

What Material to Choose?

Automating Material Selection for Product Design

[Accompanying Github repository.](#)

What is material selection?

Materials selection is a critical aspect of design, as it plays a crucial role in determining the overall performance, functionality, and cost of a product. The selection of a material is dependent on the specific application of a part, as each material has its unique properties that may be more or less suitable for certain use cases, as well as on the function of the part within its assembly, such as quadcopter parts in Figure 1.

Choosing the right materials for a product can have a significant impact on its durability, reliability, and overall quality. A poor choice of materials can result in a product that is too heavy, too weak, or too expensive, leading to reduced performance and/or increased production costs. On the other hand, selecting the appropriate materials can lead to a product that is stronger, lighter, and more cost-effective.

Materials selection also involves balancing competing factors such as performance, cost, environmental impact, and availability. Designers need to consider the properties of materials, such as strength, stiffness, ductility, corrosion resistance, and thermal conductivity, to select an optimal material while ensuring the critical design requirements of a part are properly met.



Figure 1: Example materials of parts in a quadcopter.

Automating material selection

Materials selection can typically be a long and slow process, however within CAD tools identification of appropriate materials could be inferred based on similar or historical designs. Rather than reinventing the wheel with the design of each new part, prior design geometries can be leveraged to expediently identify potentially suitable material candidates. If we can give designers insights about the best materials to use as they are designing in CAD, we can steer them towards more appropriate materials, or even suggest more sustainable alternatives.

In this challenge, your task is to come up with an open-ended solution to identify an appropriate material for a set of parts, based on their CAD geometries and assembly context. To solve this challenge, rule-based or ML-based solutions could be implemented. For example, you might manually come up with a set of expert rules to funnel each part into one of the material categories, like a decision tree. Or you might take a data-driven approach and train a neural network on the data. Another approach might make use of a pretrained large language model to predict an appropriate material category. To simplify the material selection process, we selected a set of material categories from which you will choose, found in Table 1. You will select the most viable material for each part in the test set, and report that in the submission.csv file (see *Submission* below).

Table 1: List of materials available for selection.

Material Category	Definition	Example(s)
Metal_Aluminum	Aluminum-based metal	Aluminum alloy
Metal_Ferrous	Ferrous metal (excluding carbon steel)	Cast iron
Metal_Ferrous_Steel	Carbon steel	Stainless steel
Metal_Non-Ferrous	Non-Ferrous metal	Platinum, silver
Other	Uncategorized material	Glass, fabric, ceramic
Plastic	Plastic	Thermoplastic
Wood	Natural and engineered wood	Softwood

Dataset

The dataset will be released at the start of the hackathon. <https://github.com/danielegrandi-adsk/IDETC23-Autodesk-hackathon/>

To support this challenge, we provide a dataset of 6346 assemblies with a total of 131,403 parts, each of which has a material label. Although we do not know the design goals or constraints that the designer was accounting for while creating these assemblies, these material labels in this dataset can be treated as ‘ground truth’ labels.

Each assembly also includes information about the parts that can be used for predicting the material, such as an image depicting each part, part names, part dimensions, part geometry, and other assembly-level information, such as a design category or industry. An example assembly and included data is shown in Figure 2.

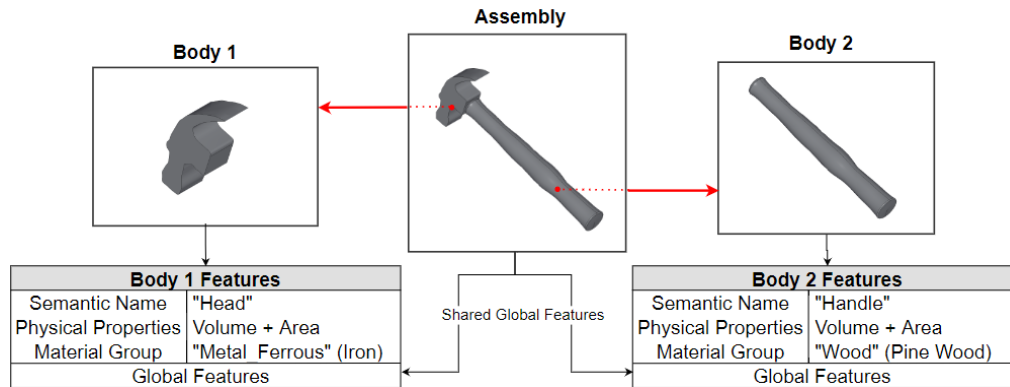


Figure 2: An example assembly of two bodies with corresponding features included in the dataset.

Submission

The dataset is divided into a **training set** and a **test set**. The **training set** contains the ground truth material category of each body, which can be used to train data-driven ML models, or to validate rule-based solutions. The **test set** contains parts from **10 assemblies** which will be used to create a 'submission.csv' file. The 'submission.csv' file will be shared with the dataset at the start of the hackathon, which you will edit to include the predicted material of each test part, selected using your method. The 'submission.csv' file will be used by the judges to evaluate the accuracy of your method. Accuracy is defined as the total number of correct predictions divided by the total number of predictions.

Judgment Criteria

Category	Criteria	Score
Quantitative evaluation (45%)	<ul style="list-style-type: none"> Teams will report their predictions for each of the parts in the test set in 'submission.csv'. Accuracy calculation: accuracy will be used as metric for this multi class classification task. 	> 90% (9-10 pts) 70-80% (7-8 pts) 50-60% (5-6 pts) 30-40% (3-4 pts) < 30% (1-2 pts)
Qualitative evaluation (45%)	<ul style="list-style-type: none"> Teams will present an overview of their method. Does the method include a feasibility metric? Scientific soundness of the approach. Readiness of the idea and the approach. Evaluation of future direction or proposed work given more time. 	Excellent (9-10 pts) Very good (7-8 pts) Good (5-6 pts) Limited (3-4 pts) Poor (1-2 pts)
Overall presentation (10%)	<ul style="list-style-type: none"> Title, headings, labels: appropriate size, location, spelling, and content. Demonstration of teamwork. Structure and clarity. Boarder impact of the idea on ME subfields. 	Excellent (9-10 pts) Very good (7-8 pts) Good (5-6 pts) Limited (3-4 pts) Poor (1-2 pts)

Domain Experts and Support



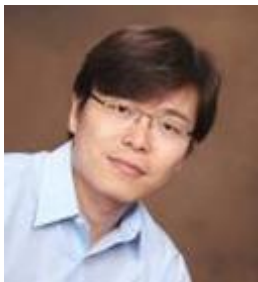
Daniele Grandi, Sr. Research Engineer, Autodesk, Inc.



Allin Groom, Senior Research Scientist, Autodesk, Inc.



Ye Wang, Principal Research Scientist, Autodesk, Inc.



Zhenghui Sha, Assistant Professor, J. Mike Walker Department of Mechanical Engineering, The University of Texas at Austin