



### Introduction

- Bioethanol fermentation shows strongly coupled changes in substrate, biomass, and ethanol over time.
- Accurate modelling of these dynamics is essential for improving process efficiency.
- Conventional neural networks fit data but often ignore known fermentation kinetics.
- Physics-Informed Neural Networks (PINNs) combine data with kinetic equations for reliable and interpretable modelling.
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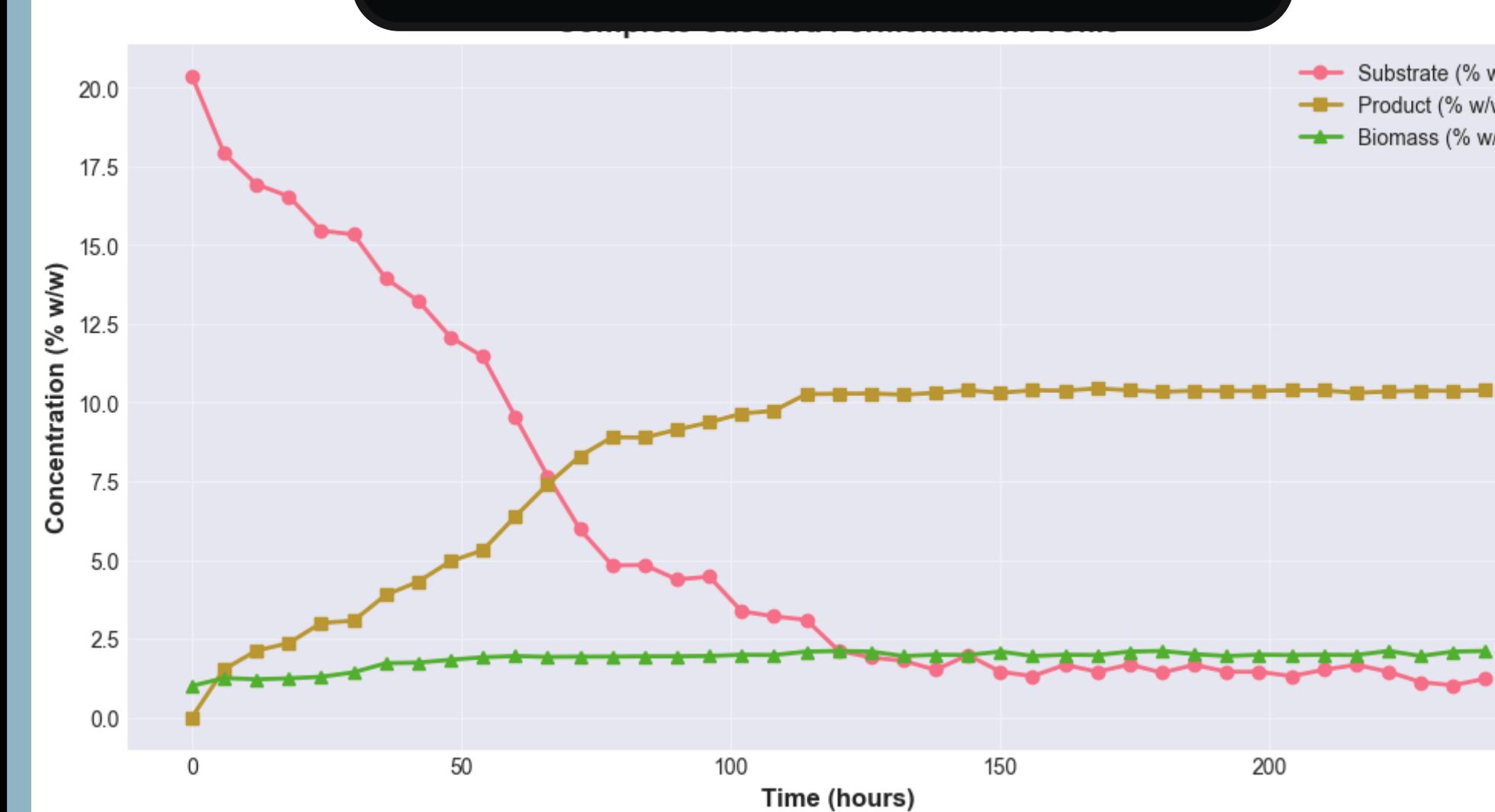
### Problem Statement

- Bioethanol fermentation involves complex, time-dependent interactions between substrate consumption, biomass growth, and ethanol formation that are difficult to model accurately.
- Traditional data-driven models provide good curve fitting but often violate known fermentation kinetics and lack physical interpretability.
- There is a need for a modelling framework that can learn from limited experimental data while strictly adhering to governing biochemical laws.

