S2 Final Presentation

Optimizing Material Composition in Aircraft Wing Design for Reduced Lifecycle Environmental Impact

Almudena Cobo-Urios and Álvaro Silva-Vilela-Caridade

Tutor: Professor Joseph Morlier

Shantanu Sapre

Institut Supérieur de l'Aéronautique et de l'Espace

SUPAERO

CONTENTS

Context & Motivation

- A320: legacy 1980s design with conventional materials
- A320s still metal-heavy vs. composite-rich A350/B787
- World's most-used single-aisle aircraft → small gains = big impact
- Demand for this class remains strong (market forecast – 43,420 in the next 20 years)
- Aims at climate targets (e.g., Paris Agreement) & lifecycle goals

Source: https://caneurope.org/europe-is-staying-the-course/

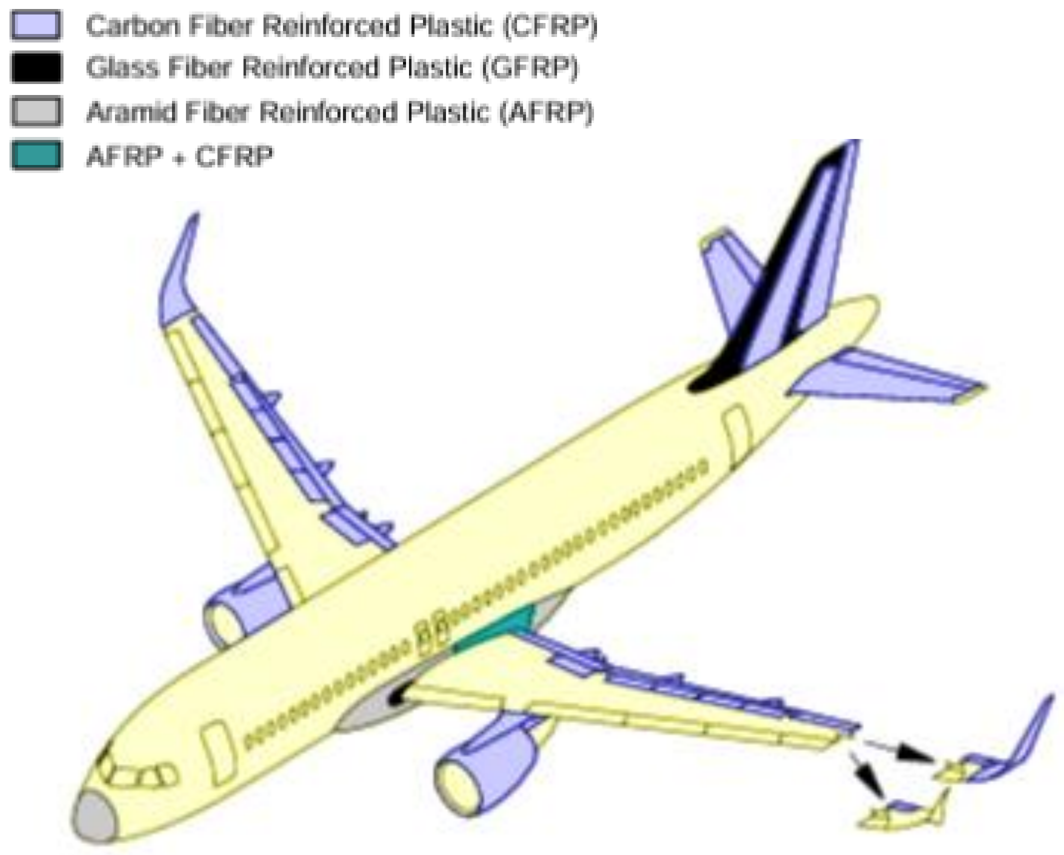


Figure 1: Structural parts made out of composite materials in A320

Source: A320 technical data sheet (https://www.airbus.com)

First Results

- **OpenAeroStruct (OAS):** low-fidelity tool for **aero-structural optimization**

- Applied to **Airbus A320 wingbox** for material trade-off analysis

- Compared **fuel burn** and **wingbox mass** across:
  ○ **Aluminium**, **CFRP**, **Titanium**, **Steel**

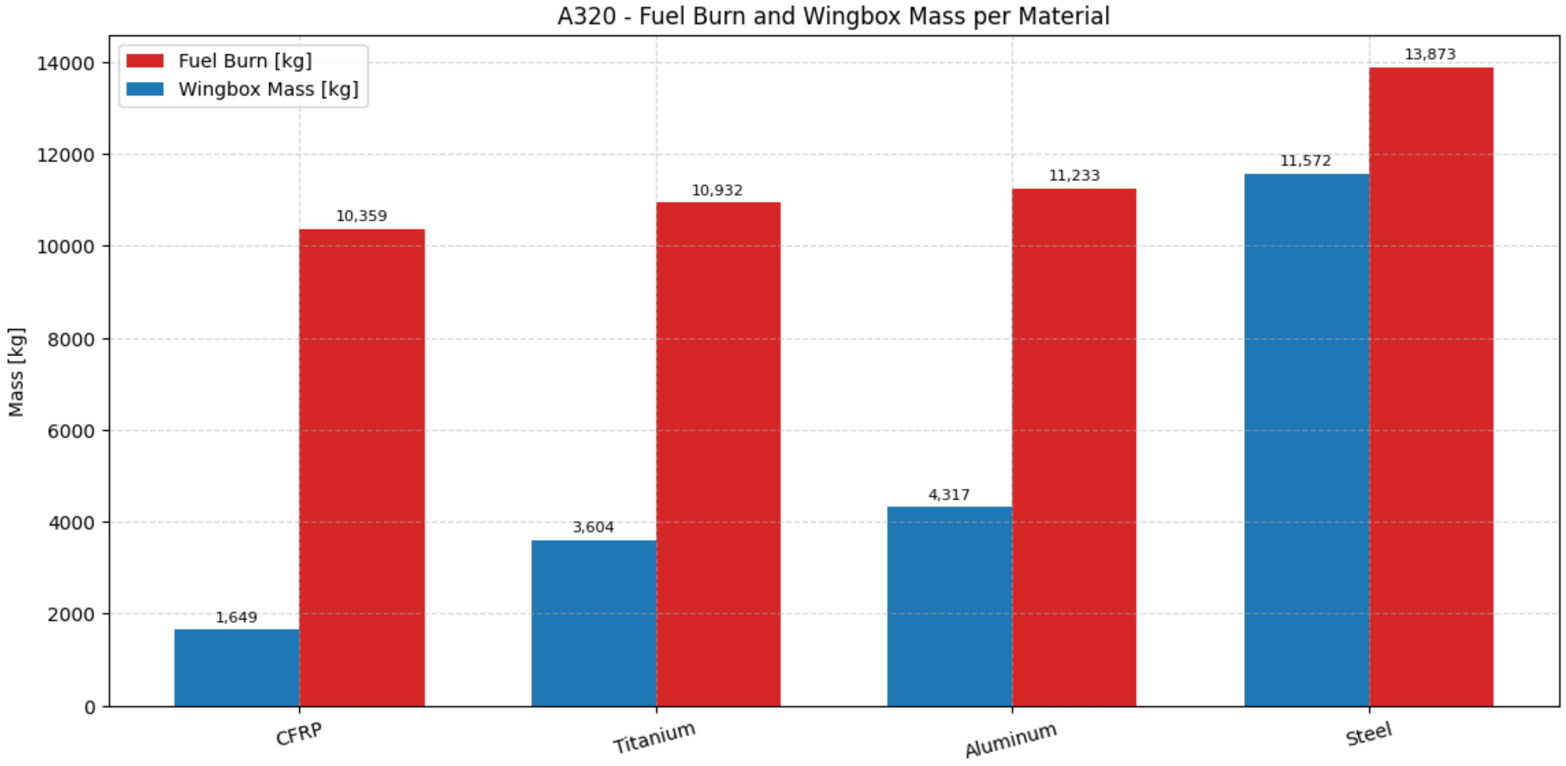


Figure 2: Comparison of Wingbox Mass and Fuel Burn Across Materials

Variational Autoencoders (VAE) [1]

It is a **neural network architecture** designed to:

- **Compress** high-dimensional data into a lower-dimensional latent space.
- **Reconstruct** the original data from that latent space.

