PhD in Intelligent Systems for Engineering

Optimization of Impact Behavior in Lattice BCC and BCC-Waved Structures through Advanced Supervised Surrogate Models

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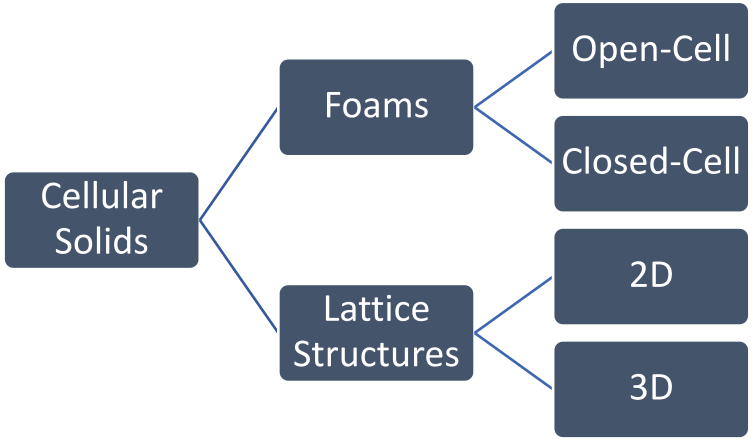
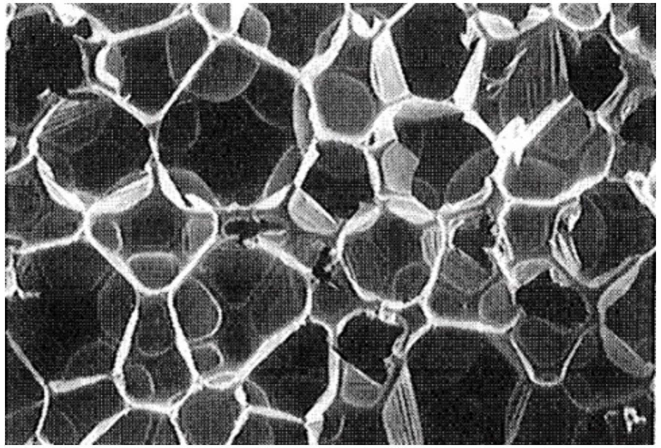
Cellular Solids

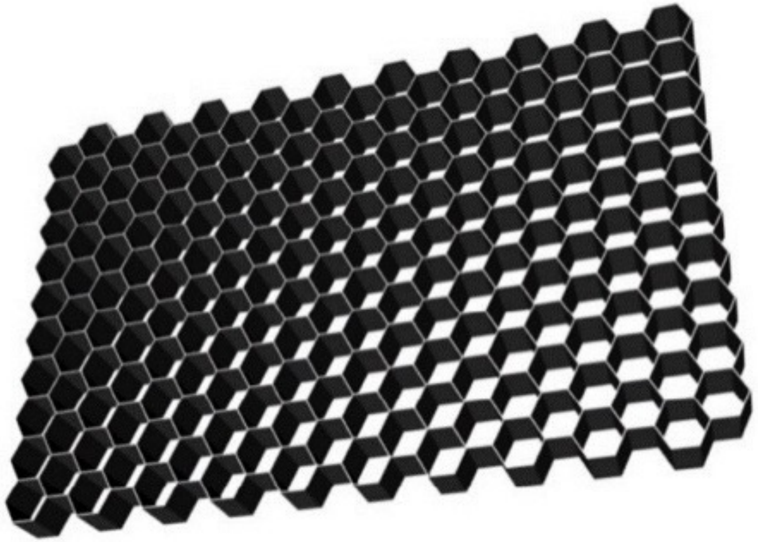
Cellular Solids are widely used today due to their lightweight properties and high resistance to compression and impact.

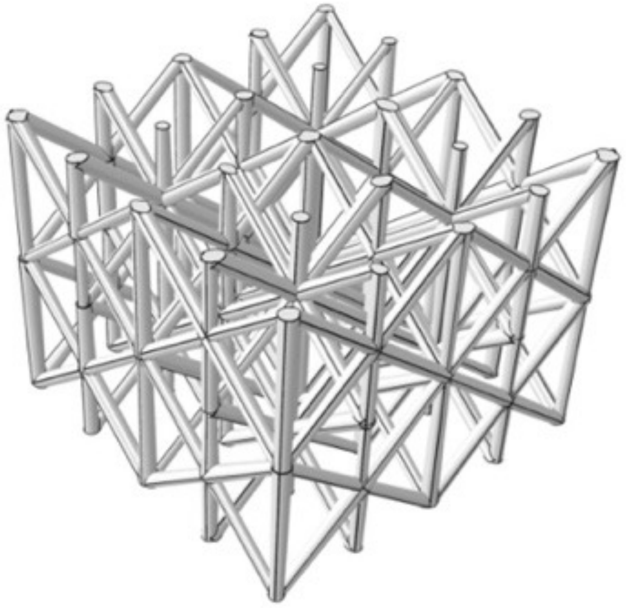


Properties:

(a) Light-weight
(b) High specific strenght
(c) Rigidity
(d) Ability to dissipate heat

