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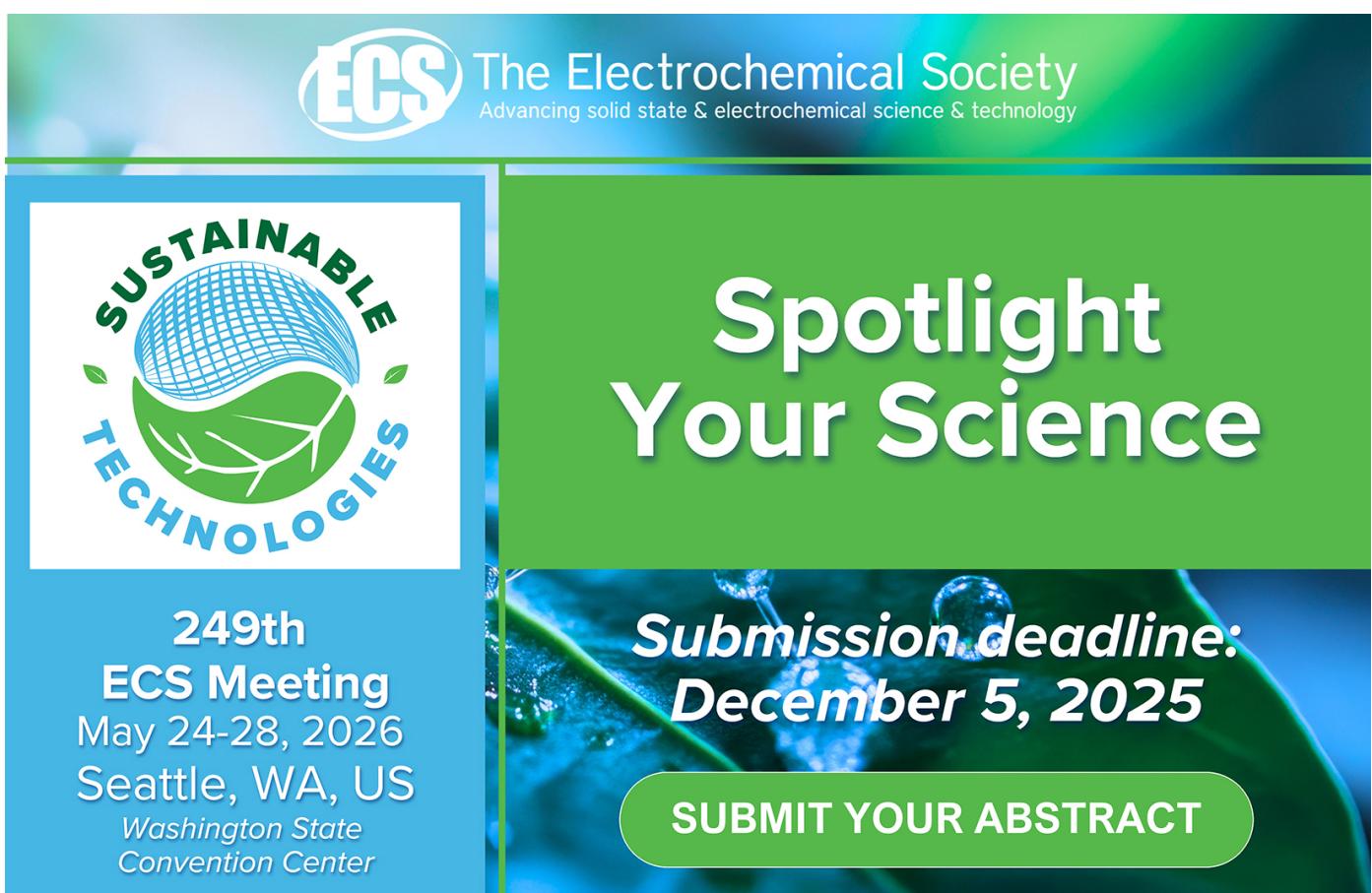
Design automation and CAD customization of an EV chassis

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Design automation and CAD customization of an EV chassis

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Abstract. This study focuses on developing an efficient approach to design and customizing electric vehicle (EV) chassis using automation and machine learning techniques. It includes 1) the design of an EV chassis using Python, 2) The implementation of a machine learning model to predict and find the suitable material for the chassis, and 3) CAD Customization of the chassis using Fusion 360 API in Python. 4) Structural Analysis of the chassis in Fusion 360. The mentioned methodology provides faster calculations, reduced manual errors, and a more efficient way of exploring design alternatives. The use of machine learning for material selection ensures a reliable and safe chassis. The study contributes to the advancement of EV chassis design processes by integrating automation and machine learning techniques, leading to faster and more reliable designs, and demonstrating the benefits of CAD customization.

