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# An Advanced Physics-Informed Neural Operator for Comprehensive Design Optimization of Highly-Nonlinear Systems

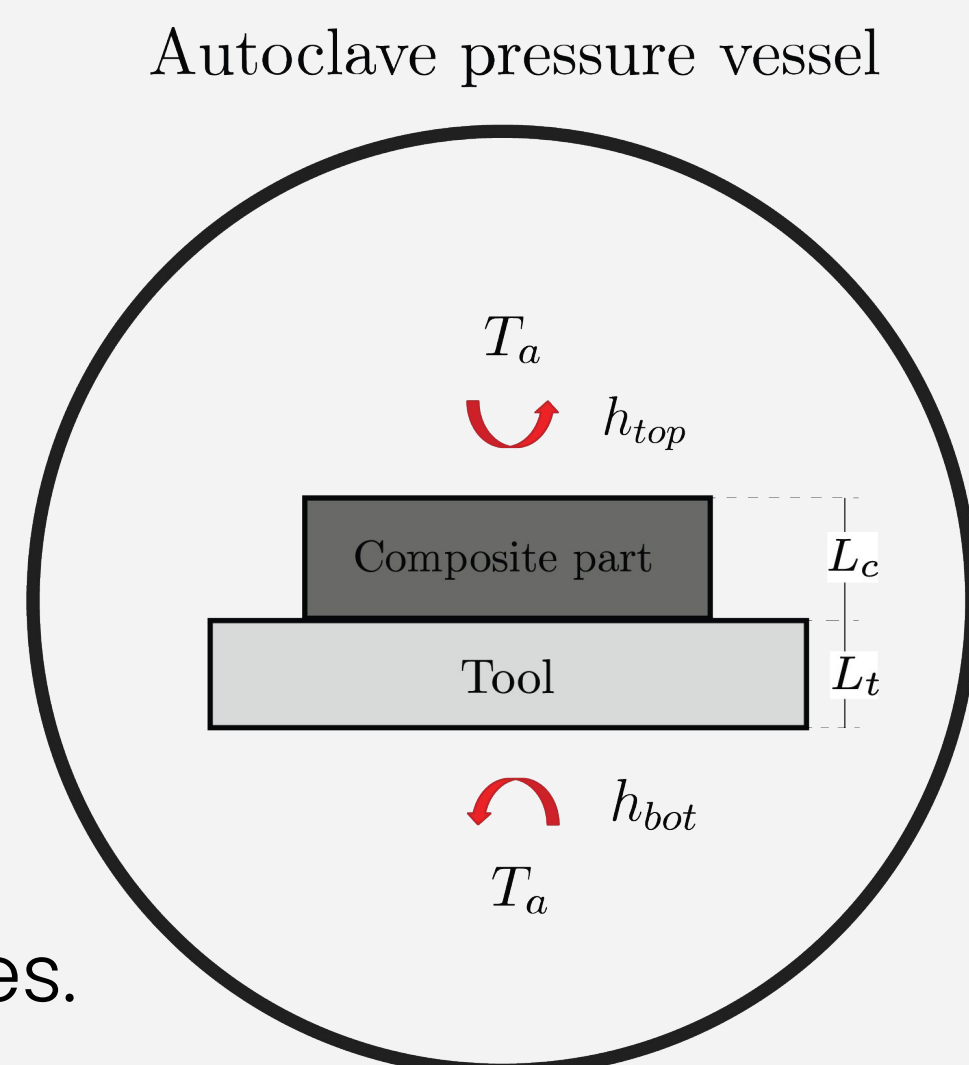
## An Aerospace Composites Processing Case Study

