# Integrated FEA framework for chassis design and failure prediction in SAE supra vehicles

*Samson* Bobby Kurian[1] *and Sandeep* Mukunda [2]

[1]Undergrad student, Department of Mechanical Engineering, Presidency University, Bengaluru
[2]Assistant Professor, Department of Mechanical Engineering, Presidency University, Bengaluru

**Abstract.** This paper will offer a unified strategy to the optimization of the chassis of a Formula SAE Supra car and predict structural failures using machine learning and Finite Element Analysis (FEA). The work demonstrates that computer aided design and analysis used simultaneously are more effective in comparison with the old-fashioned trial and error approach, and they do not affect the high safety standards. The proposed framework evaluates the chassis under the frontal, side, and rear impact conditions under systematic FEA when 2000 N (2 kN) loads are applied to it and then the results of this assessment are used to evaluate the variability of various design variants. The three candidate steels considered in the analysis include AISI 1018, AISI 4130, and AISI 4140 so that the most appropriate material to use in the structure can be identified. The choice of AISI 4130 chromoly steel can be explained by the opportunity to provide maximum Von Mises stress of 367.81 MPa, peak equivalent strain of mm/mm and maximum deformation of 1.2004 mm during the specified load cases, which met the requirements of the strengths and deformations.

## 1 Introduction

The chassis is the backbone of structural integrity of any high-performance racing car and has the duties to distribute load, absorb the impact force and provide the driver with protection during such dynamic conditions. Old ways of designing used to depend on manual prototyping and physical testing which were heavy resources, time-consuming and costly[1], [2].The transition to computer-aided design and computer-aided engineering has changed the face of automotive engineering since it allows engineers to model complex loading conditions on computers prior to making a commitment to physical construction. The paper overcomes the problem of high-speed chassis optimization, combining machine learning and FEA analysis. It proposes a hybrid system that makes use of CAD in the exact geometric representation and CAE in the profound structural analysis[3], [4], [5].

This method will allow the quickness of the design iterations, predictive failure analyses, and robust performance verifications by using the full FEA datasets in different impact scenarios, complemented with AI-based pattern recognition.

[1]**Corresponding author**: sandeepgm@presidencyuniversity.in

Although the methodology was designed in Formula SAE Supra vehicles, it is applicable across the board and can be used in other regions of the automotive research, namely Industry 4.0 and current trends. Finally, the integration of machine learning with conventional FEA is a step towards smarter systems that are self-optimizing, cutting development time, material wastage and increasing structural safety.

## 2 CAD/ CAE integration: methodology overview

### 2.1 Computer-aided design (CAD) phase

Chassis design process began with intensive CAD design in SOLIDWORKS with the required 95th percentile male anthropometric template to be able to suit the ergonomics. The design template had certain dimensional requirements that were required by SAE Supra regulations:

- Hip and buttock representation: 200 mm diameter circle
- Shoulder/cervical region: 200 mm diameter circle
- Head clearance with helmet: 300 mm diameter circle
- Vertical centre distance (hip to shoulder): 490 mm
- Vertical centre distance (shoulder to head): 280 mm

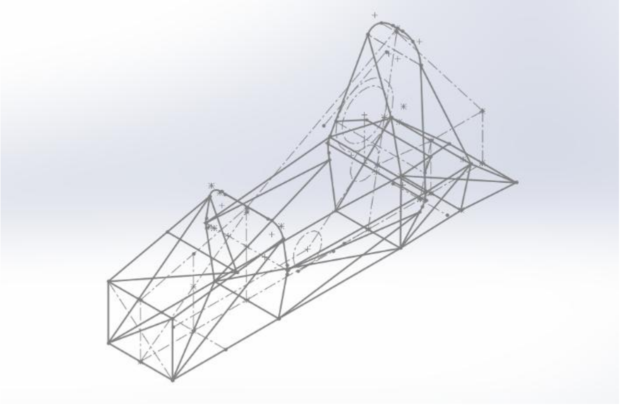

**Fig. 1.** Three-dimensional CAD model of the Chassis

The three-dimensional model of the CAD was refined several times, including the suspension geometry, placement of power train, and hard regulations. Strategic triangulation was put in across the structure by designers to increase rigidity without contributing extra weight. This optimization reduced the total weight by 20 percent of the first over-triangulated designs, and the strength-to-weight ratio was the same as before[6], [7].