It consists of two main parts:

- **Encoder**: maps inputs into latent variables z0 ,z1.
- **Decoder**: maps latent variables back into predicted properties ζ^

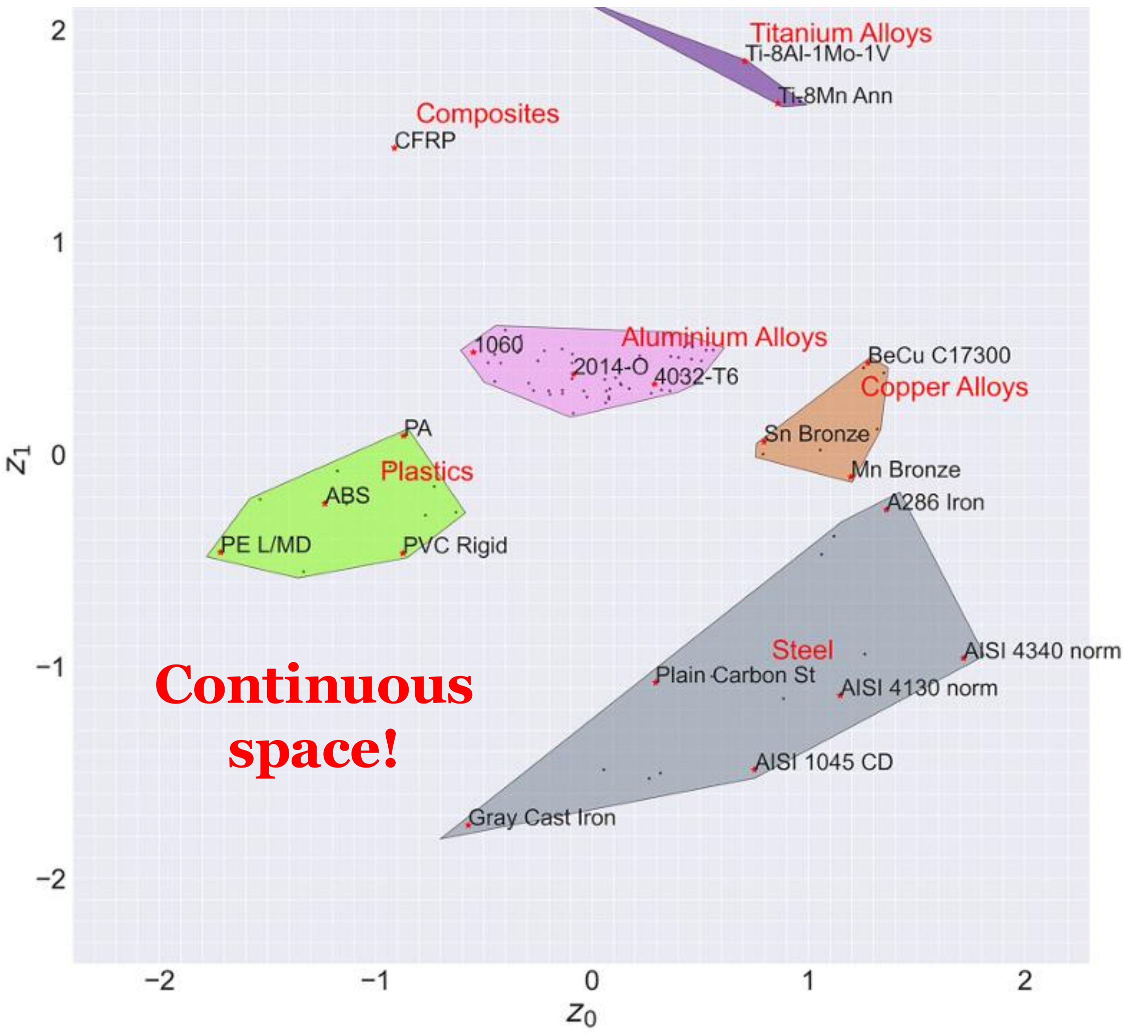
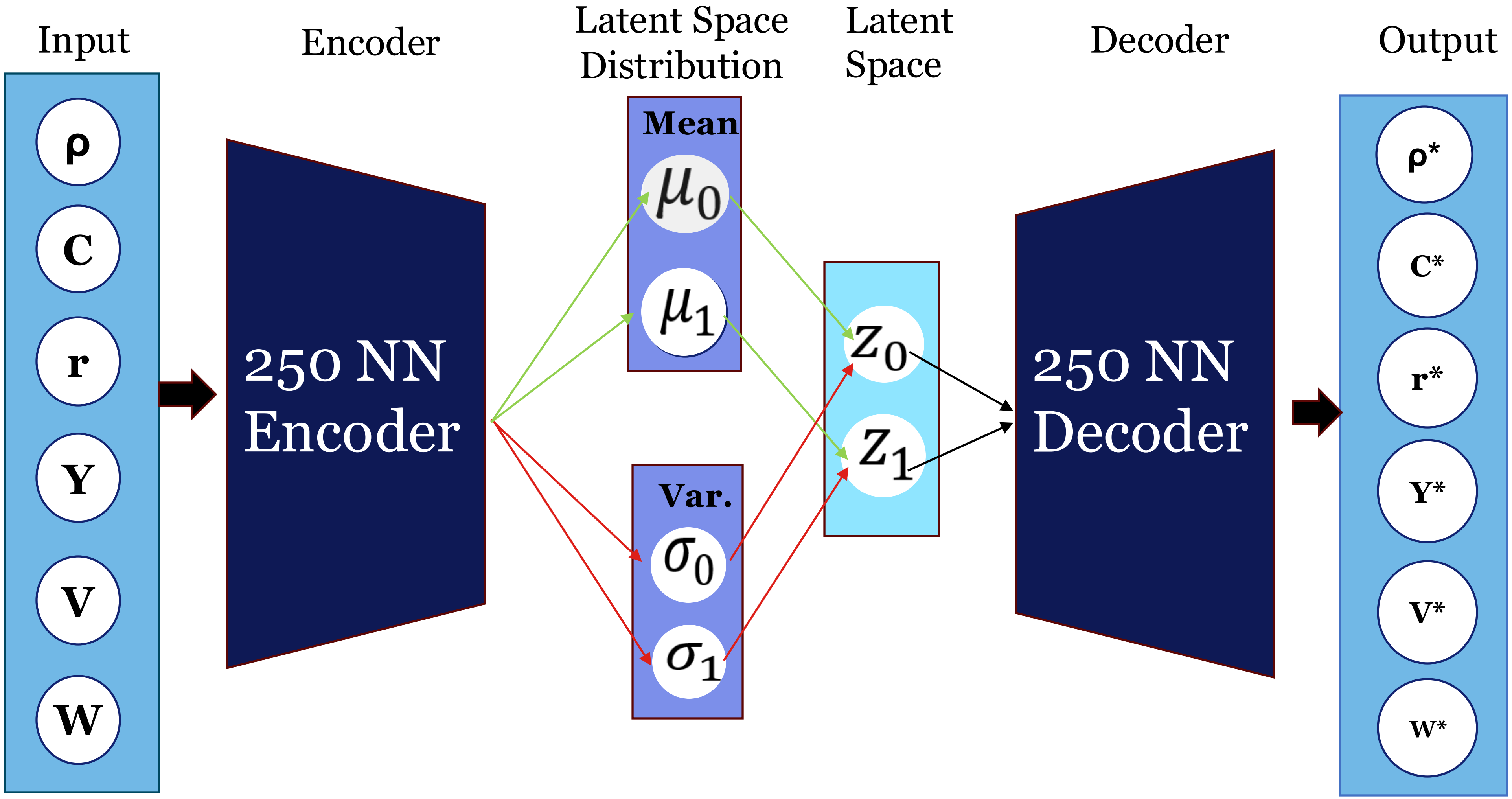


