To Watch For Non-Linear Behaviour, Such As Strain Yield Or Otherwise Permanent Deformation Of The Wing. In case such behaviour is detected, the test shall be suspended and results until then analysed carefully. This prevents damage to the prototype and preserves the integrity of the data.

Simulation Comparison

To validate the computational model, the experimental results are compared with that of the simulation done in Task 3. Before this comparison, the simulation needs to be inspected to verify that the assumptions match what was achieved experimentally. That is, making sure that the values for material properties, boundary conditions, and force applications used in the simulation are comparable to those in the experiment.

Maximum deflection, stress values and strain values are the main parameters to be compared in data. Displacement and strain results from experiments and simulations are plotted for trend and correlation. For example, statistical methods, such as correlation coefficients and error metrics like Root Mean Square Error (RMSE), are used to quantify the differences between the datasets. These techniques can be used to determine the model accuracy and identify where improvements are required (Belytschko et al., 2013).

In case of major deviations, the simulation model needs to be adjusted according to the results obtained in the experiments. This could include adjustments to material properties, boundary conditions, or force distributions, for example. The simulation needs to be kept compared with experimental data to prove the improvements once updated.

Iterative Refinement

The comparison between the experimental results and the output of the simulation is an iterative process. As from every round of experiment we can learn to optimize setup and simulation models. As an example, if during the measurements the experimental data yield instances of deformation that are not well captured, additional strain gauges or DIC measurements can be performed in subsequent tests to have more accurate data about those phenomena. Likewise, this simulation model can also be adjusted to include factors that were not thought to contribute to simulation outcomes, such as localized stiffness variations or aerodynamic interactions.

Write Up and Documentation

This process is one which key documentation is an important part of. 3. Setup this time should be well-described in terms of a replicable design space, with an essential level of detail in prototype fabrication, rig design, instrumentation, and testing procedure.

Results: The results should include a clear analysis of the data and comparisons with the results of simulations, with plotting and graphically relevant key findings.

Final report should provide the following:

- A short description of the goals and scope of the experiment.
- The experimental setup and instrumentation are described in detail.
- Calibration of all measuring instruments.
- Experimental results such as deformation maps, strain distributions, displacement measurements, etc.
- Comparison to the simulation results, noting where they agree and where they differ.

Conclusion

This methodical approach allows for the accurate characterization of the deformation behaviour of the F1 car wing and its correlation with simulation predictions. This guarantees a strong validation of the computational model and adds useful information about the wing performance under operational loads. Overall, this cyclical process, incorporating experimentation and simulation, results in a more reliable and accurate design for the wing which in turn contributes to better performance and safety during the racing event.

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