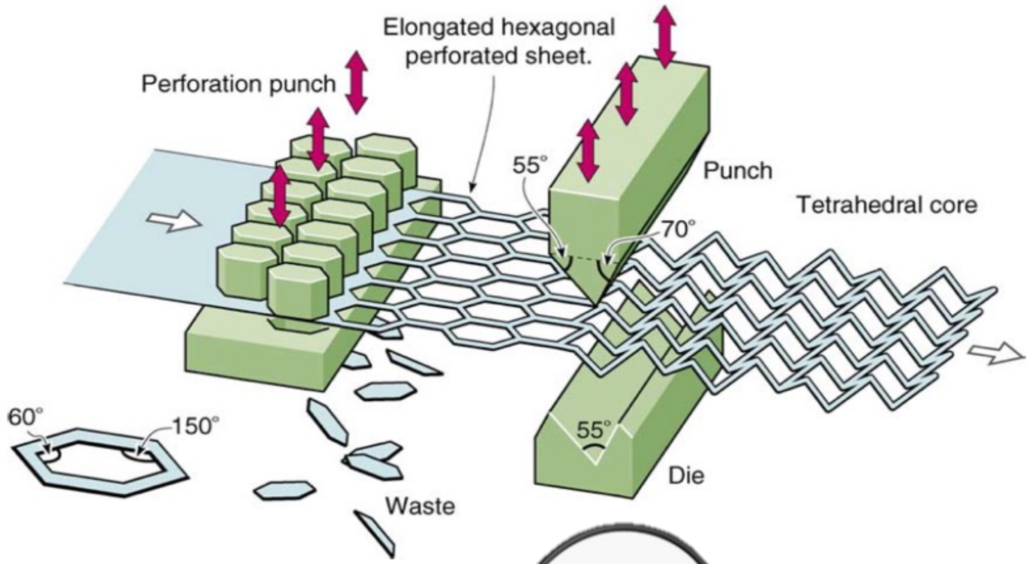


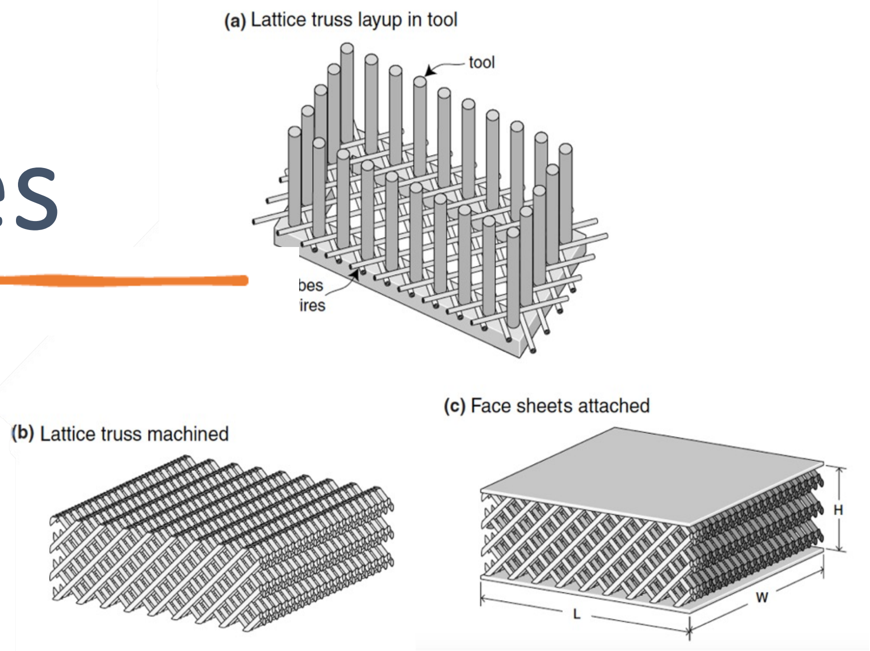




Cellular Solids can be employed in the aerospace, automotive, bio-medical and naval field.

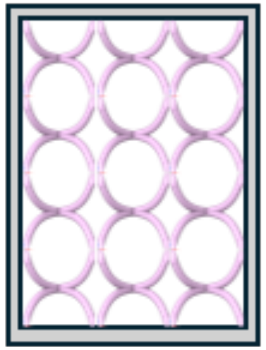
Manufacturing Methods of Lattice Structrues