Figure 3: Material representation in a two-dimensional latent space [2]

[1] Kingma, D. P., & Welling, M. "*Auto-Encoding Variational Bayes*", 2013.

[2] L. Y. Llorente, J. Morlier, S. Sridhara, and K. Suresh, "A hybrid machine learningand evolutionary approach to material selection and design optimization for eco-friendly structures", 2023.

VAE - our scenario



6D vector of material properties:

- ζ=[ρ, C,r,Y,V,W]
  - ρ : density
  - C: Cost
  - r: Density/E
  - Y : Yield stress
  - V: Energy
  - W: Waste

The VAE learns to map these into a **2D latent space**: z=[z0,z1]~N(0,1)

The **decoder** function ζ^=D(z) outputs an approximate reconstruction.

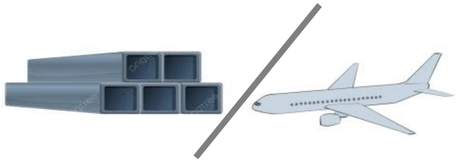
VAE Implementation

Creation of the latent space for our material database

7 pure material database

- Expanded the database to 7 materials: two aluminium alloys (**Al 2024, Al 6061**), three composite types (**CFRP Unidirectional, CFRP Woven, GFRP**), and two structural metals (**Titanium, Steel**). [3] João Vasco Lopes. *Development of a Multi-Objective Optimization Framework Using Variational Autoencoders*. MSc Thesis, Instituto Superior Técnico, Universidade de Lisboa, 2021.

- **Cost**, **Energy**, and **Waste** are computed considering **BtF** ratio. [4]



https://pngtree.com
https://easydrawingart.com/

$$\mathbf{Energy}_m = e_m \cdot BtF_m$$
$$\mathbf{Cost}_m = c_m \cdot BtF_m$$
$$\mathbf{Waste}_m = (BtF_m - 1) \cdot nrw_m$$

e_m: Specific energy (MJ/kg)

c_m: Cost per kg (€/kg)

nrw_m: Non-recyclable waste fraction

BtF_m: Buy-to-Fly ratio

[4] Sapre et al. Green Aviation Manufacturing: Addressing Environmental Impacts with MDO Methodologies. AeroBest, 2025.

- Additionally, we incorporated key structural properties such as **Young's modulus (E)** and **yield stress (σ_γ)** for performance assessment.

7 pure material database

Property	Unit	Al 2024	Al 6061	CFRP-UD	CFRP-Woven	GFRP	Titanium	Steel
Density	kg/m3	2765	2710	1565	1575	1850	4430	7740
Cost	€/kg	17.275	16.2	55.275	78	76.8	236	45.57
Energy	MJ/kg	872.5	890	1091.25	1091.25	311.7	6875	411.3
Waste	kg/kg	0.2	0.2	0.5	0.5	2	1.35	0.25
Young Modulus	GPa	73.85	68.3	141.5	65.7	33.3	114.5	200
Yield Stress	MPa	331	127.5	1955	768.5	368.5	848	698.5

Table 2: Data for the 7 material database.