1. Introduction

The automotive industry is moving towards electric vehicles due to the benefits of zero emissions, lower operating costs, and increased energy efficiency. The EV industry is growing rapidly, and the demand for EVs is increasing every day. One of the critical components of an EV is the chassis. This research paper aims to develop a more efficient approach to designing and customizing chassis using automation.

This study focuses on designing and optimizing a lightweight and durable ladder frame chassis for an electric vehicle, using a combination of automation, machine learning, computer-aided design, and analysis tools. The first part of the study involves designing the chassis using Python scripts to find the optimal dimensions that can be customized by the user. The goal is to create a chassis that can handle high stress. A Python-based machine learning model is presented that predicts the optimal material for the chassis based on its mechanical properties.

Later, the study involves the CAD customization of the designed ladder frame chassis. The selected materials are integrated into a CAD model, and the user can customize the width, wheelbase, cross-section, and material of the chassis through a user-friendly interface. The CAD customization process is automated using Fusion 360 API. The last section of the study includes structural analysis considering various loads to ensure that the chassis meets the desired specifications while also reducing manufacturing costs. The end result is a fully optimized and validated chassis that provides the desired level of performance and meets the required specifications.



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2. Literature Review

The present study is based on the concept design of a ladder frame chassis using the Fusion 360 software, as discussed by Rasheed [1]. This practical resource provides step-by-step guidance and valuable insights into the design process of ladder frames. We also utilized the study conducted by Jha et al. (2021) on the design and analysis of the chassis of a four-seater car [2].

Another study focuses on the design and structural analysis of ladder chassis, as discussed by Muthyalu (2019) [3]. The research employs finite element analysis techniques to evaluate the stress performance of ladder frames and investigates various design parameters to enhance their structural integrity. The study also includes the selection of an optimal material for the chassis and conducts torsional analysis to assess its torsional stiffness. In our material selection dataset, we incorporated diverse materials, including SAE 1018, 1020, 4130, and A36 for comparative analysis, as referenced in multiple papers [3-8]. The Material dataset was obtained from the Autodesk Material Library in Autodesk Inventor [9].

CAD customization [10] is a powerful tool that enables designers to create unique designs and enhance production efficiency using programming. There have been no studies exploring the use of the Fusion 360 API for chassis design.

3. Design Automation of an electric vehicle chassis with python

The design of an EV chassis plays a significant role in the performance, safety, and sustainability of the vehicle. The chassis is the foundation of the vehicle, and it supports all the other components. The chassis should be strong, stiff, and lightweight. The design of a chassis involves various parameters such as the wheelbase, front track, payload, and other requirements. Traditionally, designers would manually calculate the dimensions of the chassis using pen-paper. However, this process can be time-consuming and prone to errors.

We have designed a Ladder-frame chassis for an electric vehicle using machine design methods and Python to automate all the computations. By inputting the wheelbase and front track, the Python script calculates the dimensions of the side members and cross members considering bending stiffness, and torsional stiffness. This approach has enabled designers to change one parameter and obtain faster results. In this study, a rectangular cross-section chassis is used due to its high strength, instead of a C or I section.