### References

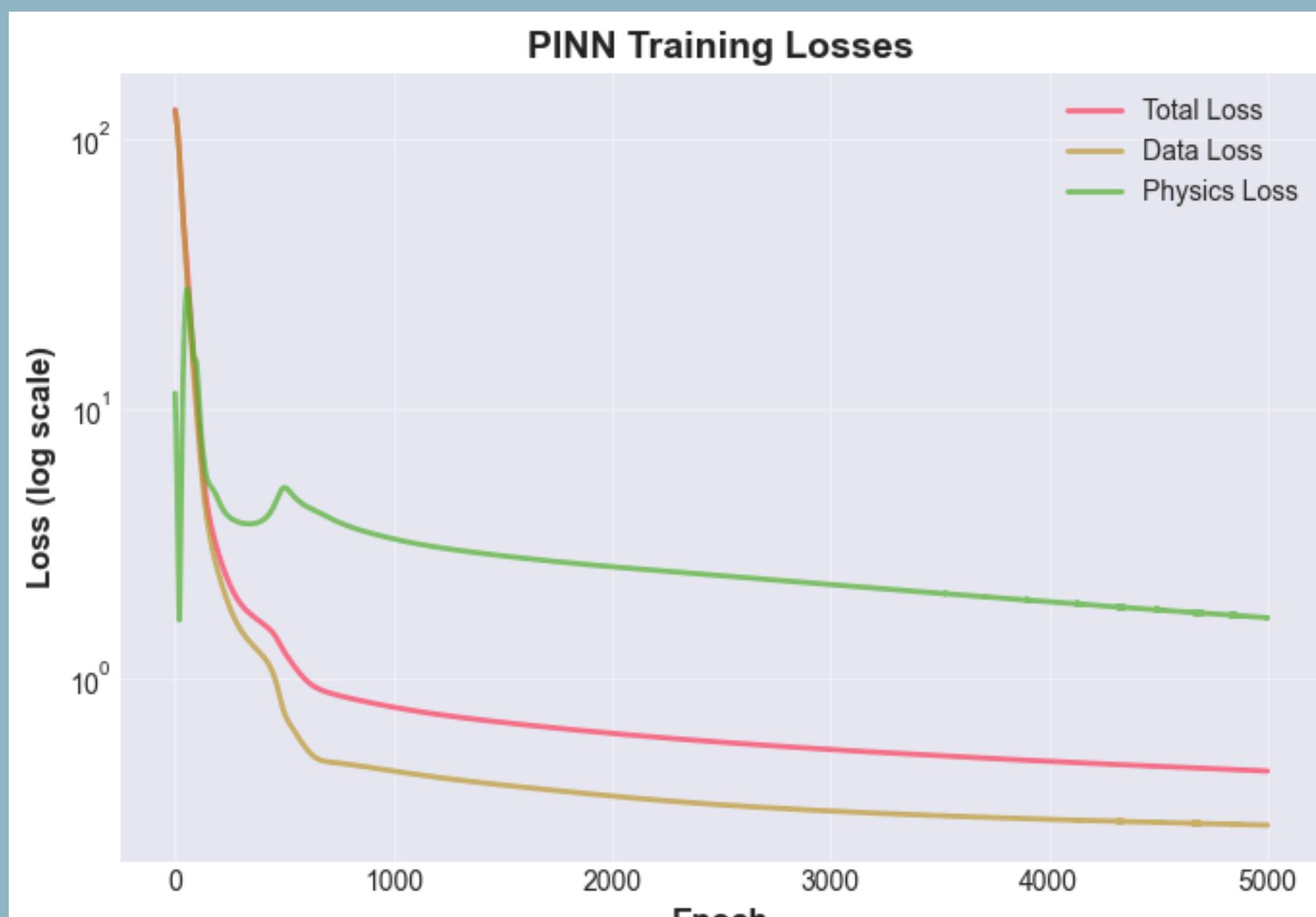
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### Cassava Fermentation Profile