[5] Granta EduPack https://www.ansys.com/fr-fr/products/materials/granta-edupack

Note: **Cost**, **Energy**, and **Waste** consider **BtF** ratio

7 pure material Latent Space

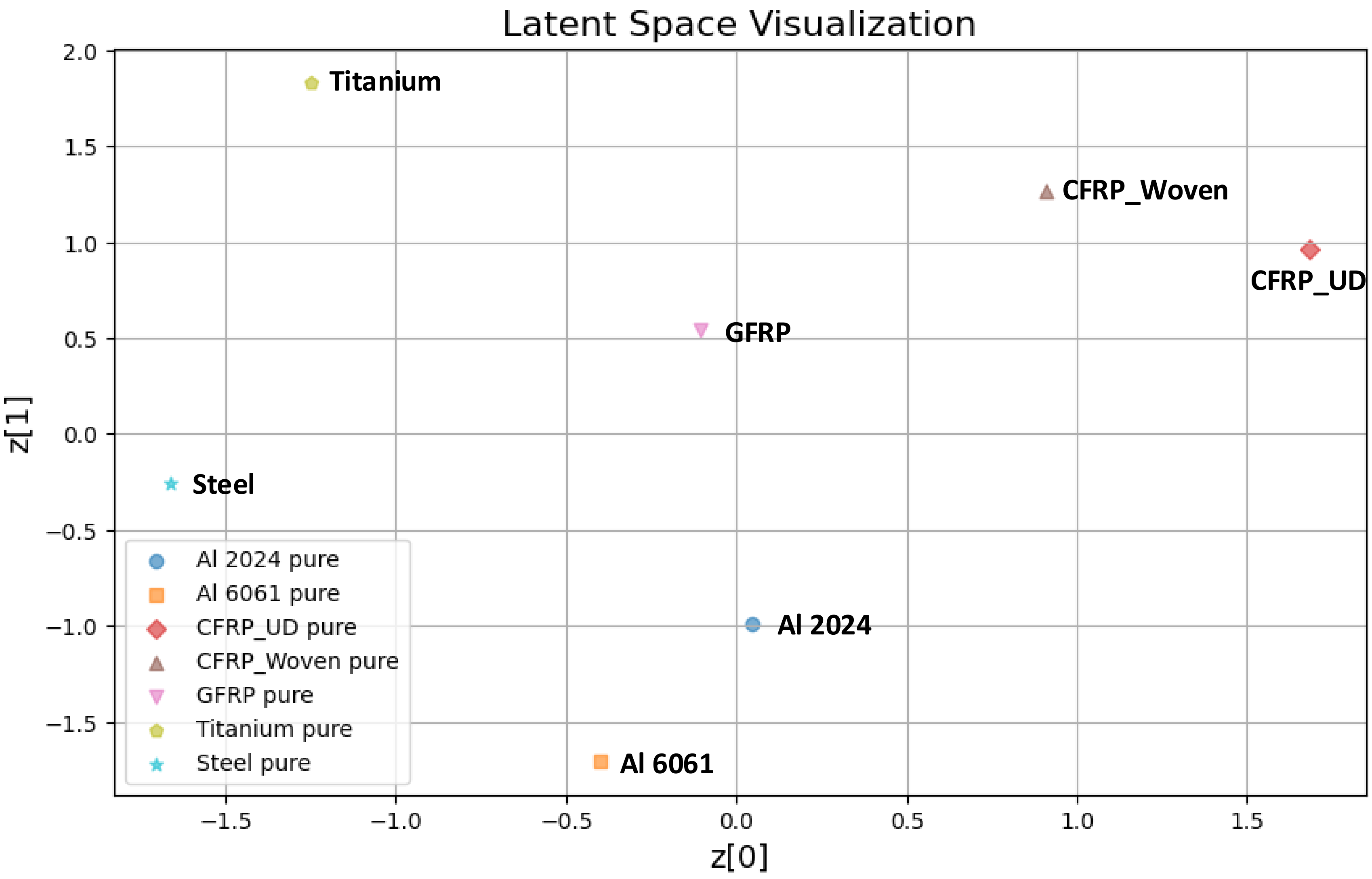


Figure 5: 7 material latent space

7 pure material Latent Space contours

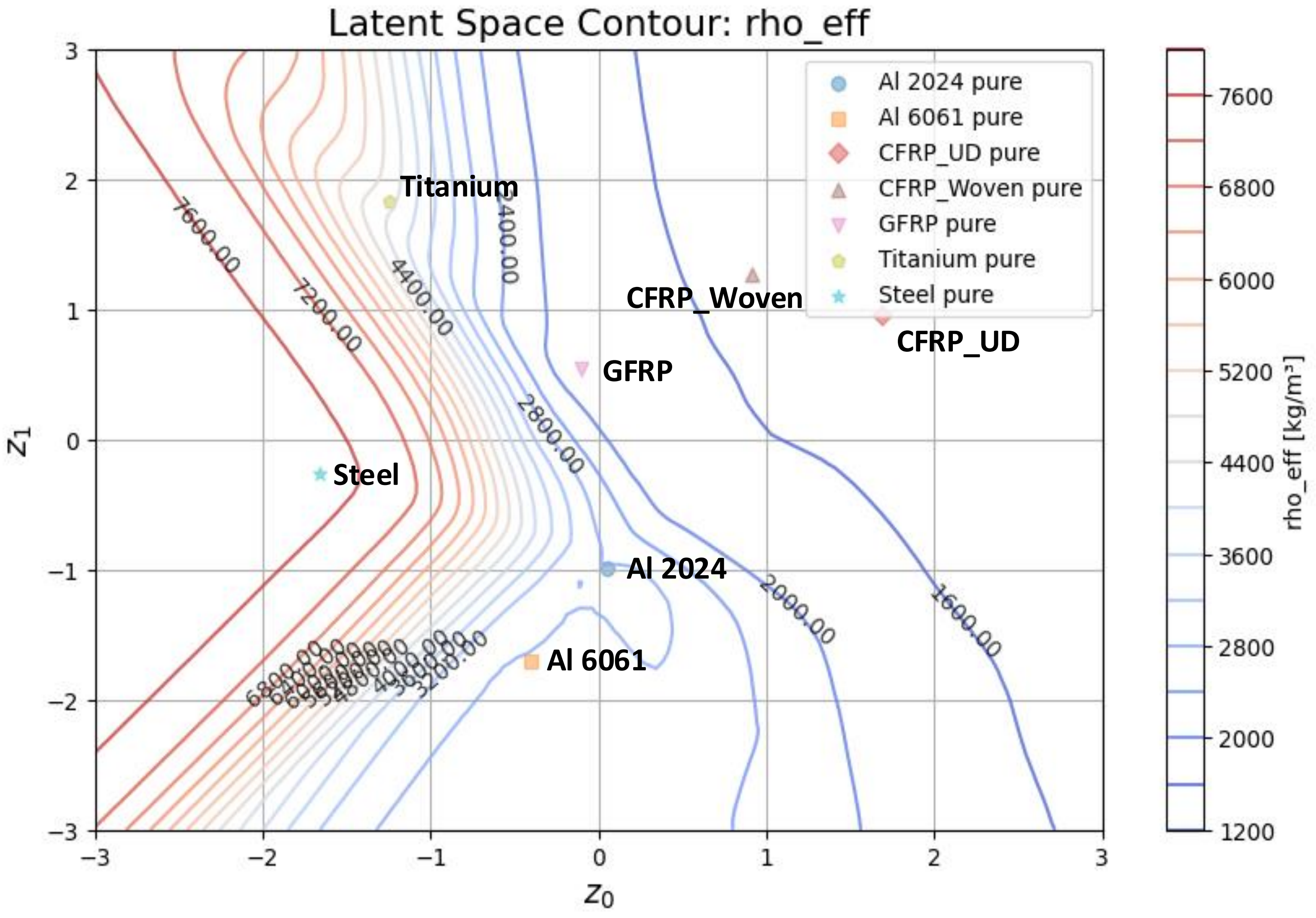


Figure 6a: 7 material latent space density contour

Note (e.g.):

- Both CFRP's sit just above **1600 kg/m³** contour
- Matches true densities: **1565 / 1575 kg/m³**
- Latent space reflects **physical accuracy**