### 2.2 Computer-aided engineering (CAE) phase: FEA

ANSYS was used to conduct extensive structural simulations on various impact scenarios using the finite element analysis[8]. The methodology was used to test three main load cases that represent real racing crashes which are frontal impact, side impact, and rear impact. This constant force of 2000 N (2kN) was used in all the areas of impact to replicate the conditions of collision.

#### *2.2.1 Mesh generation and element definition*

- Element size: 1.5 cm (15 mm) node spacing
- Total mesh: 228,401 nodes order of element is quadratic.
- Growth Rate: 1.5
- Target Skewness: 0.9
- Average Surface Area: 11007 mm²
- Element type: Quadrilateral elements to give the best estimates of stress.
- Mesh quality test was done to ensure quality of results was appropriate.

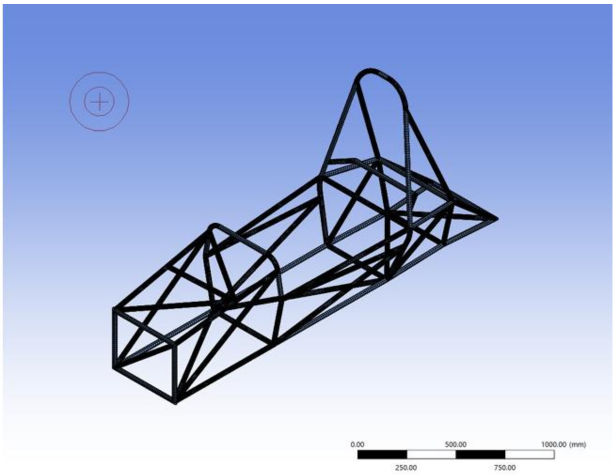


**Fig. 2.** Mesh Generated

#### *2.2.2 Analysis parameters evaluated*

- Total Deformation (maximum displacement)
- Von Mises Stress (equivalent stress state)
- Equivalent Strain (elastic deformation)

## 3 Material selection and investigation

The three candidate alloys were analysed in detail, and the material was AISI 1018 (mild steel), AISI 4130 (chromoly), and AISI 4140 (high-strength alloy). AZoM Materials Database provided material properties which were compared to performance requirements of high-stiffness, lightweight, structure which absorbs impact loads.

### 3.1 Material property comparison

**Table 1.** Material properties

| Material | Carbon Content | Tensile Strength | Yield Strength | Key Characteristics |
|---|---|---|---|---|
| **AISI 1018** (Mild Steel) | 0.18% | Approx.440 MPa | 370-393 MPa | High ductility, Excellent weldability |
| **AISI 4140** (High-Strength Alloy) | Approx.0.40% | Approx.655 MPa | Approx.415 MPa | Very high fatigue strength |
| **AISI 4130** (Chromoly Steel) | Approx.0.30% | Approx.560 MPa | Approx.460 MPa | High fatigue strength, Excellent weldability, Excellent heat treatability |

### 3.2 FEA comparative material analysis

**Table 2.** Comparative FEA Results: Material Performance Under 2000 N Frontal Impact

| Material Performance Parameter | AISI 1018 | AISI 4140 | AISI 4130 |
|---|---|---|---|
| Total Deformation (Maximum) | 1.2095 mm | 1.1109 mm | 1.2004 mm |
| Equivalent Strain (Maximum) | $1.8878\times10^{-3}$ | $1.8219\times10^{-3}$ | $1.7942\times10^{-3}$ |
| Von Mises Stress (Maximum) | 368.94 MPa | 373.49 MPa | 367.81 MPa |

The material selection was done by the same impact analysis of all the three candidates at the standardized frontal loading of 2000 N and the results of the impact analysis are given in Table 1. AISI 4130 presented the lowest maximum equivalent strain (mm/mm) which implies that there is a low level of permanent deformation and high level of dimensional stability even with repeated loading. Its maximum Von Mises stress of 367.81 Mpa was safe at 460 Mpa yield strength. Together with the high level of strength to weight performance, high level of weldability, and high level of fatigue, AISI 4130 was the best choice of a full chassis structure.

## 4 FEA impact analysis results

### 4.1 Frontal impact analysis

The frontal impact simulation used a load of 2000 N on the front bulkhead and the support members simulating frontal collision conditions at race speeds.