3.1. Methodology

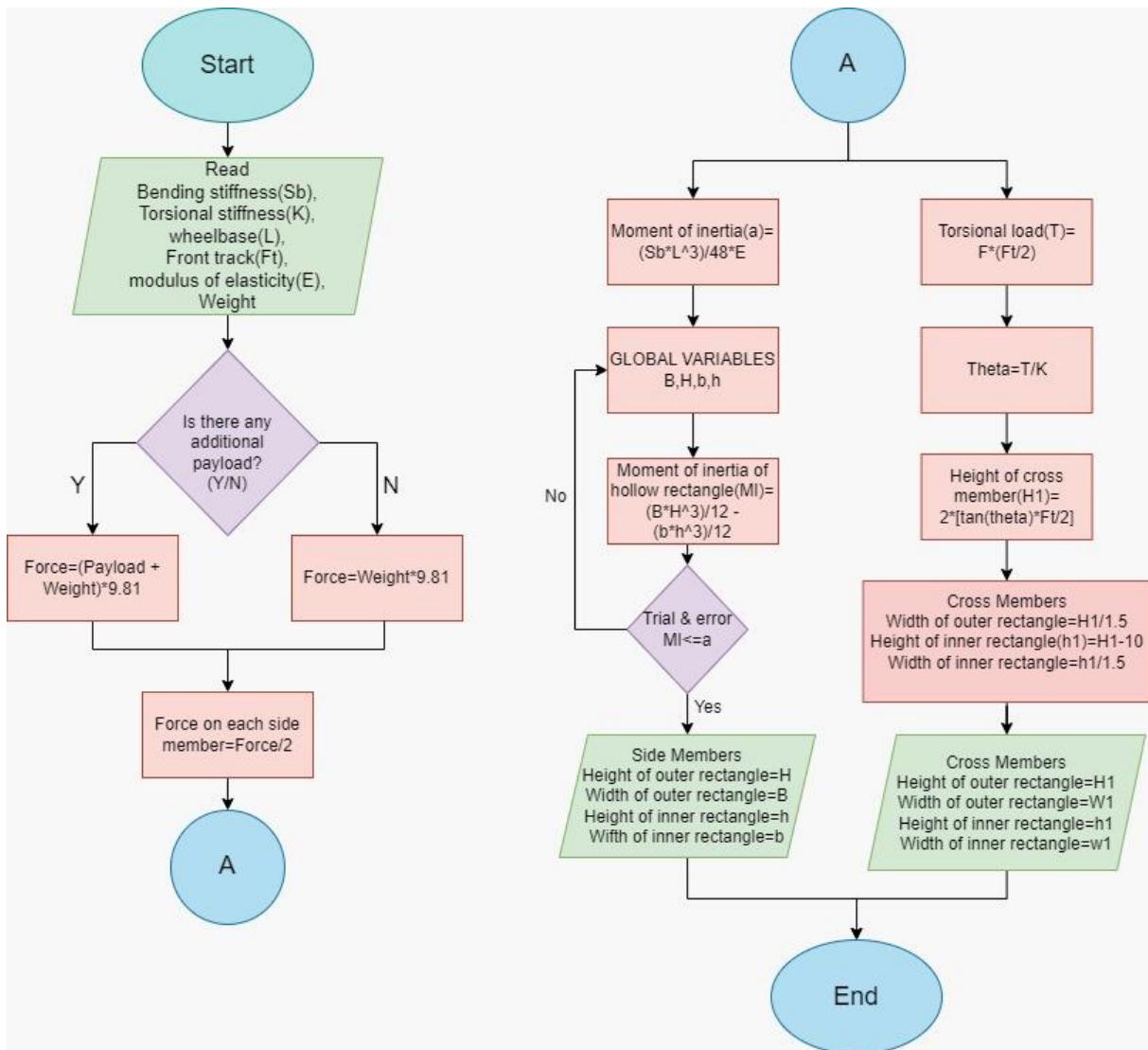
A chassis is responsible for supporting the vehicle's weight and providing a stable platform for the body and suspension components. Calculating the appropriate dimensions of the chassis components is crucial for ensuring the safety and reliability of the vehicle. The first step in designing the chassis was to consider the loads acting on it, namely Bending load, and Torsional load. The modulus of elasticity is among the mechanical properties considered for material selection and design calculations. Bending stiffness is the measure of how much the chassis/frame will bend for a load acting on its center. Because the chassis is supported by the front and rear axles, it can be modeled as a simply supported beam with two fixed ends. Torsional stiffness is the resistance of the chassis to twisting. You can find the python code in GitHub repository (Appendix A).

The first step in the design process is to calculate the dimensions of the side members. The weight of the vehicle and the payload are considered to calculate the force acting on the side members. The bending stiffness of the chassis is considered here, which should be greater than 3 kN/mm to avoid bending under load. The Young's modulus of mild carbon steel is utilized, which is a typical material for making the chassis.

Table 1. Design and Input parameters

Weight	Bending Stiffness	Elastic Modulus	Moment of Inertia	Torsional Stiffness
2000 kg	4000 N/mm	200000 M.Pa	6127552 kg.m ²	4500 N.deg

We have used python script for design purpose, following is the flowchart for the same:

**Figure 1.** Flowchart of Python Script

The moment of inertia is determined using the formula of maximum deflection $(Sb \cdot l^3) / (48 \cdot E)$, where l is the wheelbase of the vehicle, Sb is bending stiffness and E is Young's modulus. A function called `trialAndError()` is used to find the dimensions of the rectangular cross-section of the side members that will satisfy the minimum value of the moment of inertia required to sustain the bending load. The function uses a trial-and-error method to find the appropriate values for the width and thickness of the side members. The other dimensions of the rectangular cross-section are calculated using the values of width and thickness.

Table 2. Design and Input parameters 2 (All dimensions are in mm)

Wheelbase	Thickness	Front Track	Length of Cross Members
2450	7.6	1520	1348

The next step is to calculate the dimensions of the cross members, taking into account the torsional stiffness. The torsional stiffness of the chassis should be greater than 4 kN m/deg to ensure that the vehicle can sustain a torsional load. The front track of the vehicle is used to calculate the length of the cross members. The torsional force acting on the frame is calculated by multiplying the force acting on each side member by its perpendicular distance. The torsional stiffness of the chassis is then used to estimate the angle of twist, which in turn is used to determine the height of the cross member required

to resist the twisting load. We have assumed a height-to-width ratio of 1.5 for both the side members and the cross members. All resulting dimensions are listed in Table 3.