7 pure material Latent Space contours

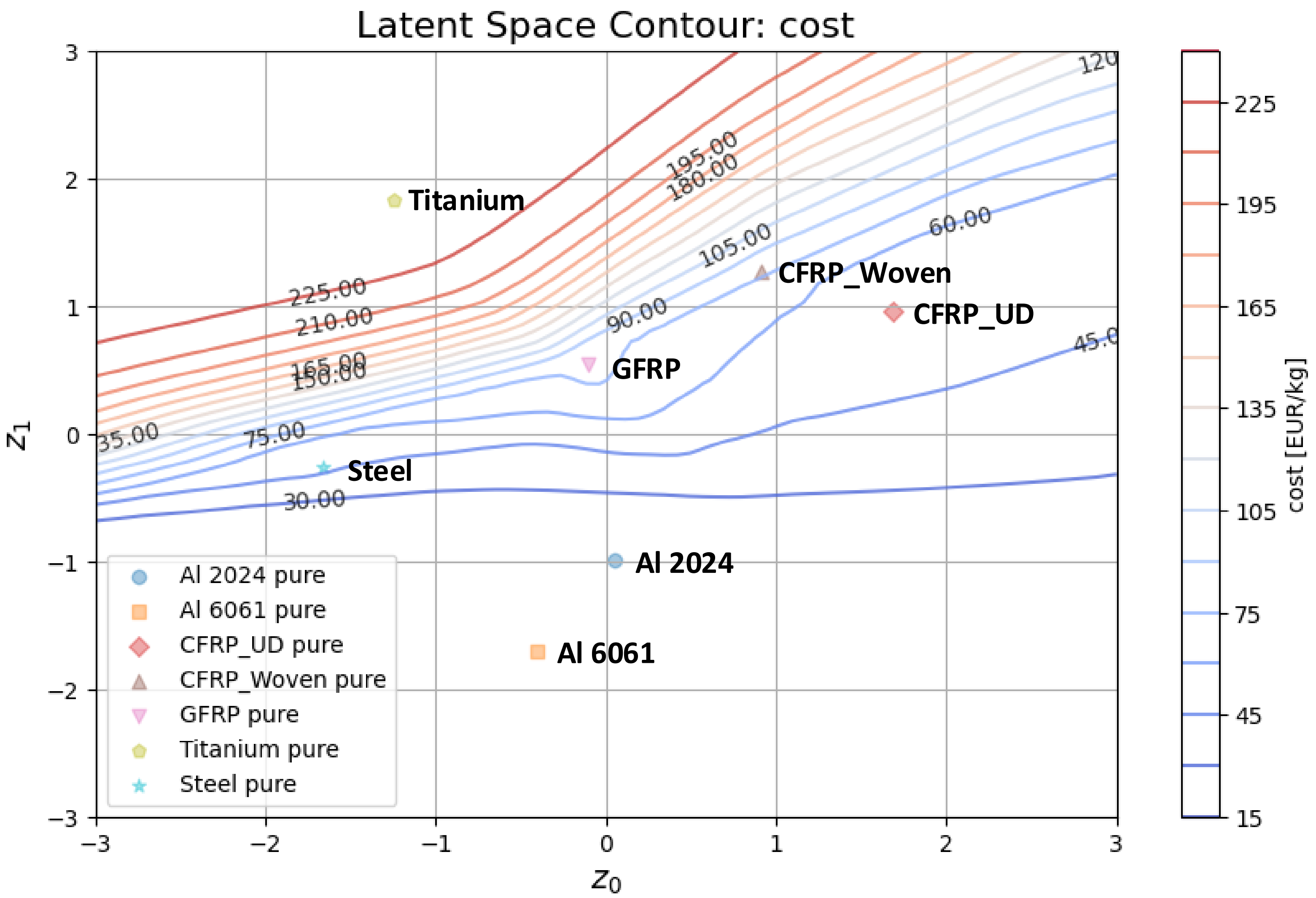


Figure 6b: 7 material latent space cost contour

Note (e.g):

- Al 2024 and Al 6061 lie bellow **30 €/kg** contours
- Reflects true costs: **17.28 / 16.20 €/kg**
- Latent space preserves **relative material cost**

Multi-Objective Optimization

Optimizing materials with a Gradient-based method

Gradient based optimization

Objective: Minimize: cost (C), density-to-stiffness ratio (r), energy (V) and waste (W)

Maximize: yield strength (Y)

- Non-gradient based methods optimizers (NSGA II).
- Interest on implementing gradient-based methods.
- Challenging optimization due to large number objective functions.

↓

Multiple-Gradient Descent Algorithm (MGDA) [6]

[6] J.-A. Désidéri, A. Minelli, and A. Zerbinati, "A cooperative algorithm for multi- objective optimization: multiple-gradient descent algorithm (mgda)," in 4th Inverse Problems, Design and Optimization Symposium (IPDO-2013), Albi, France, Jun. 2013.

Gradient based optimization

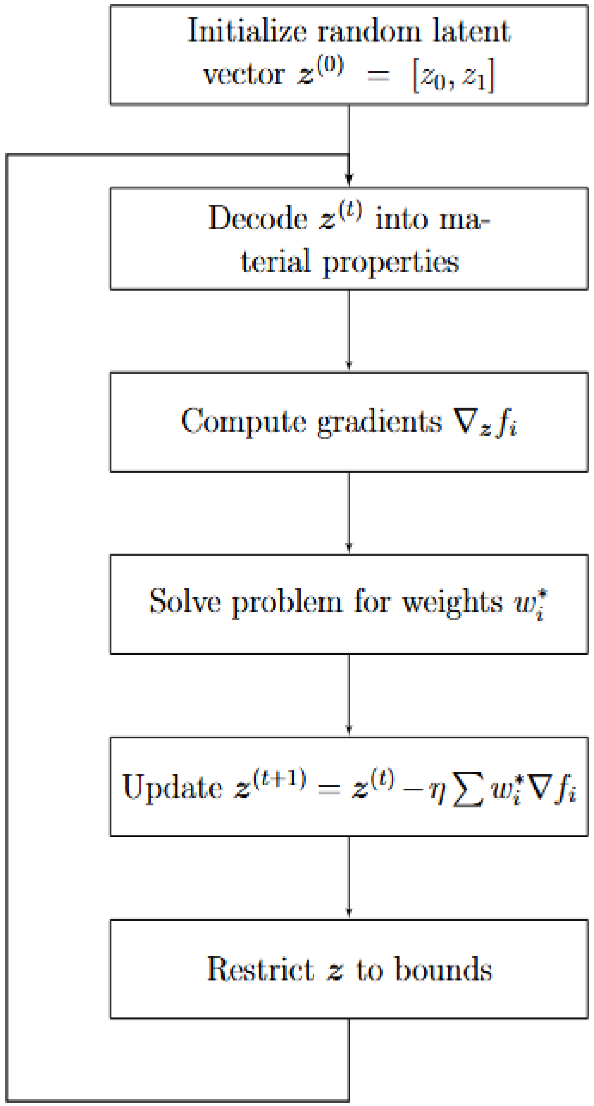


Figure 7: MGDA

Multiple-Gradient Descent Algorithm (MGDA)

1. Initialize a random latent vector: z = [z0,z1]

2. Decode material properties of such point:

   [f1, f2, f3, f4, f5] ≡ [C, r, V, W, Y]

3. Compute the gradient of each property with respect to z (PyTorch's [7] automatic differentiation)

$$\nabla f_i(z) = \begin{bmatrix} \frac{\partial f_i}{\partial z_0} \\ \frac{\partial f_i}{\partial z_1} \end{bmatrix}$$

[7] Paszke, A., et al. (2019). *PyTorch: An Imperative Style, High-Performance Deep Learning Library*. In *Advances in Neural Information Processing Systems* (NeurIPS 2019), pp. 8024–8035.

Multiple-Gradient Descent Algorithm (MGDA)

4. Solve the problem:

$$\min_{w} \left\| \sum_{i=1}^{k} w_i \nabla f_i(z) \right\|^2 \quad \text{where} \quad \left\{ w \in \mathbb{R}^k \mid w_i \geq 0 \, , \sum w_i = 1 \right\}$$

[6]

Finds the weighted sum of gradients that gives a direction which reduces all objectives the best possible way.