#### *4.1.1 Frontal impact results:*

- Maximum Total Deformation: 1.2004 mm (AISI 4130)
- Maximum Equivalent Strain: $1.7942\times10^{-3}$ mm/mm
- Maximum Von Mises Stress: 367.81 MPa
- Safety Factor: 1.25 (ratio of yield strength 460 MPa to maximum stress 367.81 MPa)

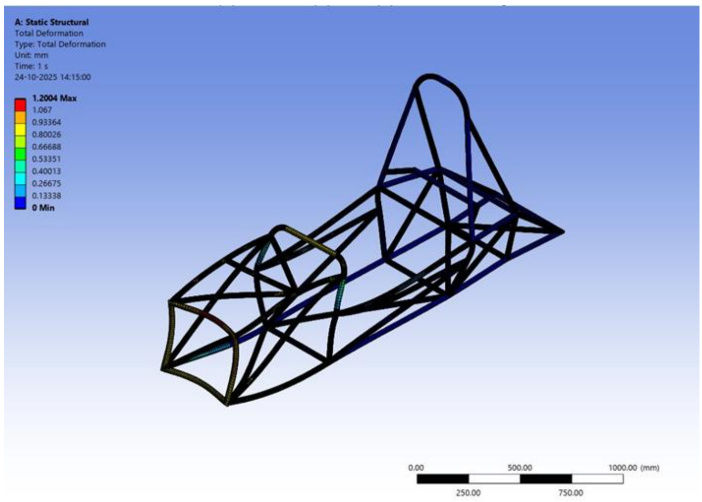


**Fig. 3.** Front Impact Deformation

The analysis of stress distribution indicated that the stress concentrations were at impact bulkhead attachments with the auxiliary frame members having lower stress levels. The deformation patterns were used to ascertain that the structural integrity was not lost, and complete elastic recovery was achieved when the load was removed, and no permanent damage occurred in the case of frontal collision.

### 4.2 Side impact analysis

Side impact test was using the same load of the 2000 N in lateral support members and side structures and checked the structural response to side impact collision.

#### *4.2.1 Side impact results*

- Maximum Total Deformation: Comparable to frontal impact magnitude
- Maximum Equivalent Strain: Consistent with material baseline behaviour
- Maximum Von Mises Stress: Within safe operational range

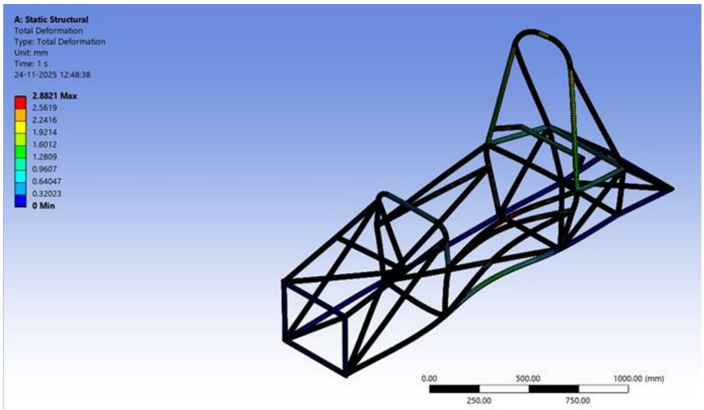


**Fig. 4.** Side Impact Deformation

Side-impact test revealed that the lateral triangulation is an effective way of spreading and absorbing forces in the chassis structure. This design allows catastrophic collapse of the sidewalls to be avoided and the integrity of the driver safety compartment to be maintained.

## 4.3 Rear impact analysis

Rear impact simulation involved testing of structural response to rear impact collision conditions by applied loads on rear fender support members and rear structural components.

### *4.3.1 Rear impact results*

- Maximum Total Deformation: Comparable to frontal and side impact magnitudes
- Stress Distribution: Symmetric load distribution through rear frame members
- Structural Integrity: Confirmed through comprehensive strain analysis