3.2. Formulas used for calculations:

$$\text{Bending stiffness } (S_B) = \frac{\text{load}(W)}{\text{deflection}(\delta)} \quad (1)$$

$$\text{Max deflection } (\delta) = \frac{Wl^3}{48EI} \quad (2)$$

$$\text{Moment of inertia of hollow rectangular section} = \frac{BH^3}{12} - \frac{bh^3}{12} \quad (3)$$

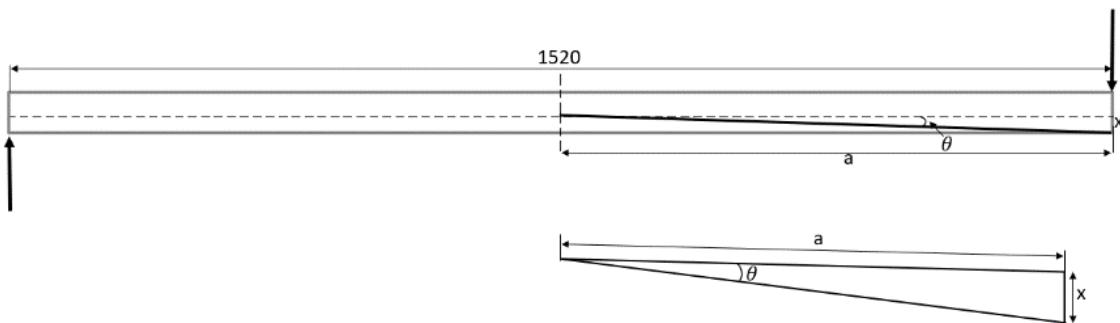


Figure 2. Torsional load acting on chassis.

$$\text{Torsional stiffness } (k) = \frac{\text{Torsional load}(F_t)}{\text{Angle of twist}(\theta)} \quad (4)$$

$$\text{Torsional load} = \text{Force applied on each side member} \times \text{Perpendicular distance } (a) \quad (5)$$

$$\tan(\theta) = \frac{x}{a} \quad (6)$$

3.3. Results and Discussions:

The Python code calculated the dimensions of the side members and cross members based on the input number of passengers, battery weight and material. This design process considers bending stiffness, torsional stiffness, and material properties to generate the dimensions. The dimensions of the cross members, along with the side members, are used to develop a CAD model of the chassis, which can be further refined and optimized for weight. This approach is not limited to chassis design but can also be used to design various industrial components more efficiently using Python scripting.

Table 3. Output of the program (All dimensions are in mm)

Rectangle	Side Members		Cross Members	
	Width	Height	Width	Height
Outer	86	129	55	82
Inner	71	114	45	72

4. Material Selection using Machine Learning

The chassis plays a crucial role in an electric vehicle as it supports the weight of the vehicle, protects the occupants, and serves as the foundation for the suspension system. Therefore, selecting the best material for a chassis is essential to ensure safety and efficiency. Machine learning (ML) can aid in this process by leveraging data and predicting the most suitable materials based on their mechanical properties. In this paper, we present a Python-based machine learning model that helps in determining the optimal material for chassis, considering its applications and mechanical properties.

4.1. Methodology

We utilized a dataset of Machine Design materials, which includes information on their mechanical properties. The dataset was obtained from the Autodesk Material Library and comprises 15 columns, also referred to as features/attributes. This dataset is a real-world dataset, and it does not contain any random values. However, due to missing values and unnecessary features, we have only utilized seven columns for our machine learning model.

To develop a ML model, we employed several Python libraries, including NumPy, pandas, scikit-learn, and graphviz, in addition to other technologies such as Weka, MS Excel, VS Code, Kaggle, Jupyter Notebook, and GitHub. We employed Weka software to swiftly visualize the data and comprehend the relationships between the features, without requiring any programming expertise. This dataset is available on Kaggle, where other researchers have also applied various ML models to it (Appendix B).

Table 4. Snippet of the Material.csv file

Material	Su	Sy	E	G	μ	ρ	Rating
Steel SAE 1018	440	370	207000	79000	0.29	7860	4
Steel SAE 1020	395	295	207000	79000	0.29	7860	3
Steel SAE 1022	483	359	207000	79000	0.30	7860	4
Steel ASTM A36	475	250	200000	79000	0.26	7860	4
Steel SAE 4130	669	436	207000	79000	0.295	7860	5

We applied two supervised learning ML algorithms, namely Decision Tree and Random Forest, to our dataset using the sci-kit learn library in Python. We chose these models because they are easy to visualize. Since supervised learning requires a class/label column to train the model on the data, we included a label column in our dataset. The columns that we are going to use are Material, Su, Sy, E, G, and mu. These columns have no missing values and are directly related to the application of chassis. We preprocessed the dataset by removing any NULL values or unnecessary string values in numeric data and dropping unnecessary columns. You can access related Kaggle notebooks in (Appendix B).