5. Update the vector in such direction (implemented with Pythorch Stochastic Gradient Descent (SGD) optimizer [7])

$$z \leftarrow z - \eta \left(\sum_{i} w_i \nabla_z f_i \right)$$

Learning rate: 0.01

Gradient based optimization

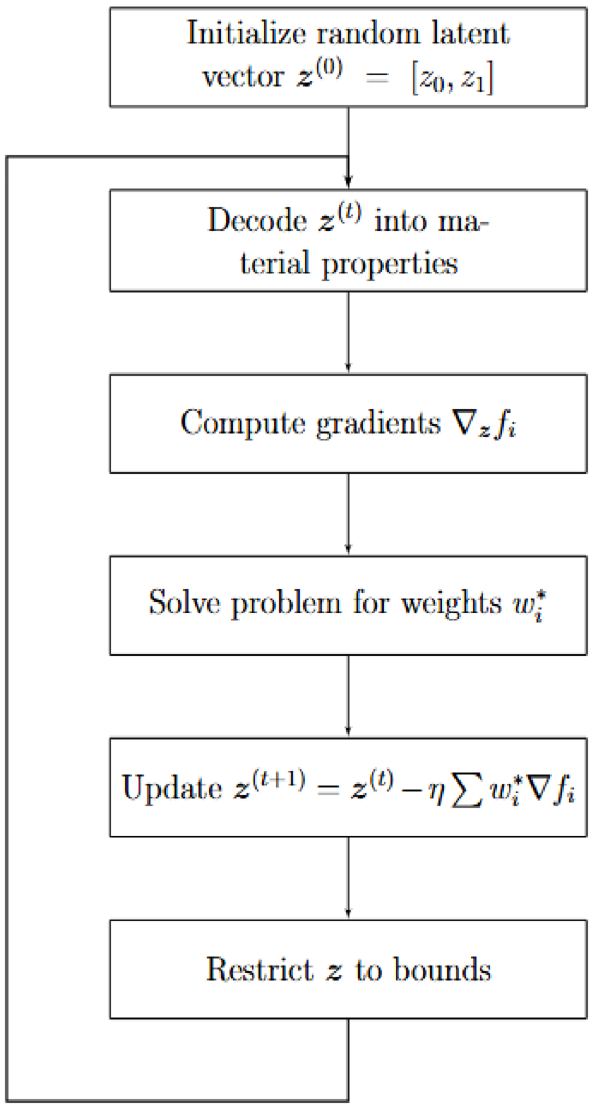


Figure 7: MGDA

Multiple-Gradient Descent Algorithm (MGDA)

6. Restrict solution to the boundaries:

   Ensure z* belongs to [z_{min}, z_{max}]

7. Repeat n=500 times to build the pareto front.

Tested multiple n = 50, 100, 200, 500 and observed similar Pareto front trends.

MGDA results

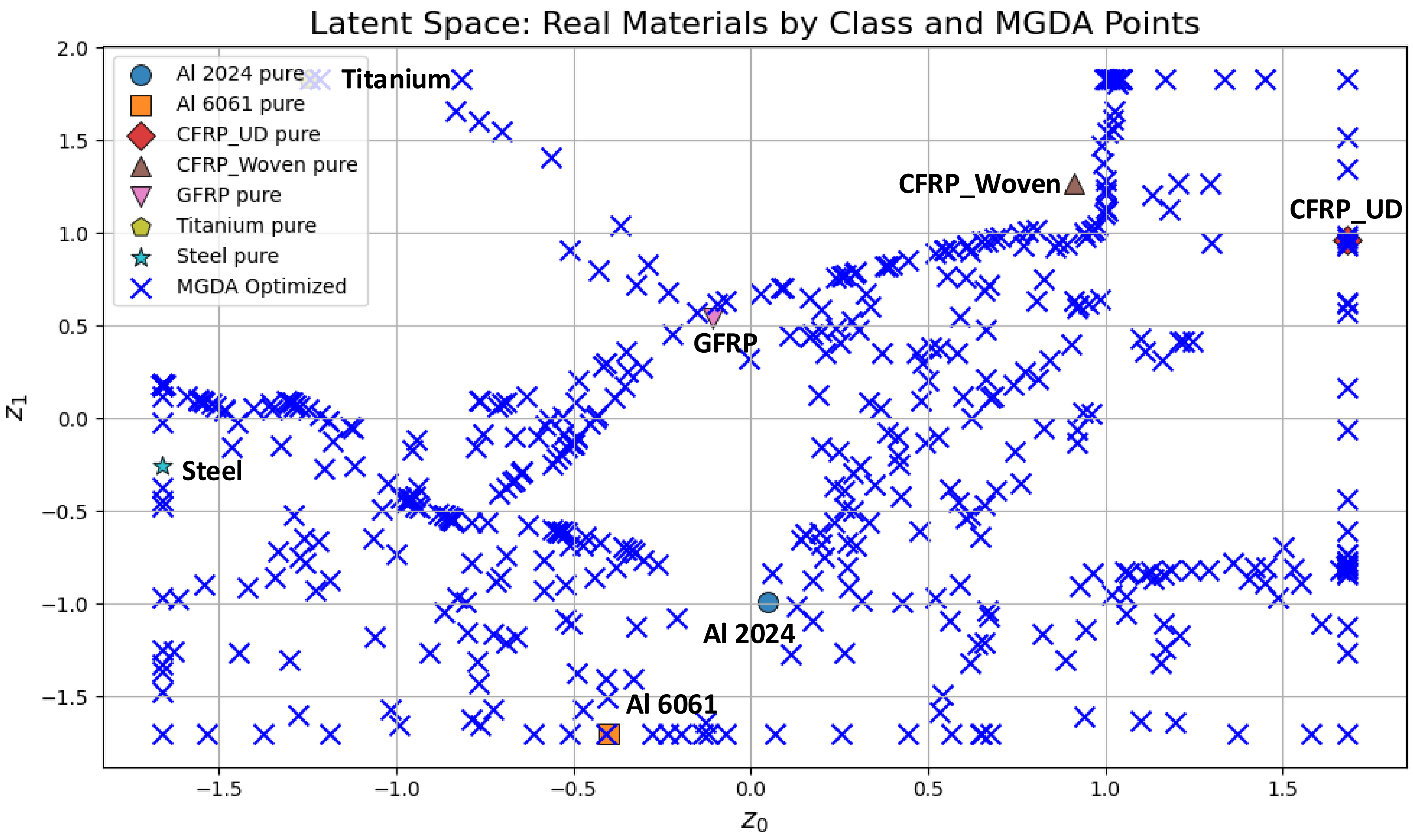
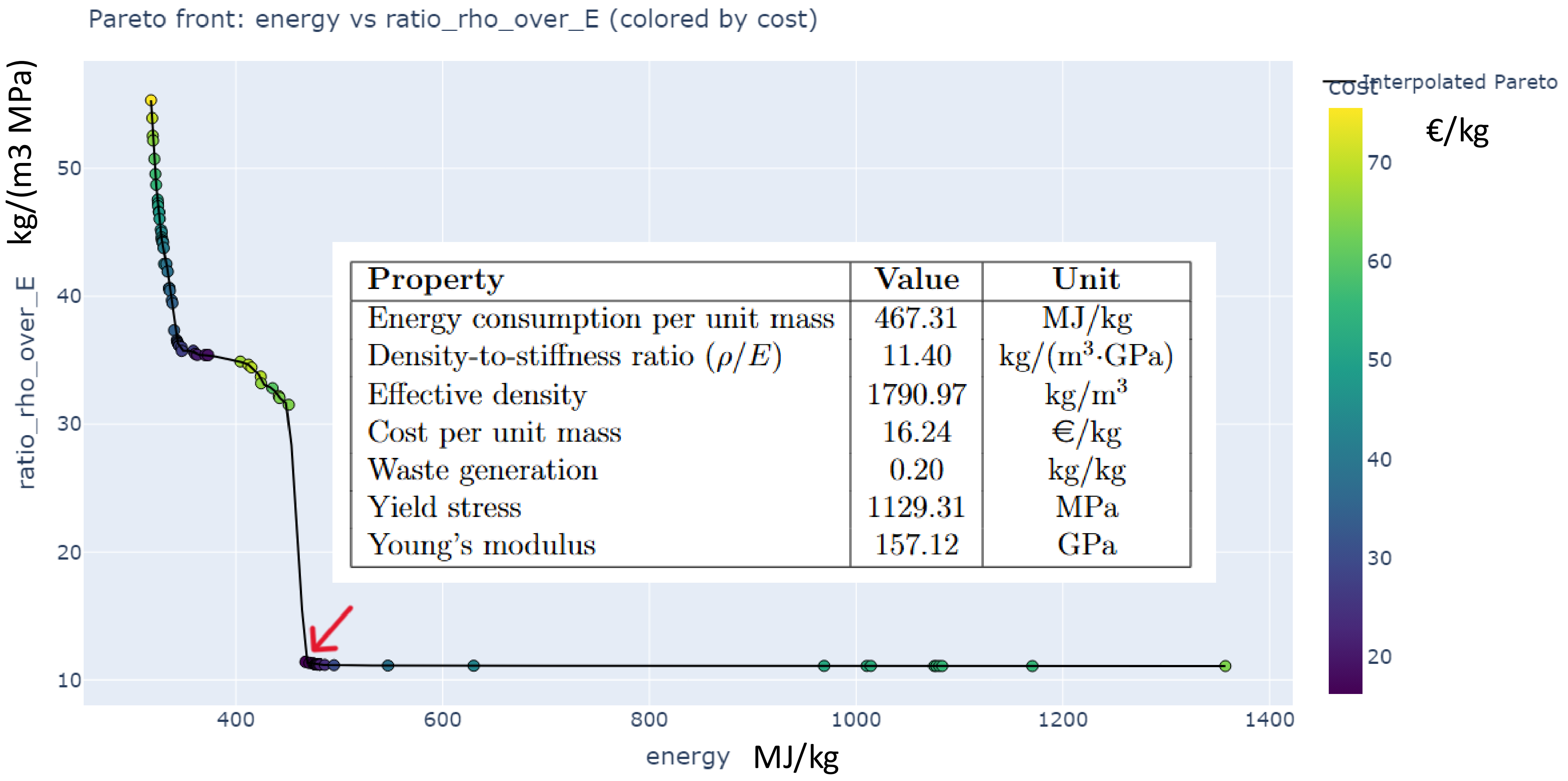


