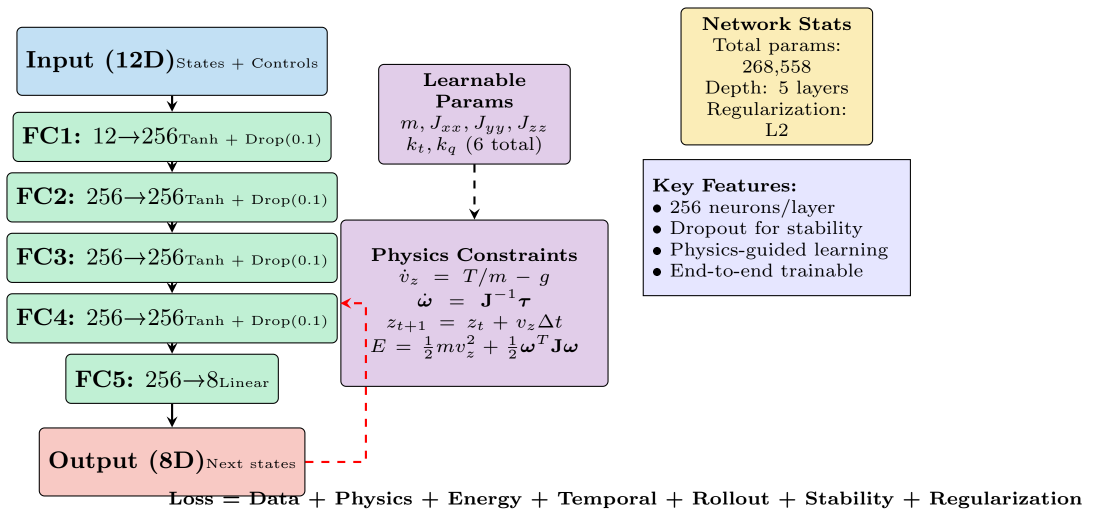
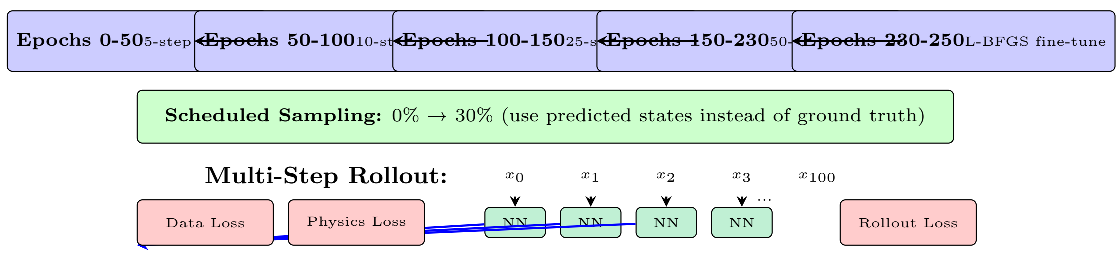
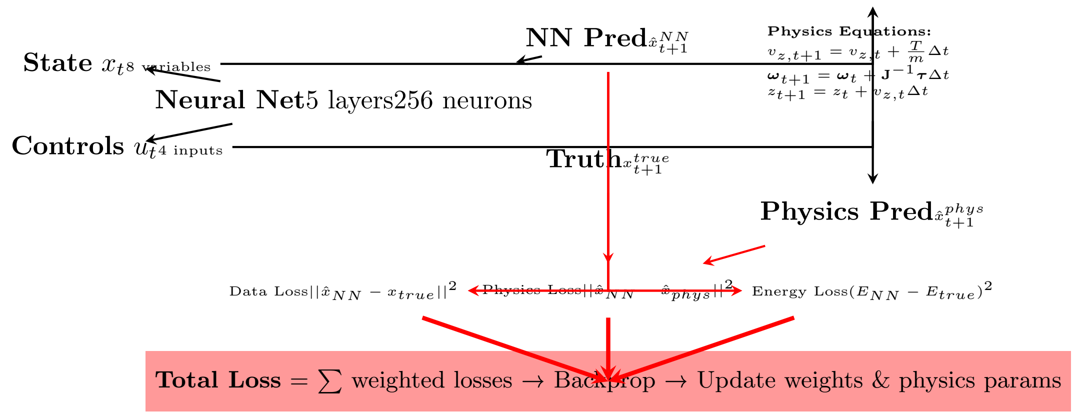
Optimized PINN v2 Architecture