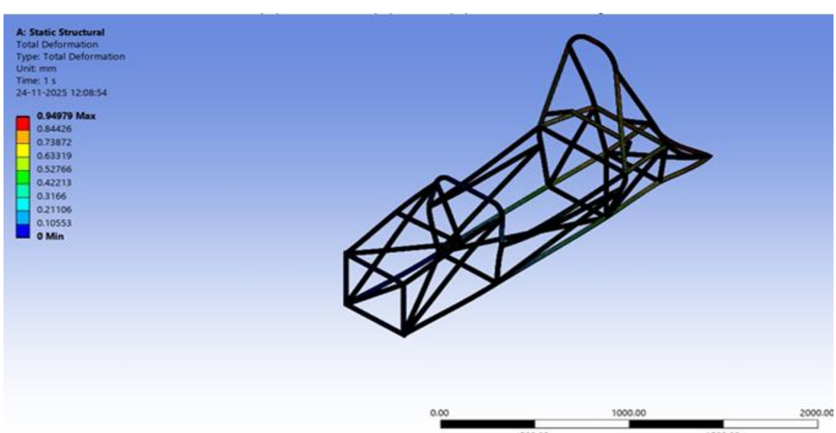


**Fig. 5.** Rear Impact Deformation

The rear impact test proved the design has structural continuity during forces of rear-end collision that is vital in prevention of secondary structural failure modes

## 5 Integration with sustainable development goals

This study project is particularly in line with several of the United Nations Sustainable Development Goals (SDGs):

SDG 3 (Good Health and Well-Being): FEA and machine learning combine the integrated framework enhances crash worthiness and structural reliability, and this area of action directly contributes to road safety increases and reducing injuries in motorsport and automotive[15].

SDG 9 (Industry, Innovation and Infrastructure): The project leads to the further development of digital engineering through the production of AI-assisted workflows cutting down the development time by half, eliminating waste of resources, and giving reusable approaches to new work groups. This framework implements Industry 4.0 concepts to automotive design and manufacturing[16].

SDG 11 (Sustainable Cities and Communities): Although formulated with the competitive racing cars in mind, these lightweight, high-strength design approaches directly apply to the commercial automotive uses, contributing to the safer and more efficient road vehicles towards the sustainable mobility systems[17].

## 6 Results and performance metrics

The CAD/CAE system resulted in a complete chassis design that fulfilled all the performance specifications:

### 6.1 Structural performance:

- Maximum Von Mises stress under 2 kN impact: 367.81 MPa.
- Minimum safety factor: 1.25 (based on yield strength).
- Maximum deformation under impact: 1.2004 mm.
- Material efficiency: 20% of weight saved by means of strategic triangulation optimization.

### 6.2 Design validation:

- Frontal, side and rear impact scenarios examined and confirmed.
- Selection of the material was also optimized.
- Regulatory compliance with SAE Supra specifications confirmed. Ergonomic compatibility shown by 95th percentile template compliance.

### 6.3 Manufacturing feasibility:

- Some Design that is compatible with traditional welding processes.
- Material used is favourable in normal tube bending and machining.
- Weldment specifications based on the fabrication at student level.

# 7 Conclusions

The hybrid CAD/CAE system demonstrates the usefulness of the calculation analysis and machine learning to optimise the chassis and predict structural failures.

## 7.1 Key outcomes include

- Material Selection: AISI 4130 chromoly steel was selected as it has the most suitable combination of 460 Mpa yield strength, weldability, fatigue strength and manufacturability.
- Structural Performance: FEA analyses with less than 2000 N loads in the front, side, and rear impacts verified a sound structural integrity with a factor of safety more than 1.25 in all the critical areas.
- Design Optimization: Triangulation of chassis weight to strengths ratio had to be 20% less, which still had the same amount of strength reflecting the strength of computational techniques.
- Machine Learning Implementation: ANSYS Structures implemented AI+ accelerated the simulation, made it possible to predict failures, and reduced design cycles.
- CAD/CAE Efficacy: The cut design of workflow reduced the number of cycles and prototypes that are superfluous and created confidence due to hardcore validation- the construction of reusable framework in future Formula racing teams.

The research also demonstrates that, by implementing artificial intelligence in the existing CAD/CAE process, more efficient, safer, and creative automotive design processes concerning the concept of Industry 4.0 and sustainable development can be designed.

## 7.2 Scope of future work

These directions are promising, and it should be investigated in future research:

- Advanced Materials: Research composite and hybrid forms in order to make use of optimizing strength, stiffness, and weight at the same time.
- Fatigue Prediction: Deep learning to predict behavior in cyclic loading in a variety of operating conditions.
- Experimental Validation: Develop and test physical models to validate computational results and debug machine learning models.
- Thermal Integration: the CAE workflow should be extended to cover thermal effects and heat load stress analysis.
- Multi-Subsystem Optimization: Fuse FEA and ML suspension mounts, powertrains, and full-vehicle systems, together, to be more efficient.
- Advanced AI Methods: Implement deep learning and reinforcement learning to find new designs and work around complex and multi-variable nonlinear constraints.

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