Figure 8: latent space with optimized solutions for 500 runs

MGDA-Pareto Front



Property	Value	Unit
Energy consumption per unit mass	467.31	MJ/kg
Density-to-stiffness ratio (ρ/E)	11.40	$kg/(m^3 \cdot GPa)$
Effective density	1790.97	kg/m^3
Cost per unit mass	16.24	€/kg
Waste generation	0.20	kg/kg
Yield stress	1129.31	MPa
Young's modulus	157.12	GPa

Figure 9: Pareto front rho/E vs. energy for 500 runs

MGDA results

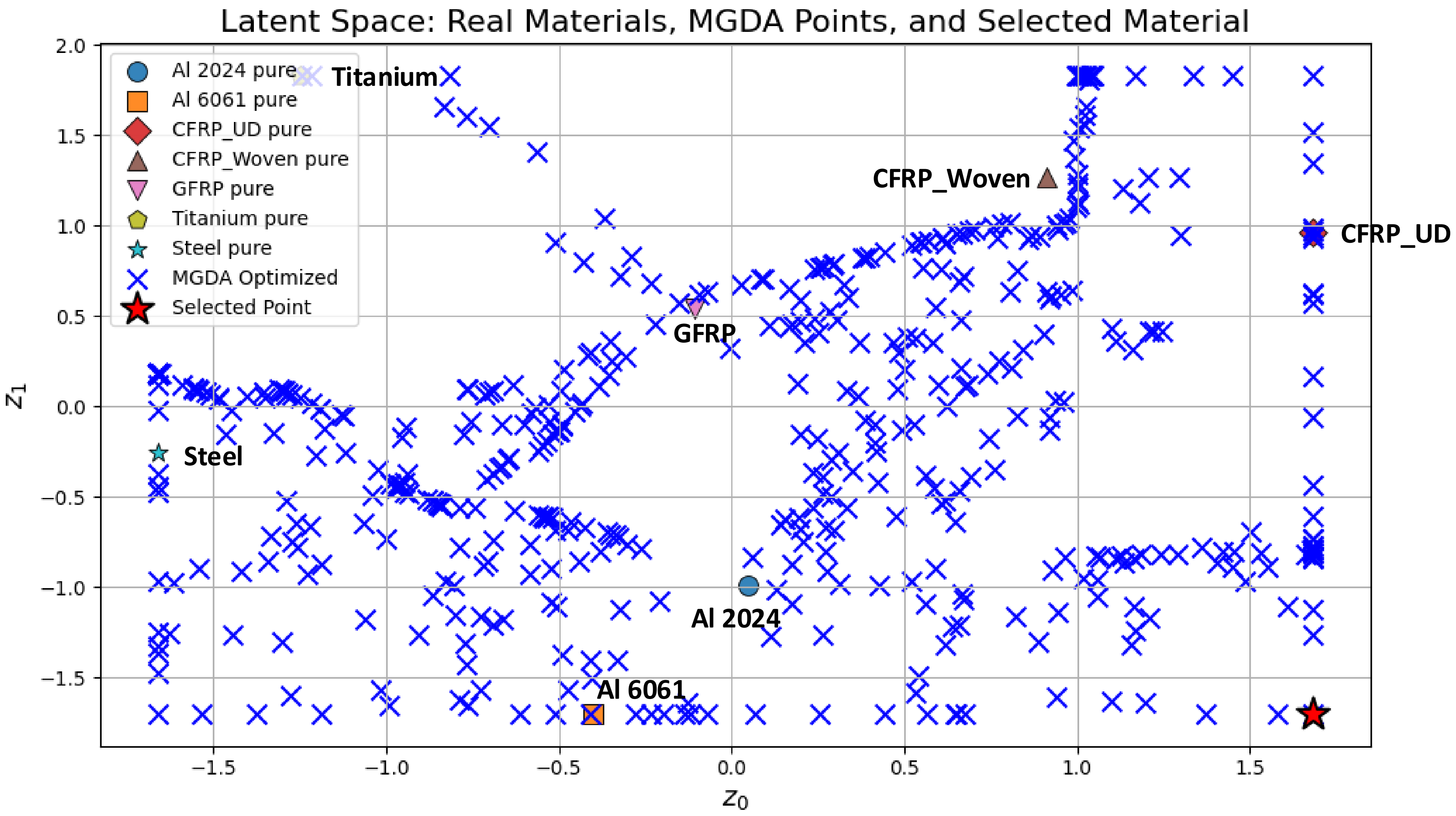


Figure 10: latent space with optimized point

OAS with optimized material

- Fuel consumption: **10,149.76 kg**
- Wingbox mass: **939.34 kg**

A320 Improvements - Optimized vs:

- CFRP:
  - Fuel ↓ 2.02%
  - Wingbox Mass ↓ 43.05%
- Titanium:
  - Fuel ↓ 7.16%
  - Wingbox Mass ↓ 73.94%
- Aluminum:
  - Fuel ↓ 9.65%,
  - Wingbox Mass ↓ 78.24%
- Steel:
  - Fuel ↓ 26.84%
  - Wingbox Mass ↓ 91.88%