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### Background

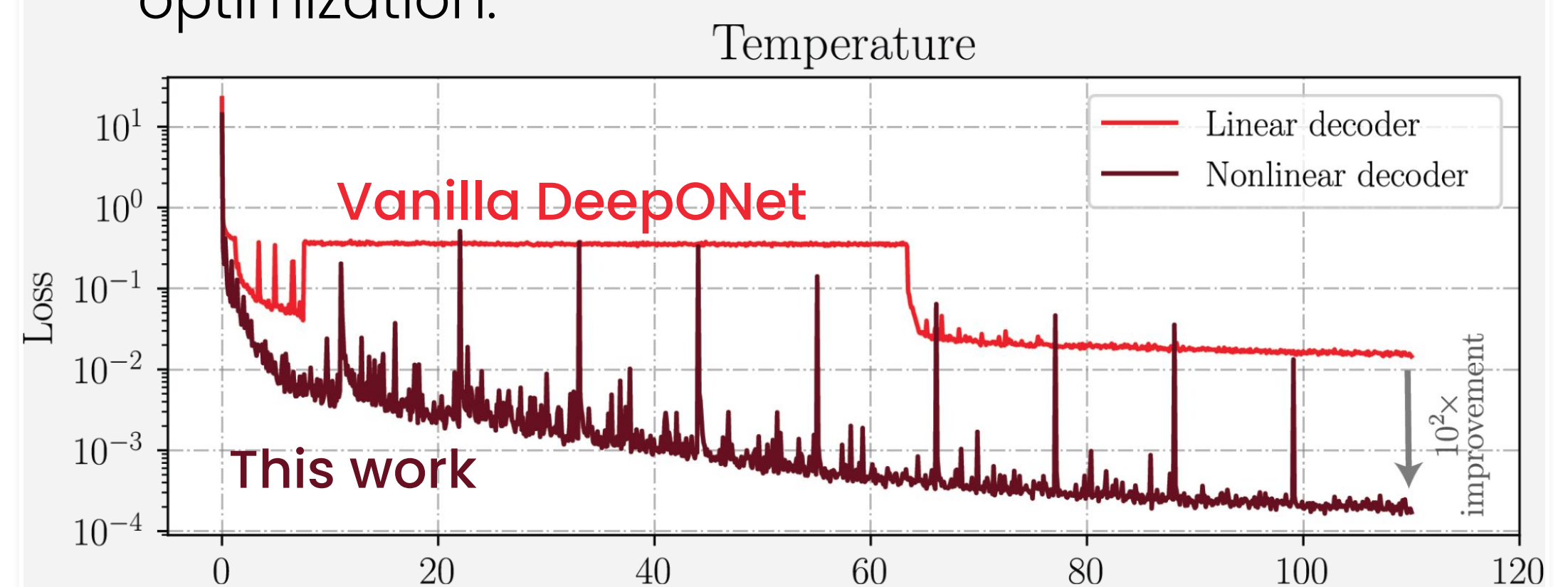
In aerospace engineering, optimizing the design and processing of composites under various conditions is challenging due to their nonlinear and complex behavior.

- **Numerical methods** can be slow, computationally intensive.
- **PINNs** lack generalization and adaptability to dynamic process configurations.
- **Vanilla DeepONet** fails to capture high nonlinearities.



### Main contributions

- An advanced Physics-Informed Deep Operator Network (PIDON) to address the complexities in simulating highly nonlinear aerospace composite processes.
- PIDON with enhanced predictive accuracy and efficiency, enabling real-time design optimization.