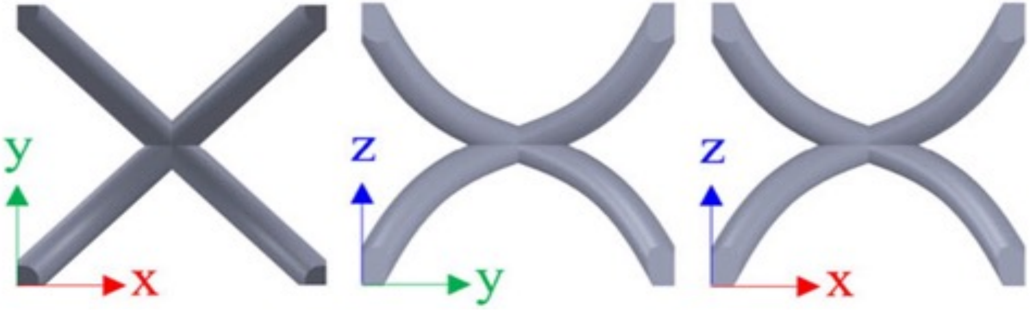




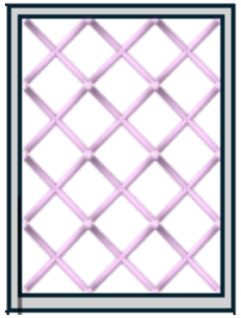
BCC and WBCC

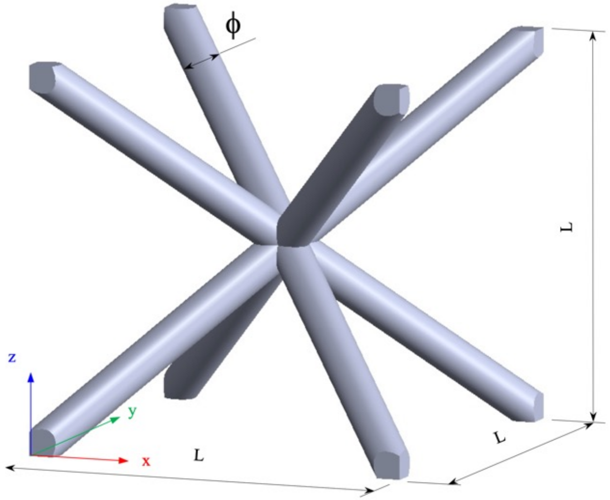
WBCC$_z$

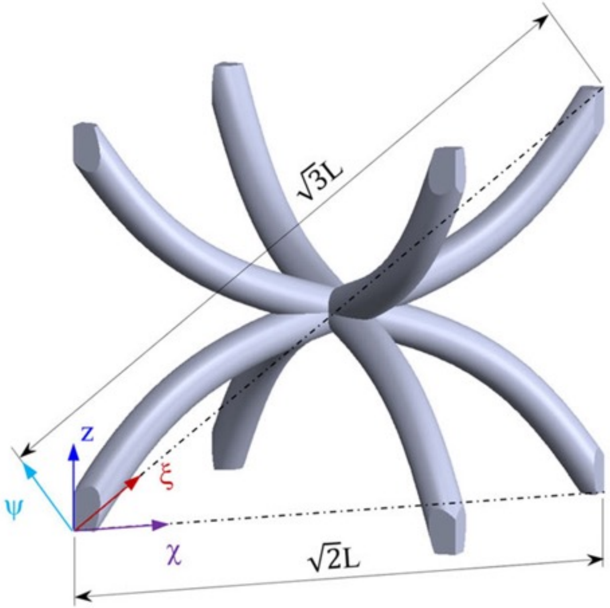




BCC







Curvature Effect

- The curvature of the struts always improves the compression properties of the material;
- It is possible to derive a value of a that optimizes the Young's modulus of the BCC cell at a specific relative density;
- The curvature of the struts greatly influences the Poisson's ratio of the cell, making these configurations highly adaptable based on the application;
- The curvature of the struts reduces the shear modulus of the cell in proportion to the value of a.

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FEM and Artificial Intelligence

Finite Element Method (FEM) numerical models are extremely useful; however, they can be computationally expensive.

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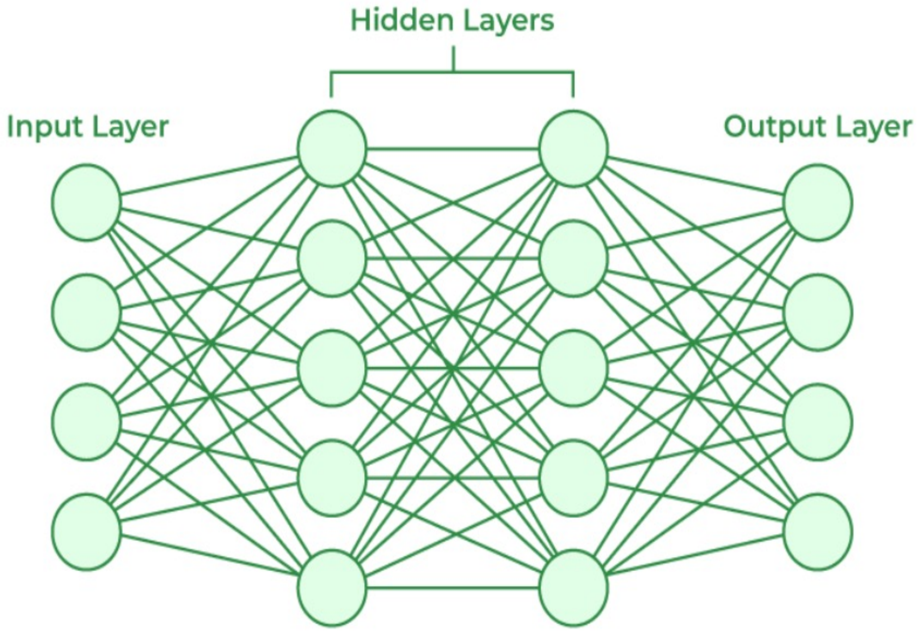
<u>Utilization of advanced supervised meta-models</u>



Artificial Intelligence (AI)

AI is a broad field with various subcategories:

1. **Supervised Learning**
2. **Unsupervised Learning**
3. **Semi-supervised Learning**
4. **Reinforcement Learning**

Most common Supervised Surrogate models

1. Neural Networks
2. Kriging
3. Second Order Polynomial Response Surface
4. Non Parametric Regression
5. Sparse Grids
6. Genetic Aggregation

Definition: A type of machine learning where the model is trained using labeled data.

Purpose: To predict outcomes or classify data based on input-output pairs.

Key Components:

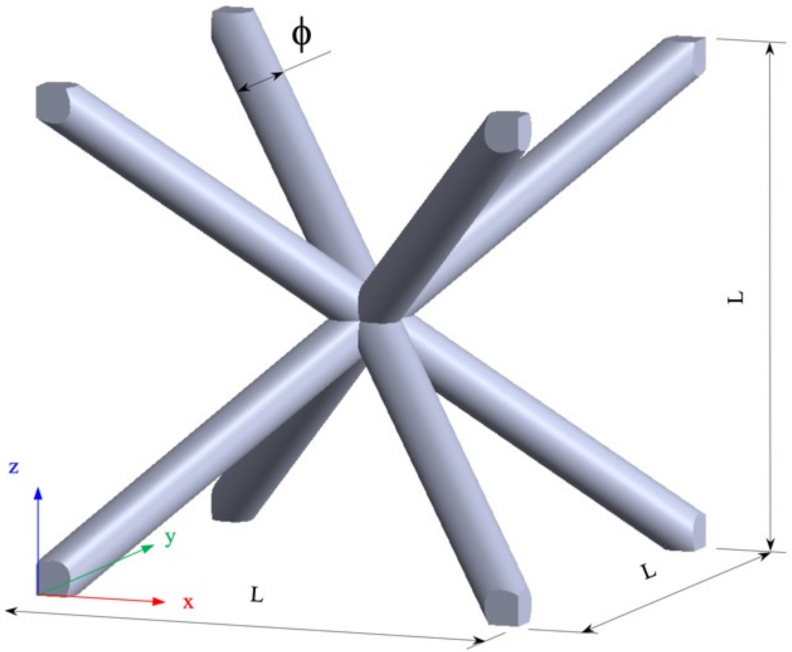
Input Data (Features): Variables that are used to make predictions.

Output Data (Labels): The actual results we aim to predict.

Quasi-static Compression on BCC

→Imposition of a -1 mm displacement.

→Double Periodicity Boundary Conditions



Material: **Poly Lactic Acid ISO (PLA ISO)**
Possible manufacturing method: Additive Manufacturing / 3D Printing

$$0.9 < \phi\ [mm] < 1.1$$
$$9 < L\ [mm] < 11$$

L	Φ
9,5 mm	1,7 mm
10,6 mm	1,9 mm

DOE-A	**Design of Experiment di Ansys**
GA-A	Genetic Aggregation – Ansys
SRSF2OP-A	Standard Response Surface – Full 2nd Order Polynomials - ANSYS
KRG-A	Kriging - ANSYS
NN-A	Neural Network – ANSYS
SG-A	Sparse Grid- ANSYS
KRG-C	Kriging – Colab
NPR-C	Non Parametric Regression – Colab
NN-C	Neural Network – Colab
SRSF2OP-C	Standard Response Surface – Full 2nd Order Polynomials – Colab

Comparison between Surrogate Models – FEM

Design of Experiment ANSYS (DOE-A)

$\phi \backslash L$	9,5 mm	10,7 mm
0,93 mm	8,6691 N	5,9496 N
1,06 mm	14,933 N	10,183 N

Genetic Aggregation ANSYS (GA-A)

$\phi \backslash L$	9,5 mm	10,7 mm
0,93 mm	8,7339 N	5,9695 N
1,06 mm	15,067 N	10,258 N

Standard Response Surface – Full 2nd Order Polynomials ANSYS (SRSF2OP-A)

$\phi \backslash L$	9,5 mm	10,7 mm
0,93 mm	8,5678 N	5,8671 N
1,06 mm	15,051 N	10,274 N

Sparse Grid ANSYS (SG-A)

$\phi \backslash L$	9,5 mm	10,7 mm
0,93 mm	8,7111 N	5,9922 N
1,06 mm	14,982 N	10,27 N

Kriging ANSYS (KRG-A)

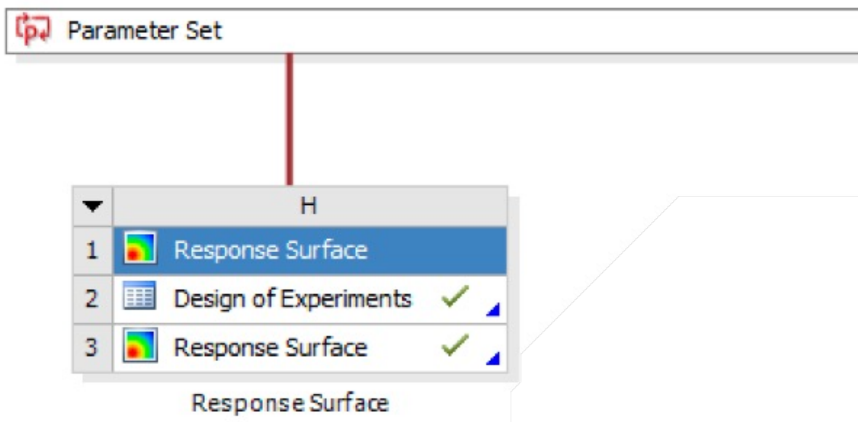
$\phi \backslash L$	9,5 mm	10,7 mm
0,93 mm	8,6129 N	5,8318 N
1,06 mm	15,185 N	10,179 N

Non-Parametric Regression ANSYS (NPR-A)

$\phi \backslash L$	9,5 mm	10,7 mm
0,93 mm	8,4742 N	5,012 N
1,06 mm	17,022 N	10,193 N

Neural Network ANSYS (NN-A)

$\phi \backslash L$	9,5 mm	10,7 mm
0,93 mm	8,7238 N	5,710 N
1,06 mm	14,857 N	10,723 N



Comparison of Surrogate Models – FEM-

$$R^2 = 1 - \frac{\sum_{1=1}^{n}(y_i - \widehat{y}_i)^2}{\sum_{1=1}^{n}(y_i - \bar{y}_i)^2}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{1=1}^{n}(y_i - \widehat{y}_i)^2}{n}}$$