First, we used a decision tree model to determine the suitability of each material for an EV chassis. We added a binary column called 'Use', which has Yes and No values. 'Yes' indicates that the material can be used for the EV chassis, while 'No' indicates that the material is not suitable for the chassis. The features (Su, Sy, E, G, mu, and Ro) and the labels (Use) were then separated into X and y, respectively. A decision tree classifier was trained on the data using the sklearn DecisionTreeClassifier() function. The decision tree was visualized using graphviz to understand the decision-making process of the classifier.

Next, we used the Random Forest algorithm, an ensemble learning method that constructs multiple decision trees. We added a new 'Rating' column to the dataset, indicating the suitability level of materials from 1 to 5, where 1 is the least suitable and 5 is the most suitable. The rating given to the materials is based on whether their mechanical properties fall within the desirable range. This rating is also determined by considering references to relevant papers, as well as the cost and usage of the materials in the automotive industry. This approach allows for the selection of materials that not only meet the required mechanical specifications but are also commonly used in industry. It is important to note that the range of mechanical properties considered as desirable may vary depending on the specific application and design requirements. We generated this column using the getRating() method, which assigns a rating based on the material's mechanical properties values of Su, Sy, E, G, mu, and Ro columns. The rating for each material in the DataFrame is determined based on these features, and the assigned rating is placed in the label column. A random forest classifier is trained using the features and labels data with 100 trees. We used this classifier to predict the rating of a new material with specific mechanical properties. To further analyze the decision trees, we visualized them using Graphviz and saved the visualization as a PNG file.

This approach could be useful in material engineering applications where different materials need to be evaluated for a specific use based on their mechanical properties. The resulting decision tree can be used to gain insights into the properties that determine material suitability and help engineers make informed decisions when selecting materials for their applications. This decision tree can be used to predict whether a material should be used or not for chassis.

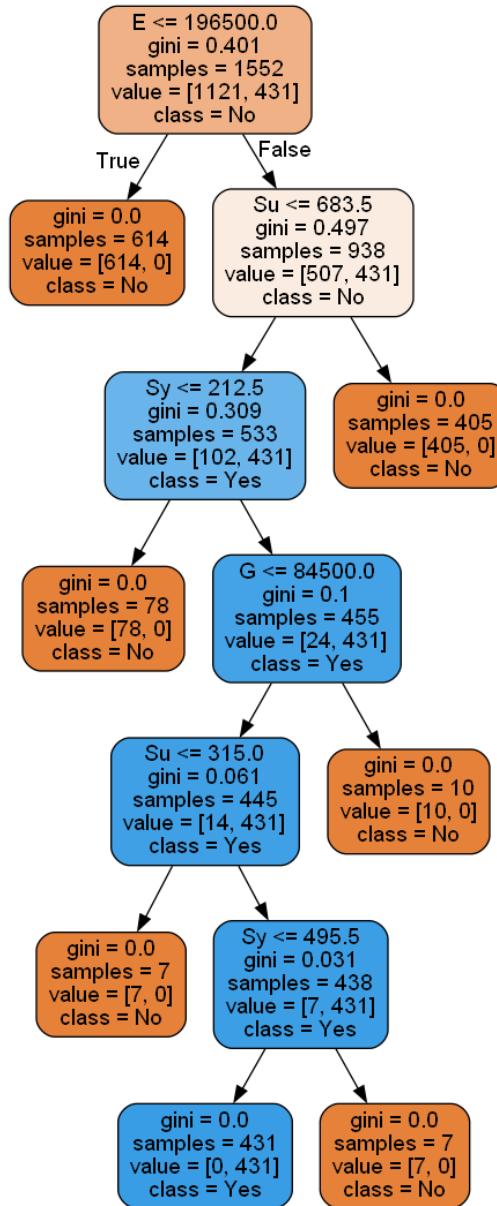


Figure 3. Decision Tree Output from Python code

4.2. Results and Discussions

Our model accurately predicted the ratings and suitability of materials for chassis based on their mechanical properties. The results demonstrate that machine learning can effectively assist in selecting the most appropriate material for a chassis, considering its applications and mechanical properties. We employed the Decision Tree and Random Forest algorithms, which are simple and interpretable algorithms suitable for classification tasks. These models achieved high accuracy and other evaluation

metrics, indicating their reliability and practical applicability. We have uploaded all related datasets and notebooks to GitHub and Kaggle (Appendix B).

It is important to note that the selection of a specific material and grade for a ladder frame chassis depends on various factors, including the intended use of the vehicle, design requirements, and cost considerations. Therefore, we have given preference to A36 over SAE 4130 due to its lower costs. However, it should be noted that 4130 has a lower weight compared to A36, making it an ideal material for the chassis.

5. CAD Customization using Fusion 360 API in Python

CAD customization of an EV chassis using the Autodesk Fusion 360 API can offer significant advantages, including greater design flexibility, improved efficiency, and reduced production costs. In this study, we utilized various technologies such as Autodesk Fusion 360, VS Code, Python, and GitHub to customize the design of chassis. This study contributes to the existing knowledge base by exploring the use of Fusion 360 for chassis customization. The resulting CAD model can be utilized for further analysis and rapid prototyping.