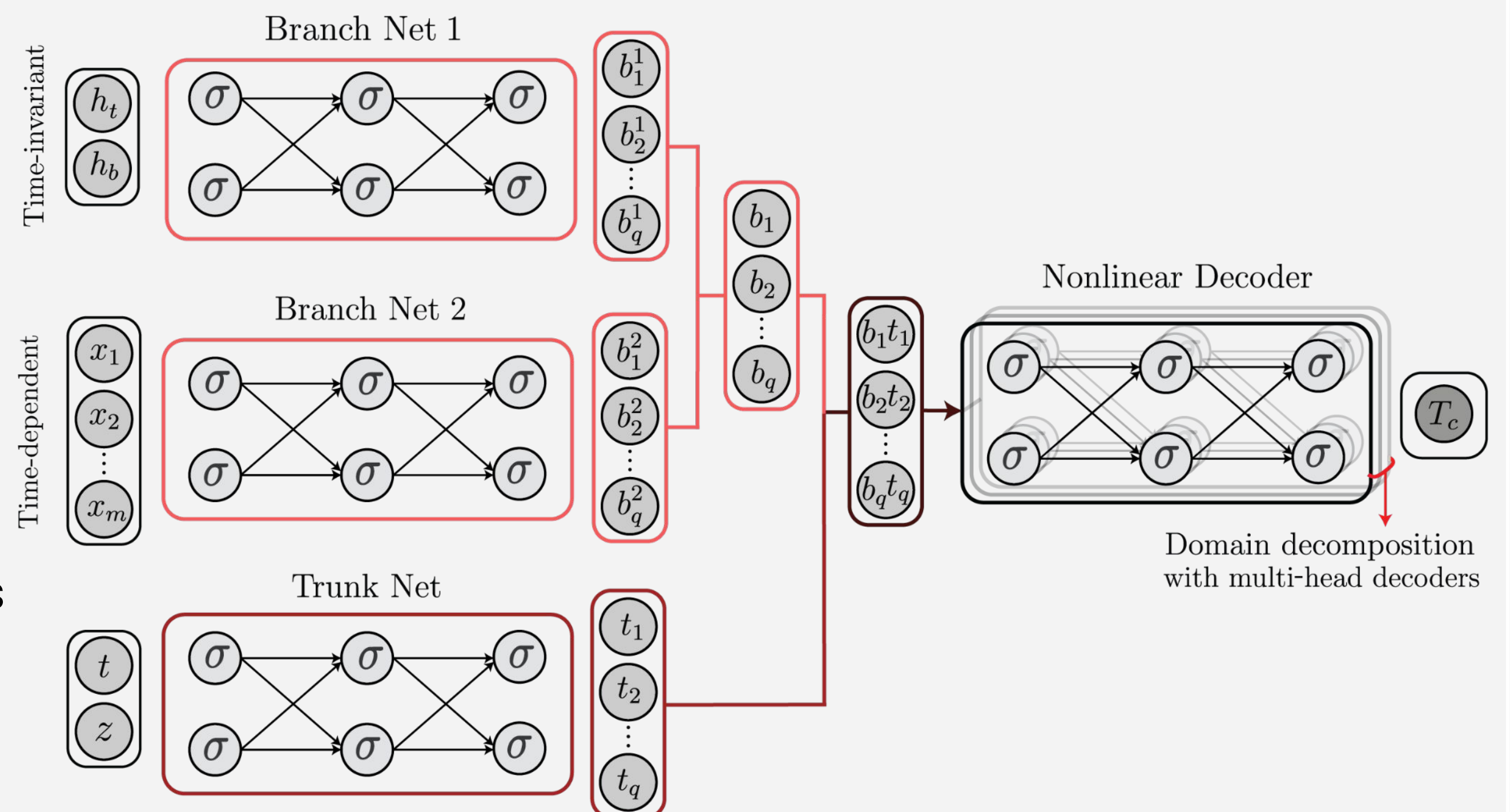
### Physics-informed DeepONet architecture