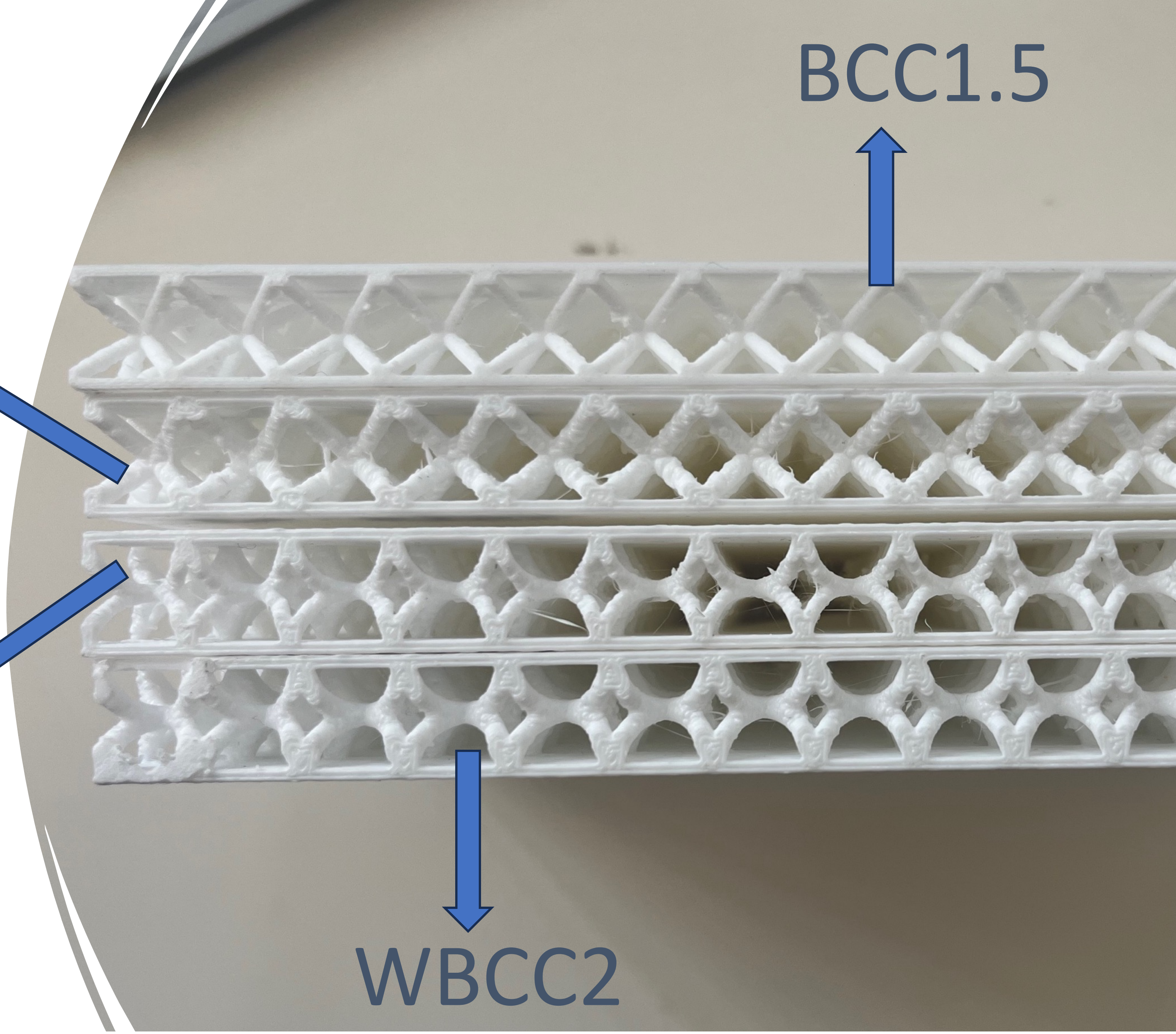
$$\text{MARE} = max_{i=1,2,\ldots,n}\left(\frac{|y_i - \widehat{y}_i|}{y_i}\right)$$

Modello Surrogato ANSYS	R_squared	RMSE	MARE
1. Sparse Grid	0.9996814111838465	0.05819957044514999	0.008543651183344766
2. Genetic Aggregation	0.9993374615526894	0.08415320849498277	0.008973414585147013
3. Full 2nd Order Polynomials	0.9990765266001118	0.09908700722092686	0.013866478418717302
4. Kriging	0.9981058036831328	0.1419113103314887	0.019799650396665307
5. Neural Network	0.9915871628152427	0.29907200220013963	0.053029559069036725
6. Non-Parametric Regression	0.8758189205283856	1.1490322852296182	0.15759042624714276

Performance evaluation in MATLAB -

AI model	MATLAB tool
SRSF2OP	CurveFitter App
NN	Machine Learning and Deep Learning App
NPR	Machine Learning and Deep Learning App (Regression Learner)
KRG	ooDace Toolbox

