Physics-Informed Neural Networks for Biomass Gasification

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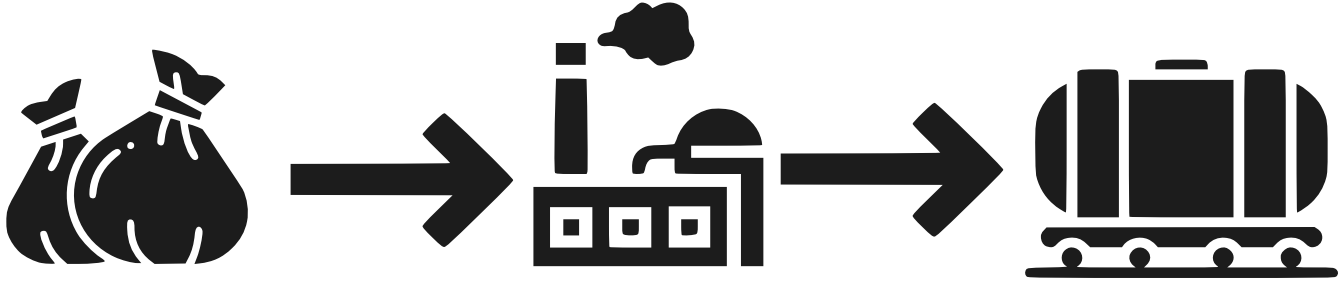
Biomass gasification



WASTE GASIFIER SYNGAS

- Heterogeneous feedstock
- Scarce/uneven data
- Complex thermochemistry

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Data & features

Waste

Biomass
MSW
Agricultural residues

Waste analysis

C | H | Ash
Volatiles | Moisture

Gasifier conditions

Temperature | ER
Gasifying agent
Catalyst presence

Gasifier Properties

Scale | Reactor type
Bed material

Target

H_2

Dataset size

>1000 rows
8 numerical features
5 discrete features

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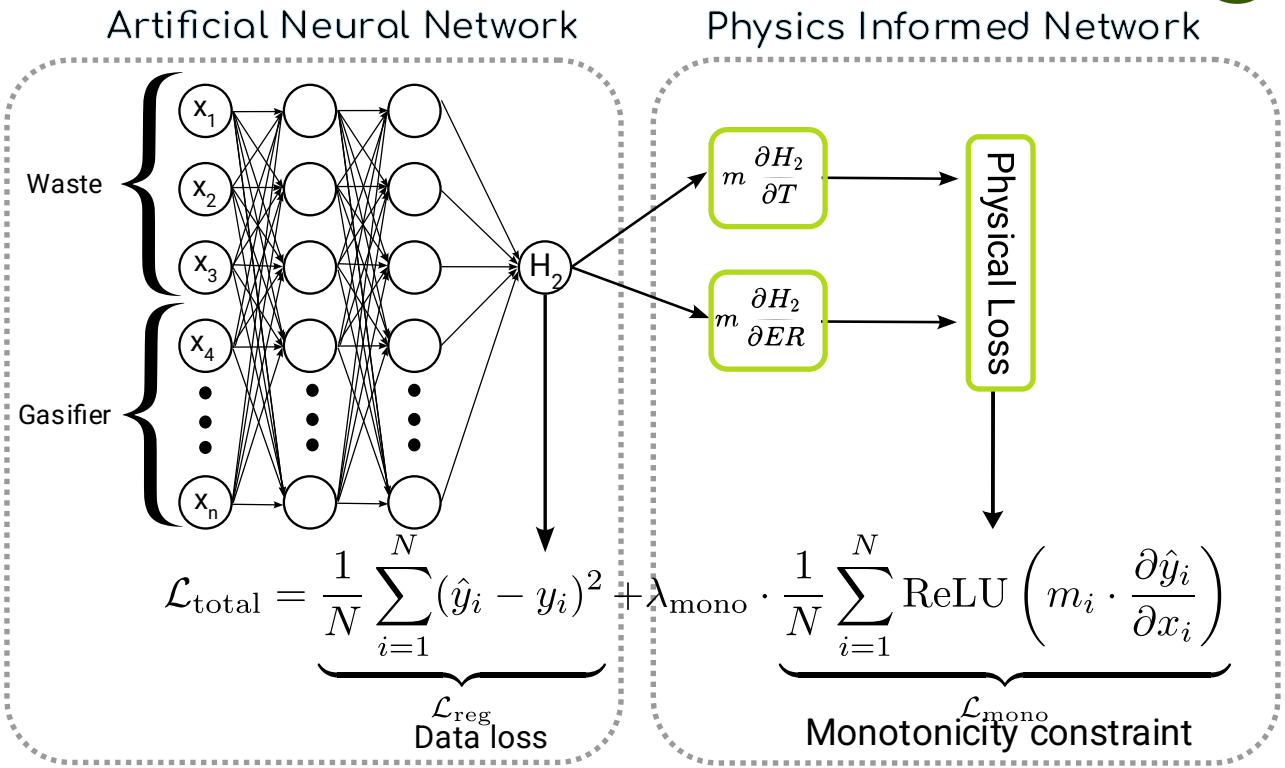
Methodology