**Nonlinear decoder:** Improves the representation of complex system behaviors.

**Multiple branch networks:** Allow the model to capture a wide range of physical phenomena.

**Domain Decomposition:** Divides the problem into smaller, more manageable sub-problems.

**Curriculum Learning:** Gradually increases the complexity of training tasks to enhance model performance.



### Model component analysis

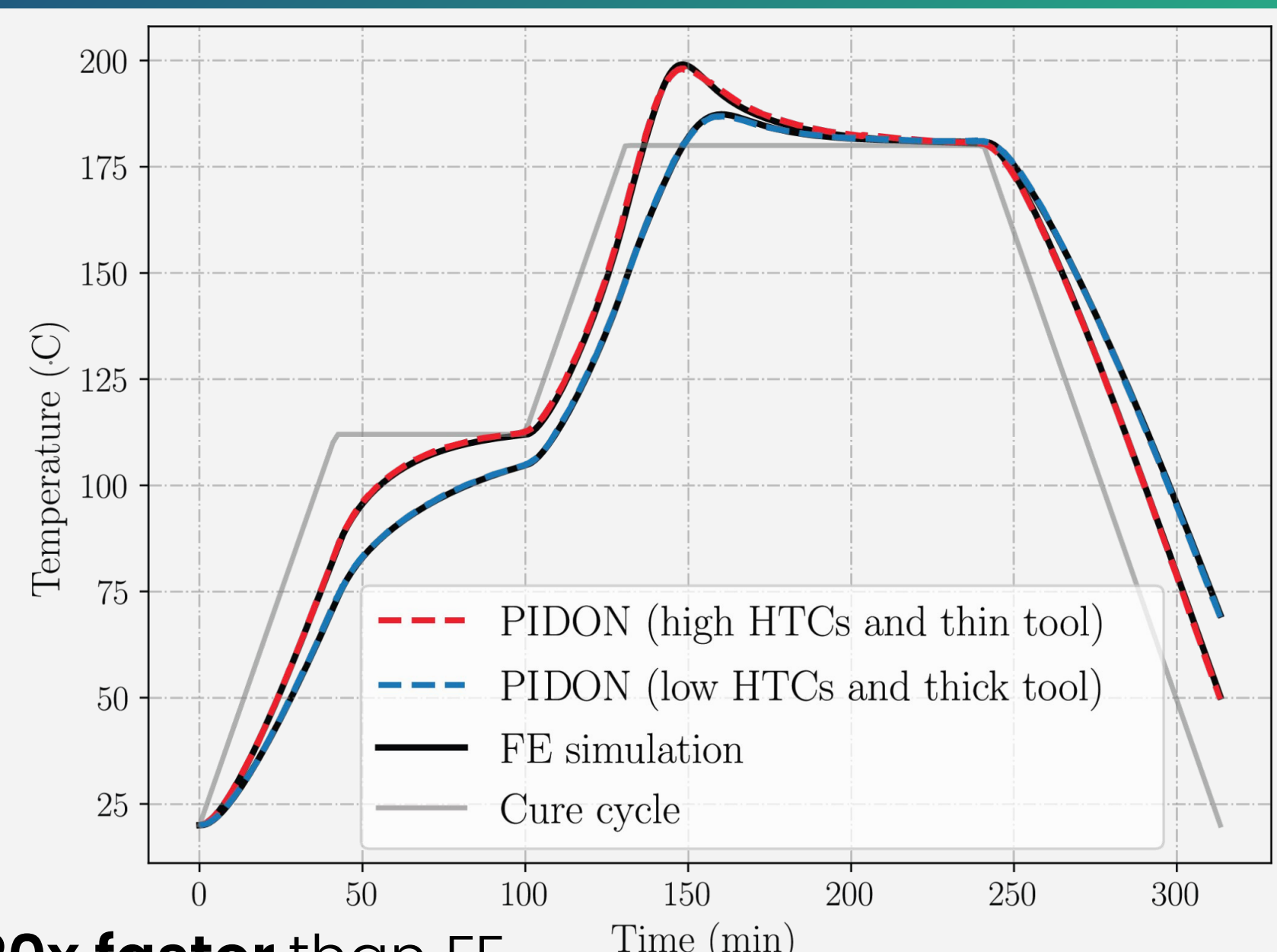
Effect of **curriculum learning**:

Design space size (Rel. $L_2$ error $\times 10^{-3}$ )	Regular training	Curriculum learning
Small	6.8	<b>2.8</b>
Medium	9.22	<b>3.27</b>
Large	13	<b>4.32</b>

Effect of **domain decomposition**:

Metric	Number of nonlinear decoders		
	1	5	7
Max error ( $^{\circ}\text{C}$ )	6.1	3.1	<b>2.3</b>
Seconds/epoch	40	56	61

### Comparison with FE simulations



- **20x faster** than FE.
- **Real-time predictions** for dynamic configurations.
- Excels in **high-dimensional design** input spaces.