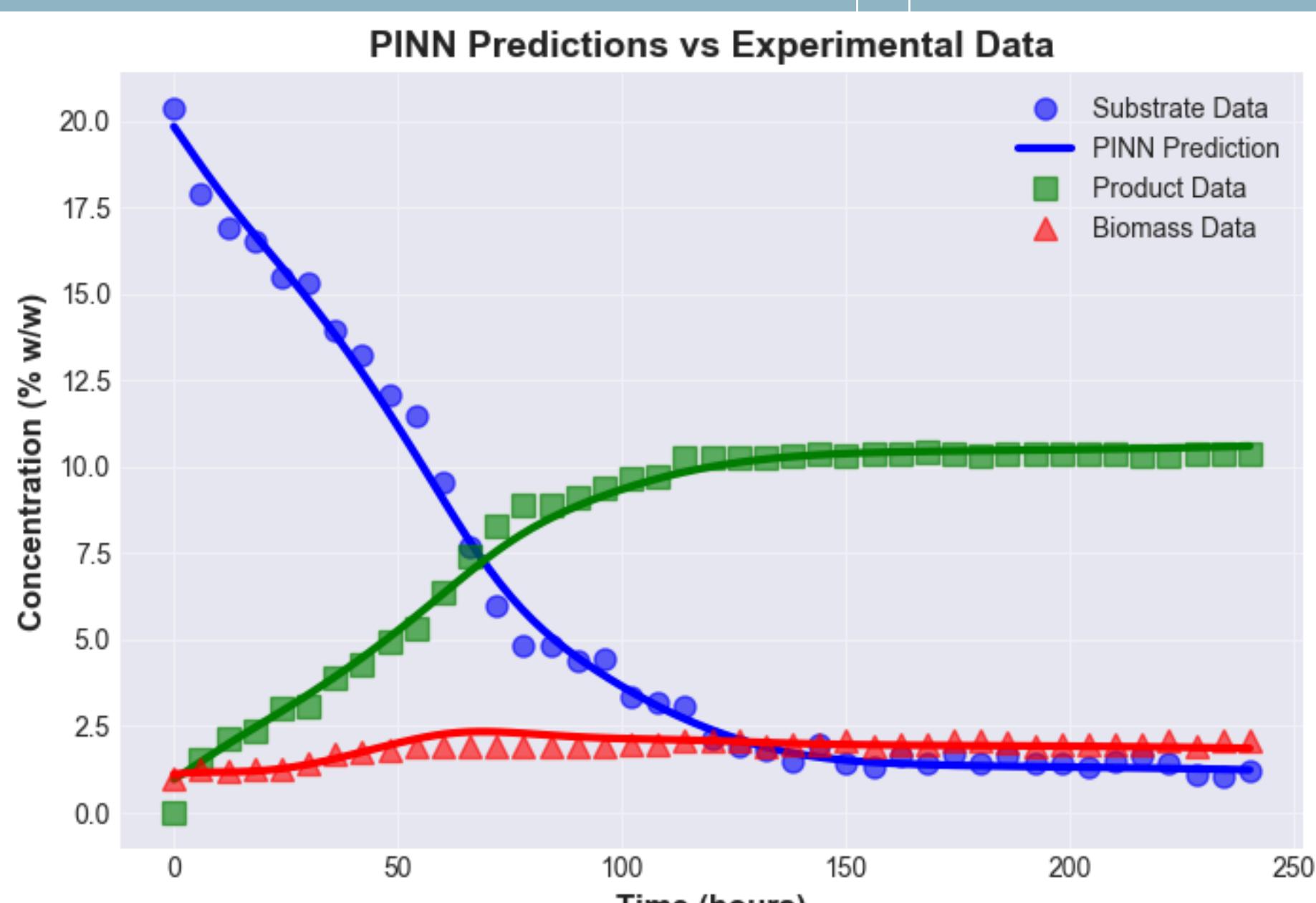


- Substrate concentration decreases steadily over time due to microbial consumption.
- Ethanol concentration increases and eventually plateaus, indicating fermentation completion.
- Biomass exhibits initial growth followed by stabilization.
- Overall trends are consistent with Monod-based fermentation kinetics.