5.1. Methodology

For the purpose of customizing the chassis using Fusion 360 API, we have selected Python as our programming language due to its user-friendly syntax and ease of use. However, the API also offers C++ as an option for those seeking faster results. Custom parameters, such as wheelbase, width, material, thickness, and width and height cross-section of the rectangular side members and cross members, have been created for the chassis. The R&D team can modify these parameters using a Dialog Box, allowing for faster and more efficient visualization of changes made to the chassis in real-time. The design process involved creating sketches in various construction planes, extruding, sweeping, mirroring, choosing materials and appearance, and other related tasks using Python programming.

Table 5. Exported data to the CSV File 1

Young's Modulus	Wheel Base	csWidth	csHeight	Thickness	icsWidth	icsHeight	Passengers	Battery Weight	Total Load
200000	245	8	12	0.8	4.559205	6.838807	5	200	2075
200000	245	8	12	0.8	4.669134	7.0037	5	250	2125
200000	245	8	12	0.8	4.779067	7.168601	5	300	2175
200000	245	8	12	0.8	4.889006	7.333508	5	350	2225
200000	245	8	12	0.8	4.998949	7.498424	5	400	2275
200000	180	6.4	9.6	0.64	4.053593	6.080389	1	270	1845
200000	180	6.4	9.6	0.64	4.218456	6.327684	2	270	1920
200000	245	8	12	0.8	4.383329	6.574993	3	270	1995
200000	245	8	12	0.8	4.548212	6.822319	4	270	2070
200000	245	8	12	0.8	4.713106	7.06966	5	270	2145
200000	290	9.1	13.6	0.91	4.878012	7.317017	6	270	2220
150000	245	8.6	12.9	0.86	4.713106	7.06966	5	270	2145
180000	245	8.2	12.3	0.82	4.713106	7.06966	5	270	2145
200000	245	8	12	0.8	4.713106	7.06966	5	270	2145
220000	245	7.8	11.7	0.78	4.713106	7.06966	5	270	2145

Table 6. Exported data to the CSV File 2

Mass (kg)	Volume (cm ³)	Density (g/cm ³)	Area (cm ²)	X	Y	Z
351	44633	8	124763	72.0796	199.7	-6.84835
229	29084	8	96512	73.109	162.7535	-6.037233
372	47264	8	137977	71.7	198.6299	-6.999925
294	37398	8	128758	71.0783	191.9391	-7.134292

We have streamlined the design and CAD customization process by incorporating custom parameters such as wheelbase, width, and cross-section. Additionally, we have applied the same approach to parameters such as the number of passengers, battery weight, and Young's Modulus. All design automation calculations and CAD customization are performed through a Python script, and resulting data such as Young's Modulus, wheelbase, cross-section, material, total load, and passenger count are exported to CSV file 1, while mass, volume, and center of mass data are exported to CSV file 2.

By analyzing the data in the CSV file, we can determine that an increase in battery weight results in larger cross member dimensions. Similarly, an increase in passenger count leads to larger side member dimensions and wheelbase. On the other hand, increasing the Young's Modulus results in decreased side member dimensions, while a lower Young's modulus leads to increased dimensions. This indicates that for weaker materials, larger cross-sectional dimensions are generated.

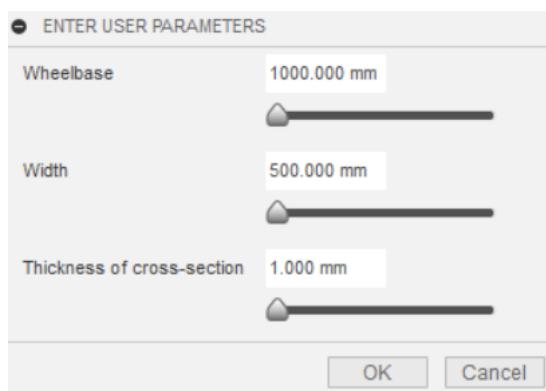


Figure 4. Add-in for User Parameters

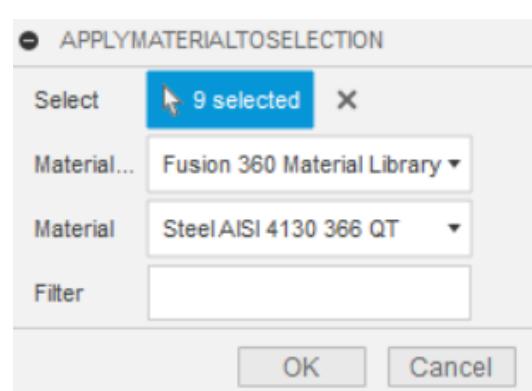


Figure 5. Dialog Box Material Selection

5.2. Results and Discussion

Using the Fusion 360 API to customize a chassis has resulted in a more efficient and sustainable design. The chassis has a wheelbase of 2450 mm and a width of 1520 mm. It features a rectangular ladder cross-section measuring 86 mm x 129 mm and has five cross members made of low alloy Steel ASTM A36 grade. The Python Scripts and Add-Ins used have been stored on GitHub (Appendix A).