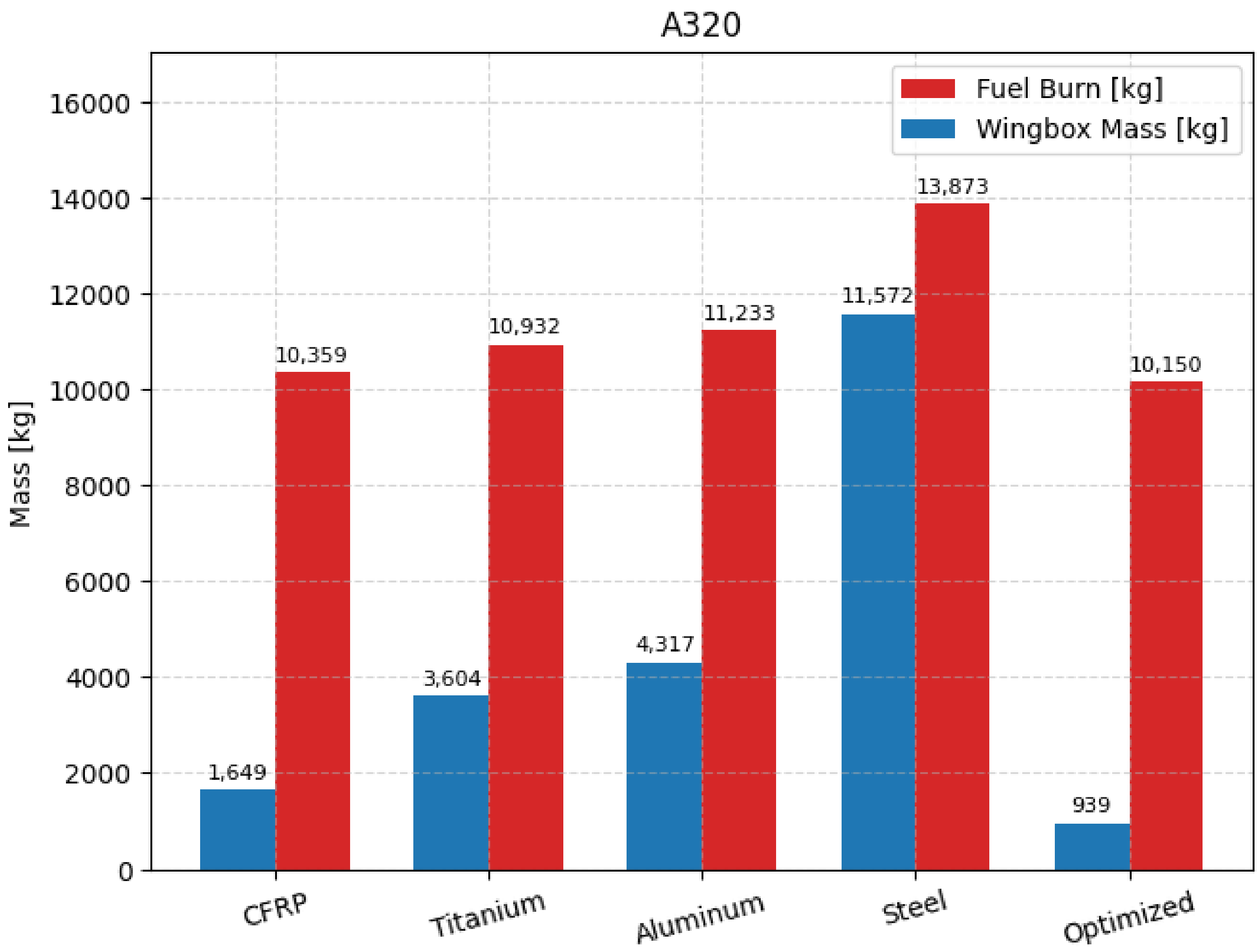


Figure 10: Comparison of Wingbox Mass and Fuel Burn Across Materials

OAS with optimized material

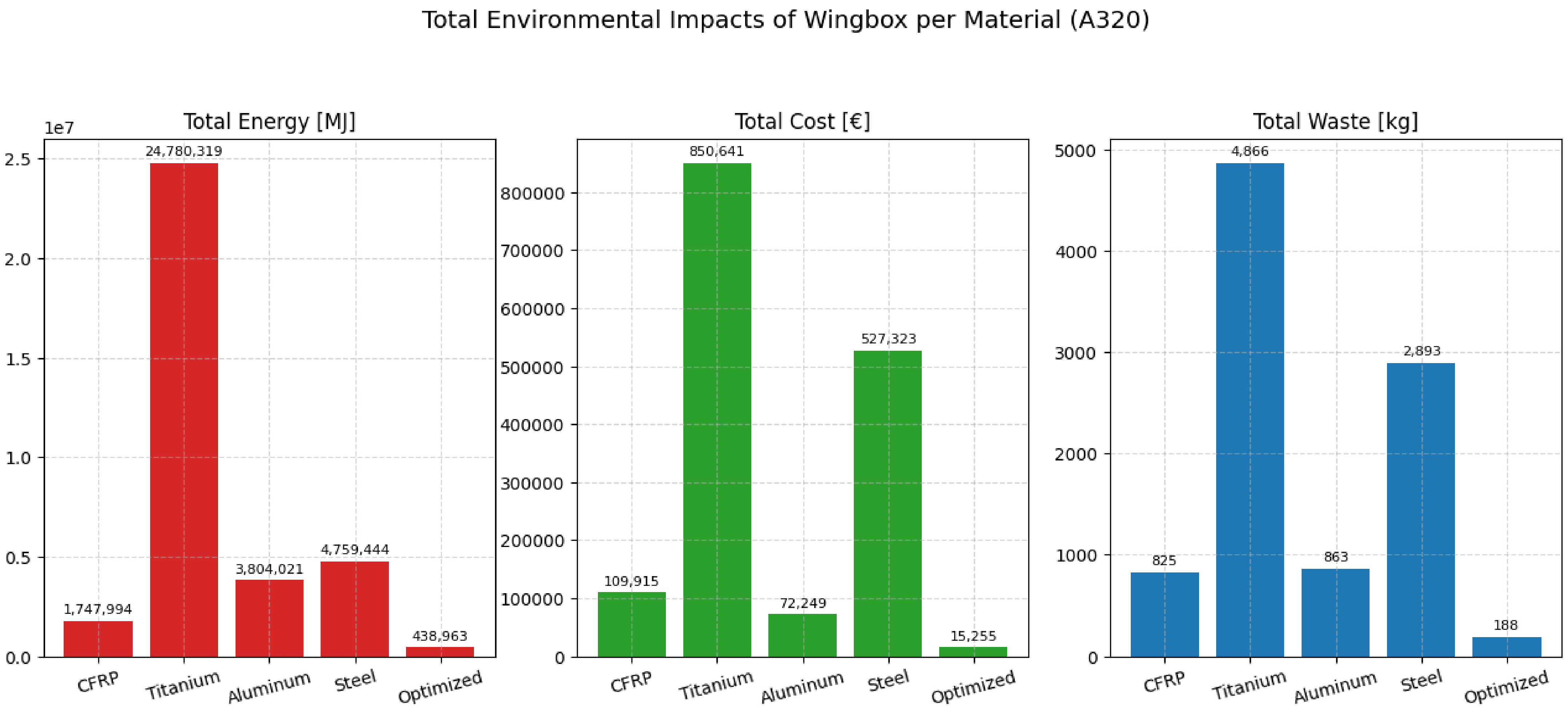


Figure 11: Environmental impact of A320 wingbox materials including the optimized solution.

Next Steps

- Explore **high-performance materials** from sources like **Arkema.**
- Extend **OpenAeroStruct** to support **multi-material wingbox configurations**
- Assign different materials to structural components (**skin, spars, ribs**) as design variables.
- Benchmark against standard aircraft (**A320, A321**)

Thank you for your attention!

Institut Supérieur de l'Aéronautique et de l'Espace
SUPAERO