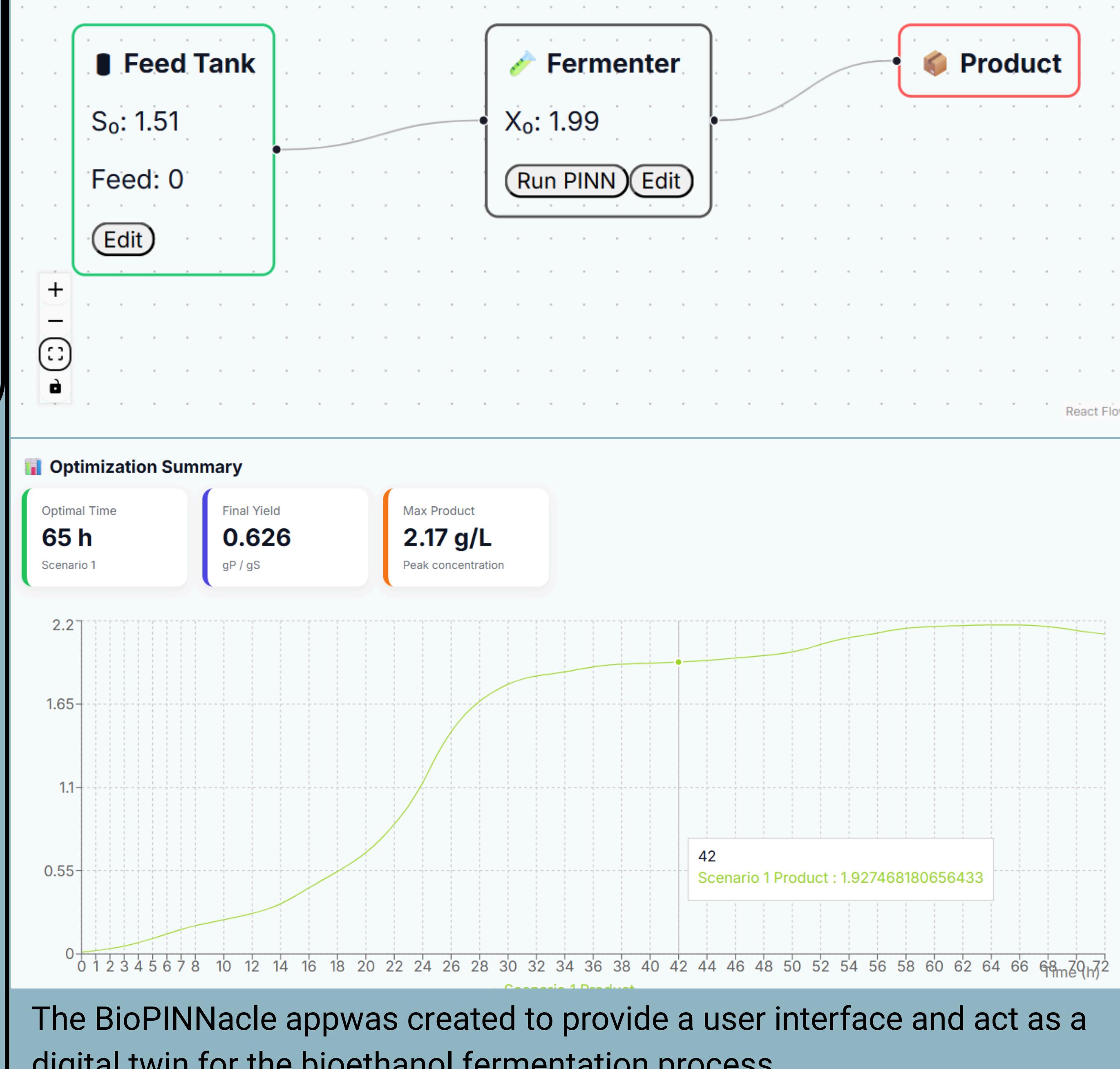
### PINN Performance



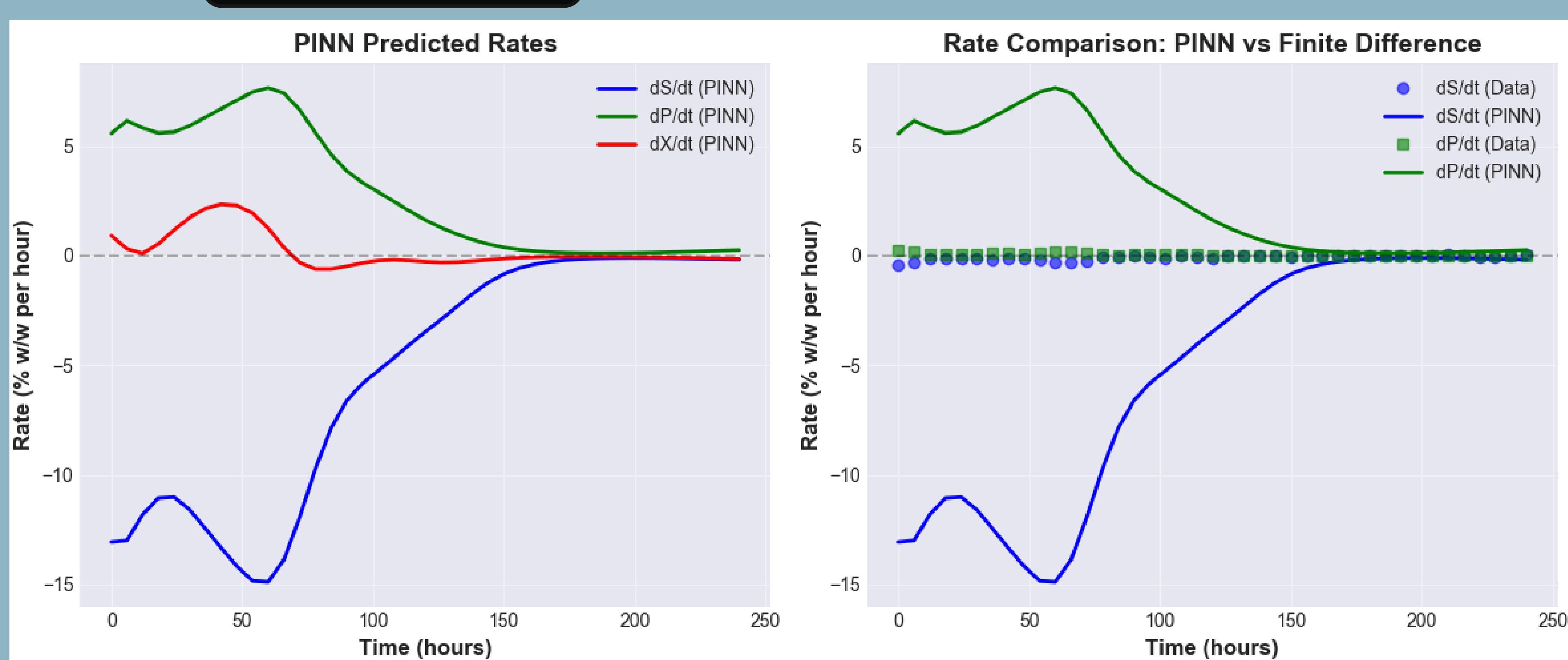
### PINN Predictions vs Experimental Data



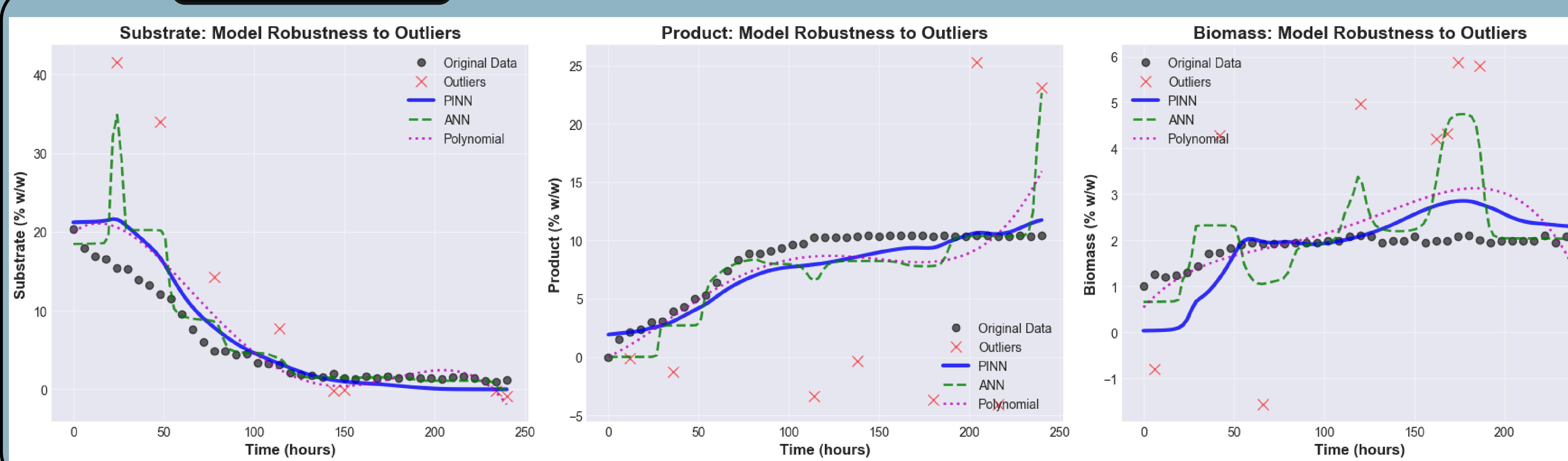
### BioPINNacle App



### Saliency Plot



### Outlier Scenario



### R<sup>2</sup> Result For Outlier Scenario

Model	Substrate	Product	Biomass
PINN	0.8075	0.823	-3.3067
ANN	0.5748	0.3261	-9.6572
Polynomial	0.7903	0.6837	-3.6555