Figure 6. Final output from Fusion 360 API

Our study demonstrates the potential of Autodesk Fusion 360 API for chassis customization. The use of custom parameters and programming automation allows for greater design flexibility, improved efficiency and reduced production time and cost. However, challenges such as the lack of programming expertise may hinder the widespread adoption of CAD customization. Further research is needed to explore the impact of customized chassis on vehicle safety, durability, and sustainability. At present, Generative Design and Simulation are not supported in the Fusion 360. However, integrating these features into the API would provide considerable time savings and automation benefits. In this study, we opted to customize a ladder frame chassis due to its relatively simple design. If we were to apply CAD customization to a monocoque chassis, the increased design complexity would present greater challenges for programmers tasked with creating the chassis. Nonetheless, it is still possible to develop a monocoque chassis with the assistance of an expert team.

6. Structural Analysis of the chassis

In this paper, we utilized Fusion 360 software for conducting Structural Analysis. Two types of analyses were performed on the chassis: Static analysis and Torsional analysis.

6.1. Static Analysis

The Static analysis involved multiple simulations with various boundary loading conditions and chassis parameters.

- Front: The front section includes the suspension system (60 kg), motor (50 kg), axle (130 kg), and body (100 kg), totaling 340 kg with a force of 3335.4 N.
- Centre: The central section consists of passengers (375 kg), seats (150 kg), battery (300 kg), steering (50 kg), and body (200 kg), totaling 1055 kg with a force of 10,349.55 N.
- Rear: The rear section comprises the suspension system (60 kg), axle (120 kg), payload (250 kg), and body (100 kg), totaling 530 kg with a force of 5199.3 N.

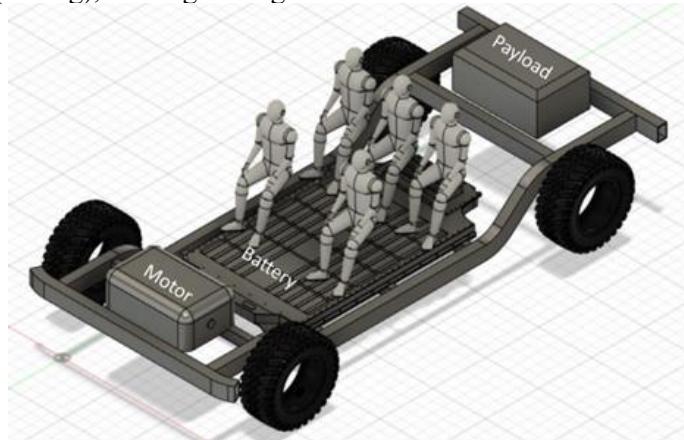


Figure 7. Boundary conditions for Static Analysis

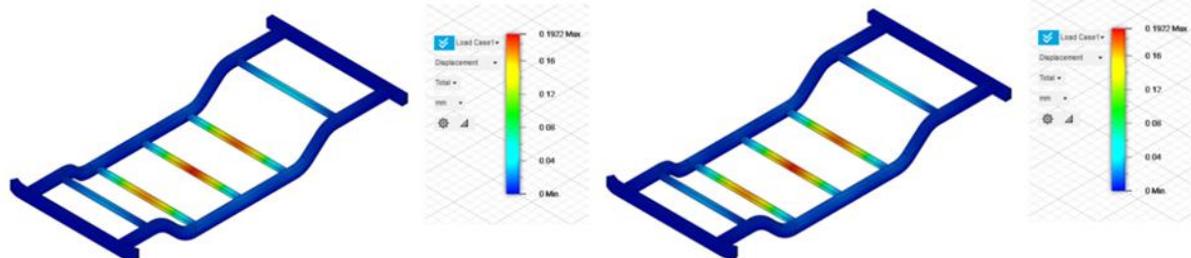


Figure 8. Displacement result of the chassis

Figure 9. Stress result of the chassis

The results consistently demonstrated a factor of safety for static loading conditions exceeding 8, indicating a highly secure design.

6.2. Torsional Analysis

We conducted Torsional stiffness analysis to ensure that the ladder frame chassis of a small car possessed sufficient torsional stiffness. For calculating torsional stiffness, the load applied on the chassis is chosen as the total GVW provided i.e., 2295 kgs/22491N. GVW is chosen because maximum load carrying capacity of any vehicle will not exceed GVW. Hence, to get torsional stiffened chassis, load applied is taken as GVW.