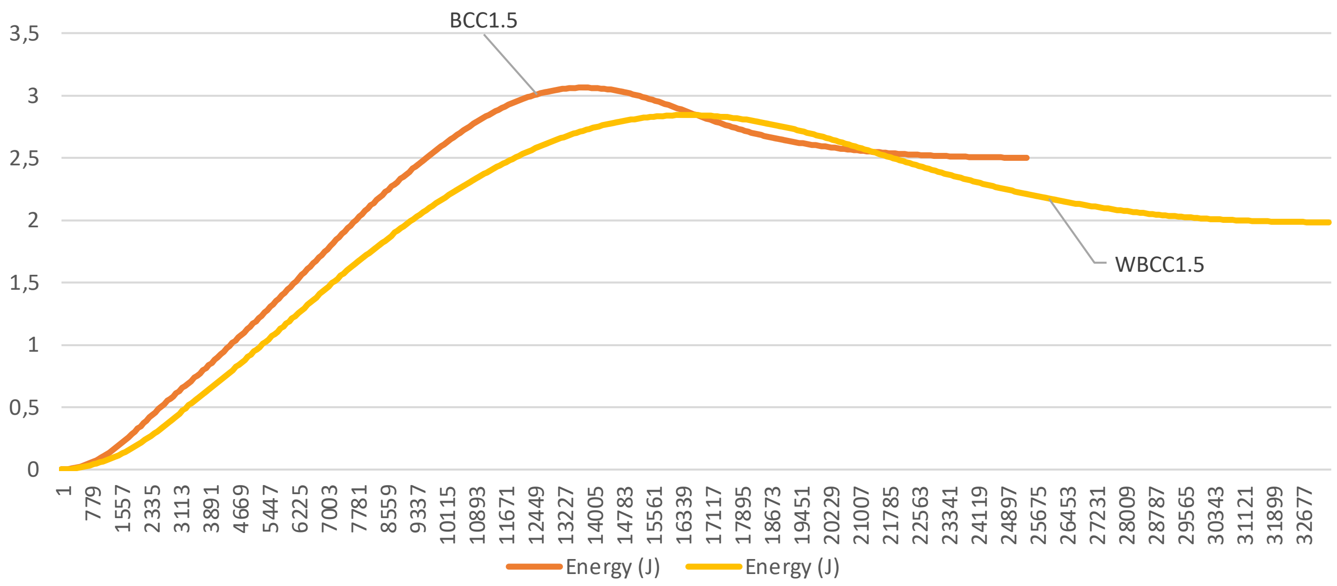
3D-printed Samples

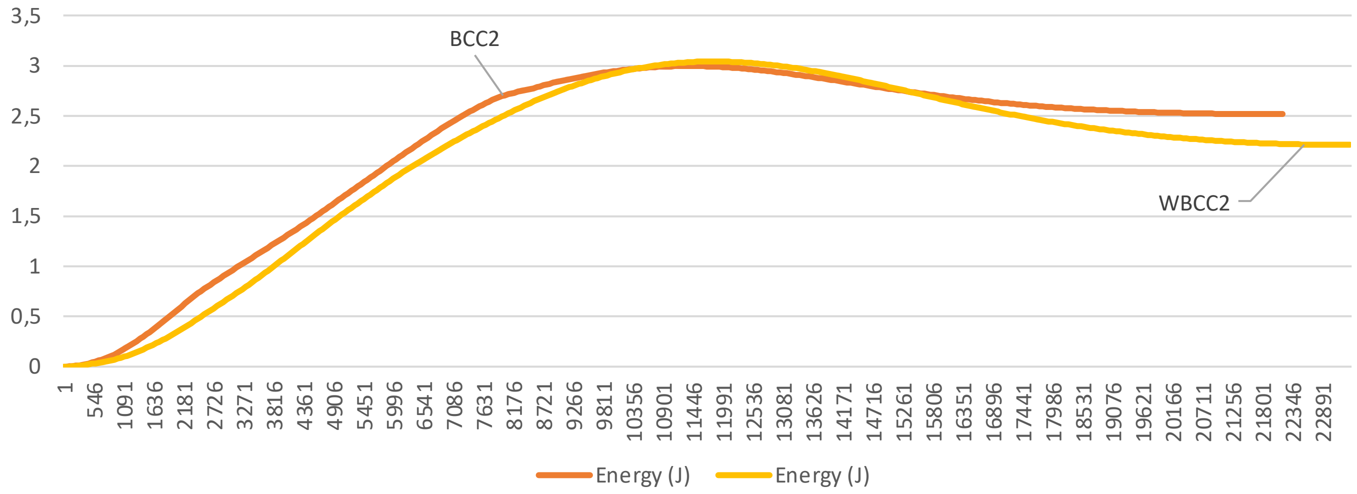


Comparison Time-Energy

Impact tests on BCC and WBCC samples

- Dimensions: 150 x 100 mm
- ASTM D7136 standards
- Falling height: 150 mm
- Impactor mass: 2 kg