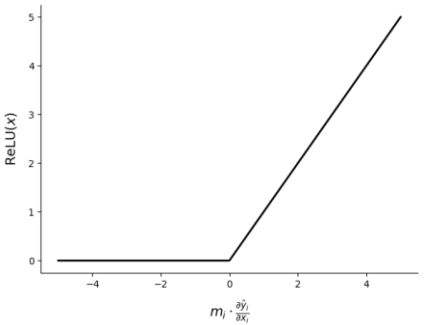


Monotonicity

ER↑ ⟶ H_2↑

MC↑ ⟶ H_2↑

ReLU function



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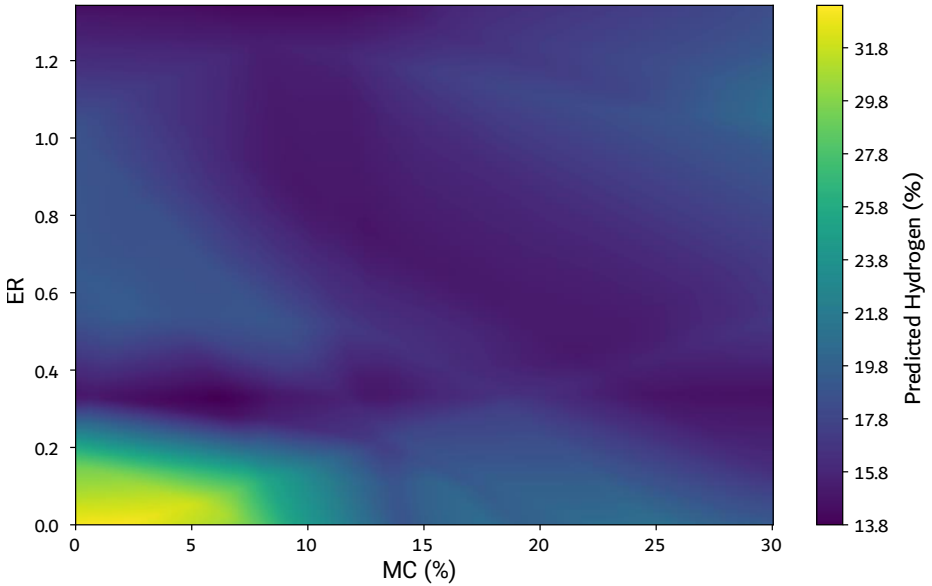
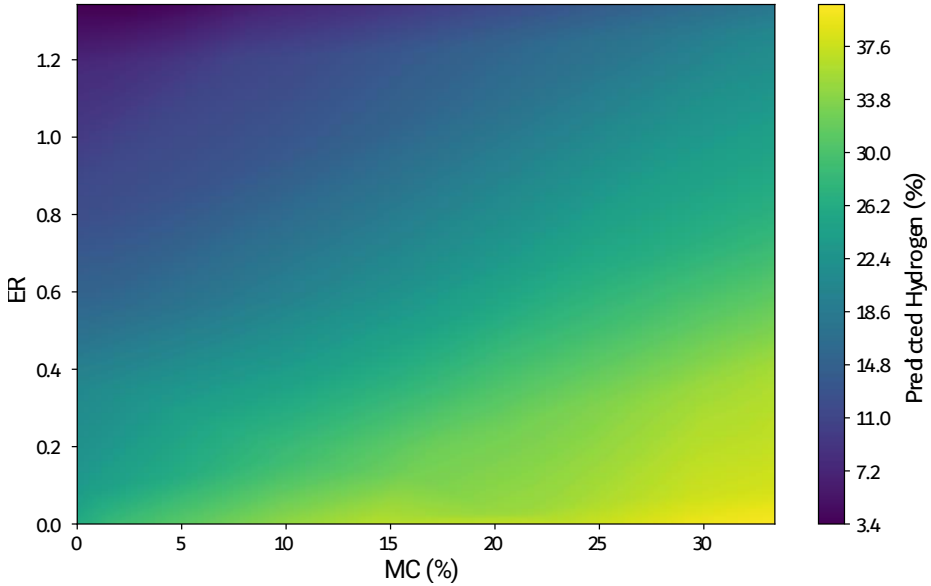
Results

Classic NN R^2=0.91 MSE: $3.3 \cdot 10^{-3}$



PINN R^2=0.96 MSE: $1.1 \cdot 10^{-3}$



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Conclusions

- Embedding monotonicity constraints improves generalization and robustness.
- PINN delivers more reliable predictions than standard NN.
- PINNs are a promising path toward efficient green H_2 production.

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Thank you for your time!

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