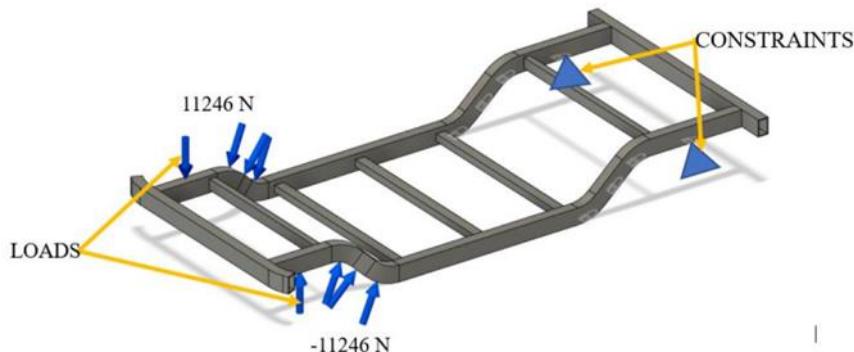


Figure 10. Boundary conditions for Torsional Analysis

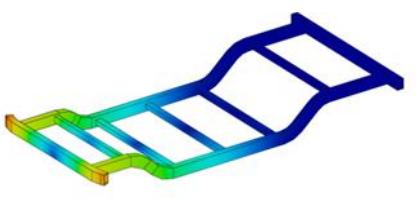


Figure 11. Displacement result of Torsional Analysis

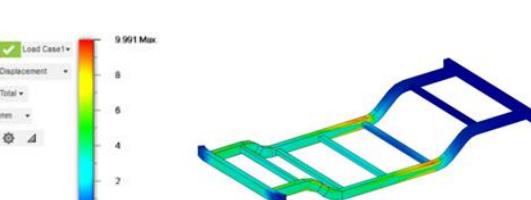


Figure 12. Stress result Torsional Analysis

Given below is the result table obtained from the torsional analysis of the chassis, as torsional stiffness is influenced by factors such as the material's modulus of elasticity and other variables. Also, cost is mentioned to give better brief while choosing the material for the chassis.

Table 7. Result comparison for torsional analysis

Material	Modulus of Elasticity	Cross section	Thickness	Factor of Safety	Chassis Weight	Cost
AISI Steel 4130	205 GPa	79 x 118 mm	7.90 mm	8.613	344 Kg	150/Kg
Steel ASTM A36	200 GPa	91 x 136 mm	9.10 mm	3.139	470 Kg	100/Kg

7. Conclusion

In conclusion, the proposed design approach using machine design methods and Python is an efficient and cost-effective way to design and customize chassis, allowing engineers to focus on other aspects of the design process. This approach can save time and cost associated with traditional manual design iterations, making it an attractive option for the automotive industry moving towards electric vehicles.

Our Materials dataset and machine learning methodology can serve as a valuable resource for researchers and practitioners interested in developing machine learning models for material selection in the context of chassis design. The dataset has the potential to be utilized in various domains and

applications in the field of Artificial Intelligence. In future work, it is possible to create alloys based on the machine learning model and chassis requirements, which can potentially improve the performance and characteristics of the chassis. This approach could provide a more tailored and optimized solution for material selection in chassis design, and further advance the use of machine learning in this area.

Fusion 360 does not currently offer the same level of CAD customization as PTC Creo, which has a parametric modelling feature that generates code simultaneously with CAD creation. If Fusion 360 were to adopt this feature, it would undoubtedly be a game-changer in terms of efficiency and productivity for designers and engineers. The ability to generate code along with the CAD design would streamline the design process and enable more accurate and faster modifications.

Further research could be conducted into the potential automation of design and CAD customization for an electric vehicle chassis. This could be followed by automating the simulation process and integrating it with rapid prototyping techniques. The end goal would be to create a fully connected and automated system that streamlines the entire design and prototyping process for chassis, making it more efficient.

8. Appendices

8.1. Appendix A: Design and CAD Customization of EV Chassis GitHub repository

<https://github.com/purushottamnawale/cad-customization-of-ev-chassis/>

The code utilized to customize the EV chassis described in this paper can be accessed on GitHub at the provided link. This repository includes the CAD files, a comprehensive project report, and Python scripts utilized to generate the customized chassis. Additionally, any future updates related to this study will be shared on this platform.

8.2. Appendix B: Material Selection using Machine Learning GitHub Repository

<https://github.com/purushottamnawale/material-selection-using-machine-learning/>

Kaggle

<https://www.kaggle.com/datasets/purushottamnawale/materials>

The codes used for material selection through machine learning are available on GitHub at the provided link. The repository contains both the Python codes and datasets used to train the machine learning models. Additionally, the Kaggle link also offers more recent machine learning models applied to the dataset by a community of users from around the world.

These repositories also contain detailed instructions for replicating the results presented in this paper. We encourage readers to review the code and use it as a starting point for their own customizations of EV chassis.

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