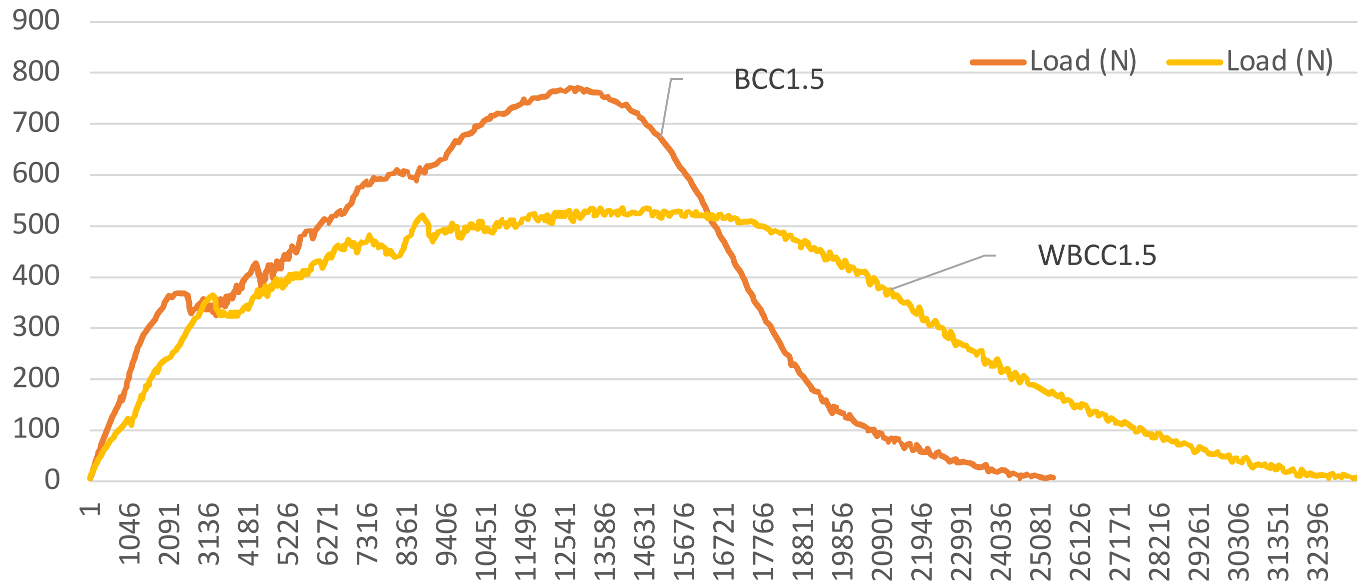


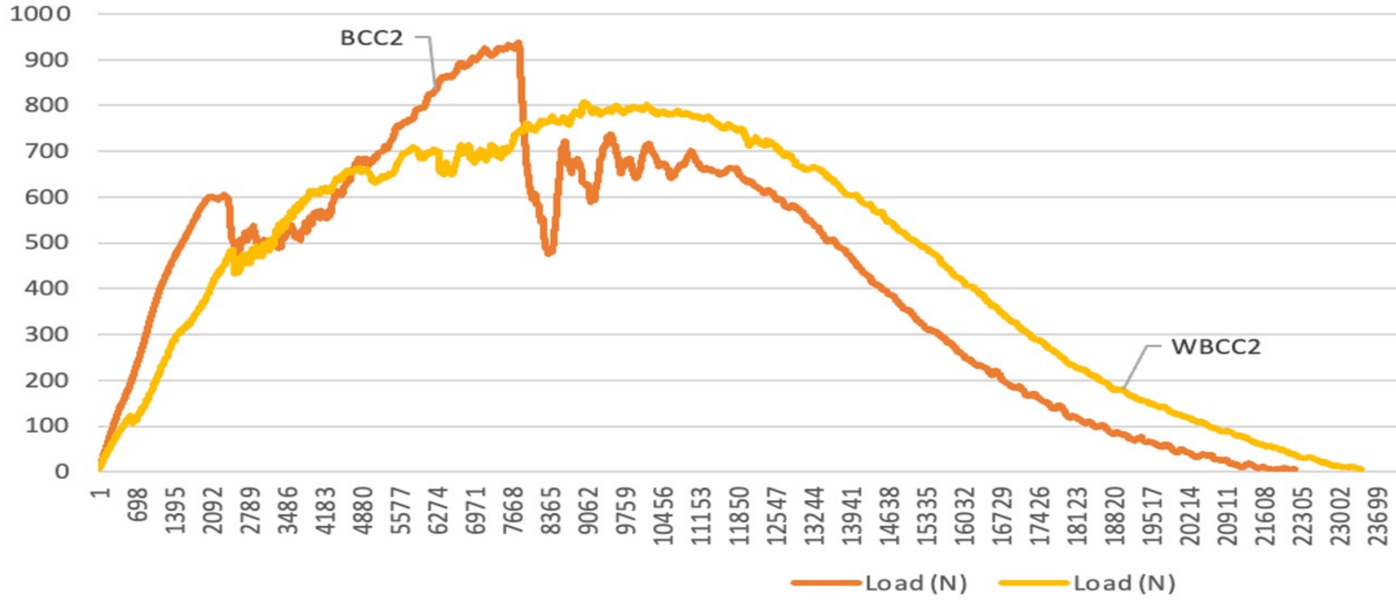


Comparison Time-Force

Impact tests on BCC and Waved BCC samples

- Dimensions: 150 x 100 mm
- ASTM D7136 standards
- Falling height: 150 mm
- Impactor mass: 2 kg