Training Pipeline: Curriculum Learning

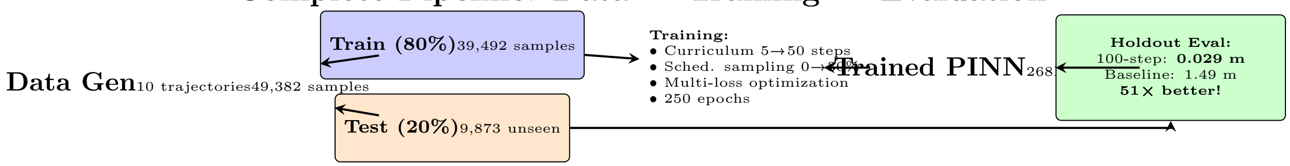


Physics-Informed Learning: How It Works



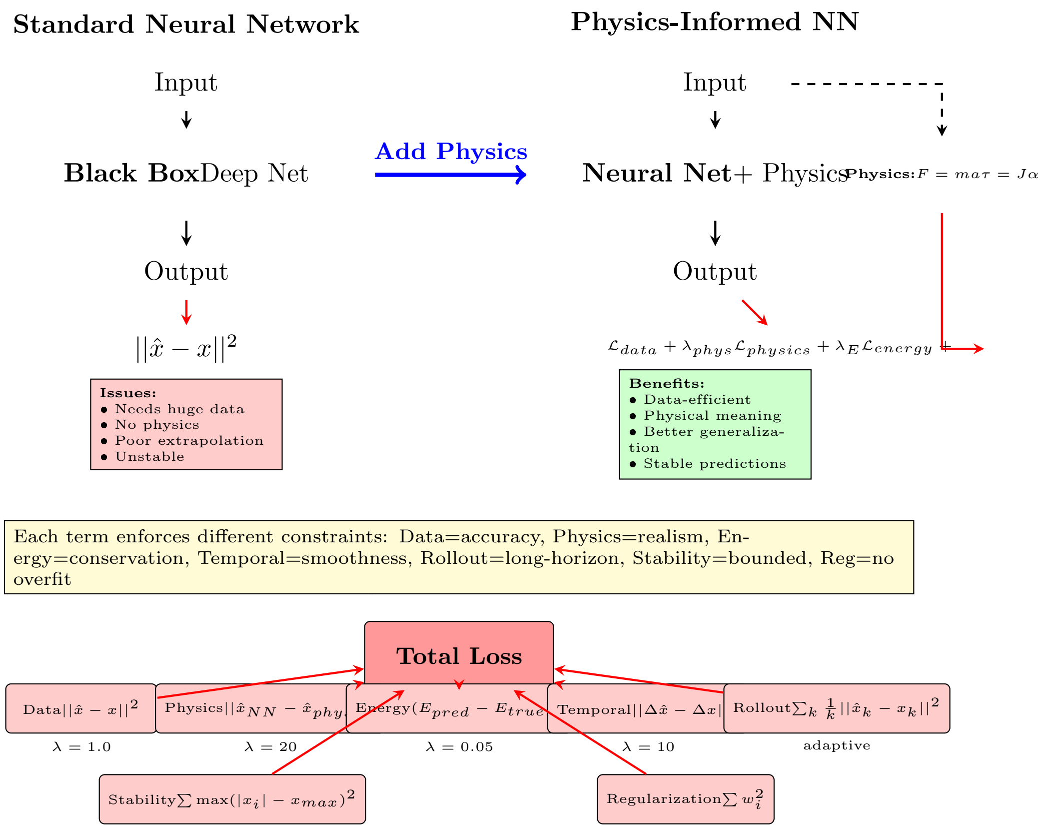
Why this works: NN learns from data (flexible), physics ensures predictions obey laws (stable). Combined = accurate + physically consistent predictions.

Complete Pipeline: Data → Training → Evaluation

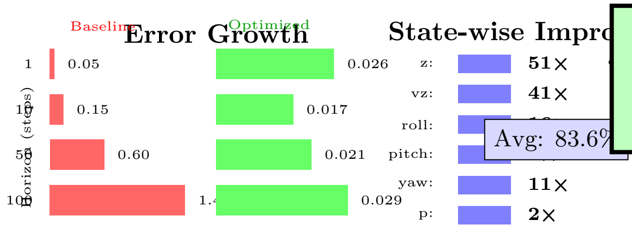


Critical: Time-based split (not random) ensures test set is truly unseen continuous trajectory. Physics params learned: within 5% of true values.

Comparison: Standard NN vs Physics-Informed NN



PINN v2 Performance on Held-Out Test Set



100-step: 0.029 m
(vs 1.49 m baseline)
51× improvement

Stability:
Baseline growth: 17×
Optimized growth: 1.1×
15× more stable

Physics Accuracy:
Mass (m): 0% error
Motor (k_t, k_q): 0%
Inertias (J): <5%

Evaluation:
9,873 unseen steps
Time-based split
No data leakage

Achievement: Physics-informed approach achieves 51× improvement with 10× less data than pure NN would need. Learned parameters match true physics (m, k exact; J within 5%). Predictions stable for 100-step (10 second) horizon.

Error Trajectory Shape: