Biomass Characterization using Physics-Informed Neural Networks

Aleix Fornieles, Maddi Etxegarai, Daniel Gibert, Jordi Planes

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eurecat Centre Tecnològic de Catalunya

Motivation

Europe currently produces...

300M

tonnes of waste

potential to produce

30M

tons of green hydrogen.

...potential that HYIELD aims to unlock.

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Motivation

- Biomass
- Characterization
- Conversion
- Energy fuels & chemical compounds

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Objective

- **Predict elemental composition** of biomass from proximate analysis
- Ensure these predictions are accurate, while enforcing **physical laws**
- Incorporate these predictions into **a full DT model** for green hydrogen production

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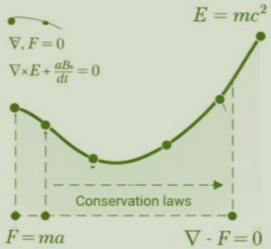
Problem statement

AI Predictions

Fits data blindly

Physical laws



Constrained by physics

Accuracy does not imply physical consistency

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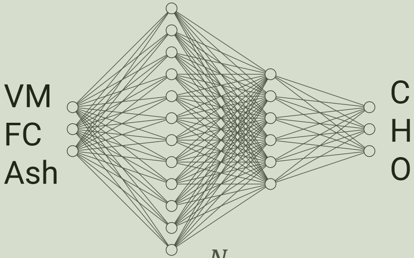
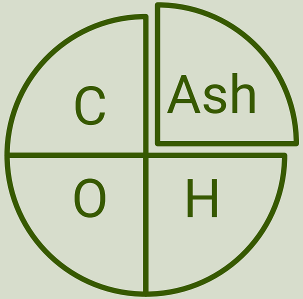
Physics-Informed NN

Data domain



$$\mathcal{L}_{\mathcal{NN}} = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2$$

Physics domain



$$\mathcal{L}_{\mathcal{PINN}} = \mathcal{L}_{\mathcal{NN}} + \mathcal{L}_{\text{Physics}}$$

PINN combines data-driven flexibility with physical consistency

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Dataset & model

Dataset

- 830 biomass samples
- Phyllis2 database
- Dry basis

Inputs

- Volatile Matter
- Fixed Carbon
- Ash

Outputs

- Carbon
- Hydrogen
- Oxygen

Loss function

- $$\mathcal{L}_{PINN} = \underbrace{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}_{\mathcal{L}_{reg}} + \underbrace{\lambda_p ReLU(|C + H + O + Ash - 100| - 2)}_{\mathcal{L}_{Physics}}$$

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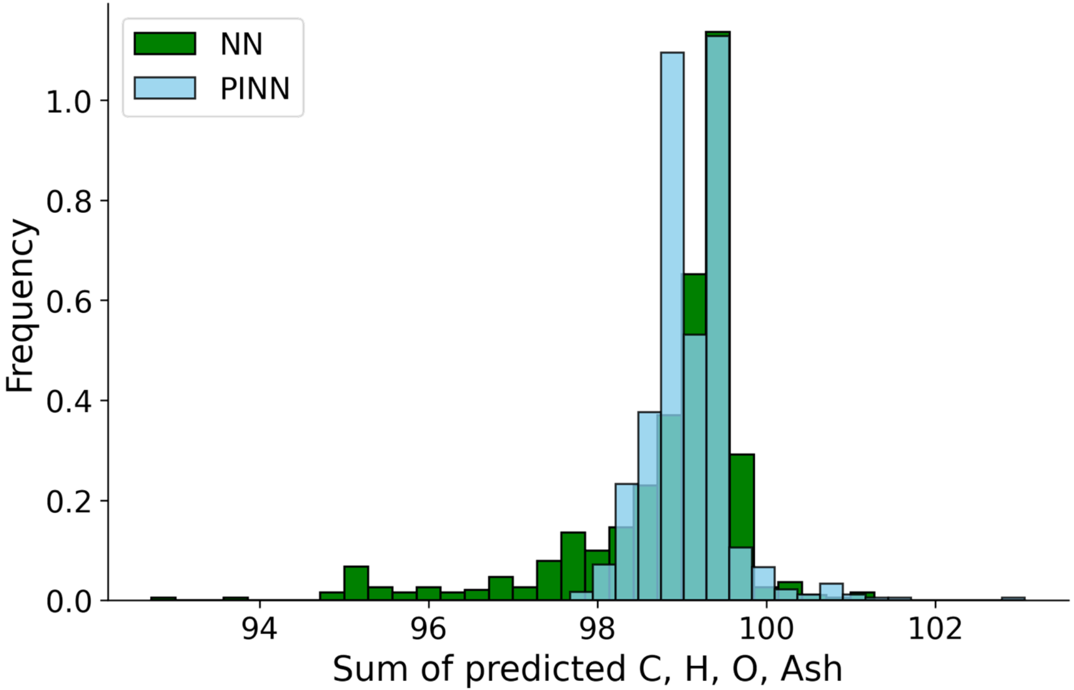
Results



Output	NN R^2	PINN R^2
C	0.94	**0.96**
H	0.70	**0.73**
O	0.93	**0.95**

PINN not only enforces physical laws, but also improves generalization.

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Conclusions

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- PINNs provide a **robust framework** for biomass characterization
- Embedding physical constraints improves both **accuracy and reliability**
- Promising for future integration into process simulation and **digital twin for green hydrogen**

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Thank you for your time!

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