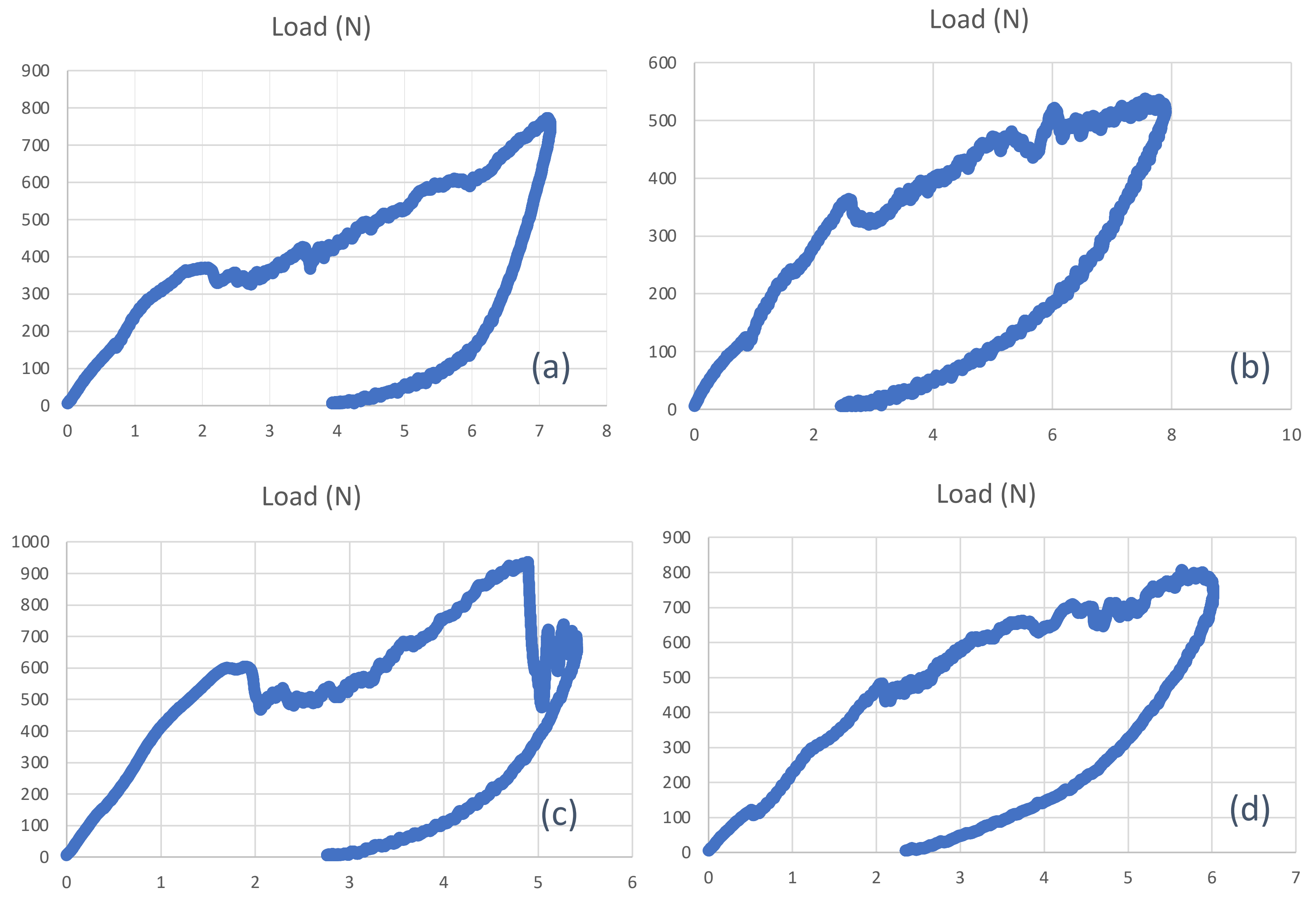
Experimental Impact Test

(a) BCC 1.5

(b) WBCC 1.5

(c) BCC 2 mm

(d) WBCC 2



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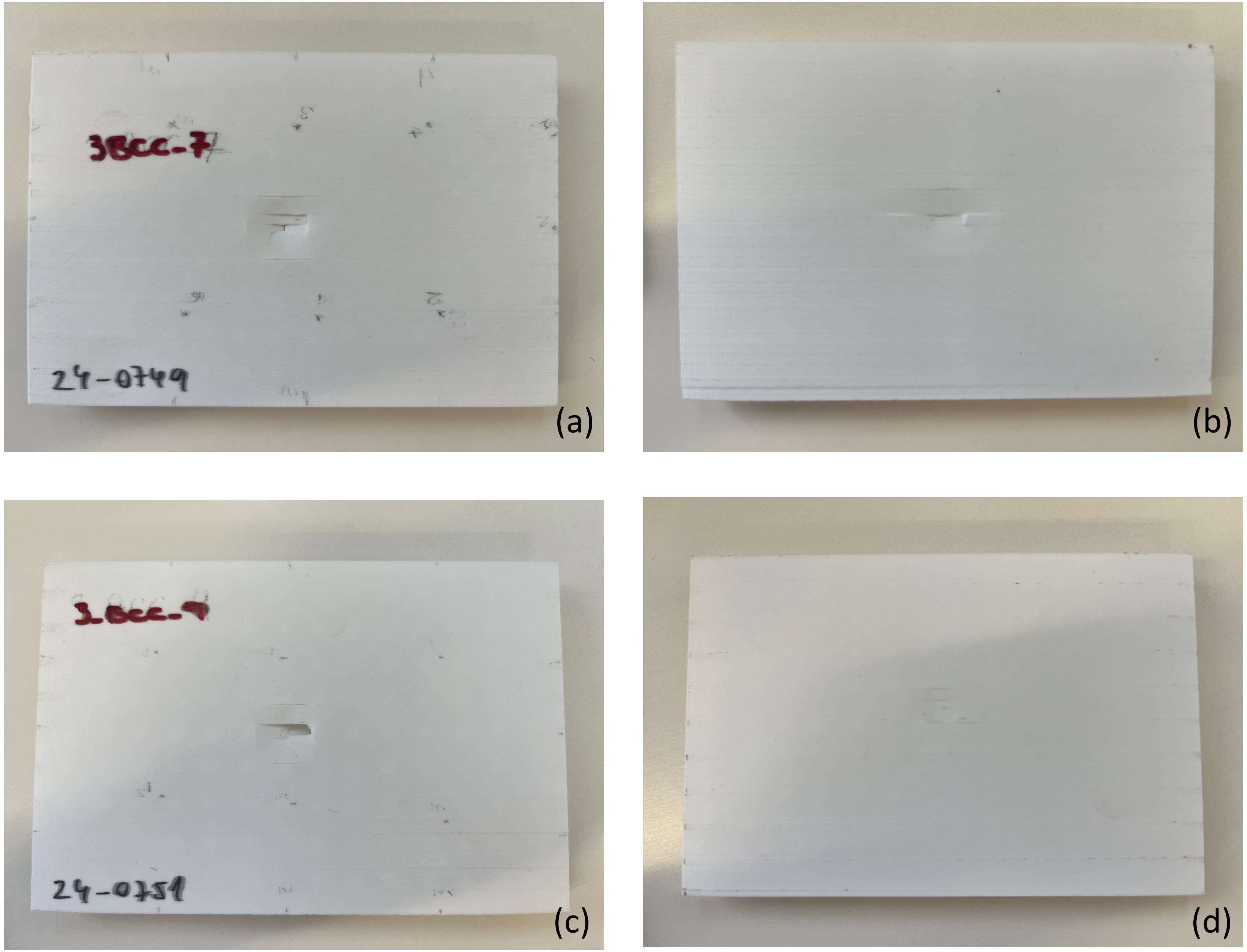
Experimental Impact Test

(a) BCC 1.5 mm

(b) BCC 2 mm

(c) W-BCC 1.5 mm

(d) W-BCC 2mm



Future Developments

→ Application of surrogate models in ANSYS to predict EA.

→ Application of surrogate models in Matlab to predict EA.

→ Evaluation of accuracy indices, error percentage, MATLAB function prediction time, mean, median, and standard deviation of output values for each individual meta-model.

→ Optimization of the best model through Multiobjective Optimization to maximize EA.

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