# Generalizable Temperature Nowcasting with Physics-Constrained RNNs for Predictive Maintenance of Wind Turbine Components

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## Quick Summary

We develop a RNN constrained by partially known physics (PCRNN) for gearbox bearing temperature nowcasting of a wind turbine (WTG) for predictive maintenance. We compare the model with a standard RNN and a physics-based linear model.

Results: **better generalization** and **faster convergence**.

## Motivation

### Predictive Maintenance for WTGs

**WHY?** Downtimes are costly; continuous monitoring of real and expected system behavior helps to detect degradation to prevent faults and schedule maintenance.
**HOW?** Surrogate model learns system behavior in healthy conditions; deviations from observations indicate damage.
**WHAT?** Focus on gearbox bearings (faults especially severe); surrogate model for prediction of current bearing temperature (nowcasting).

### Phyiscs-constrained ML

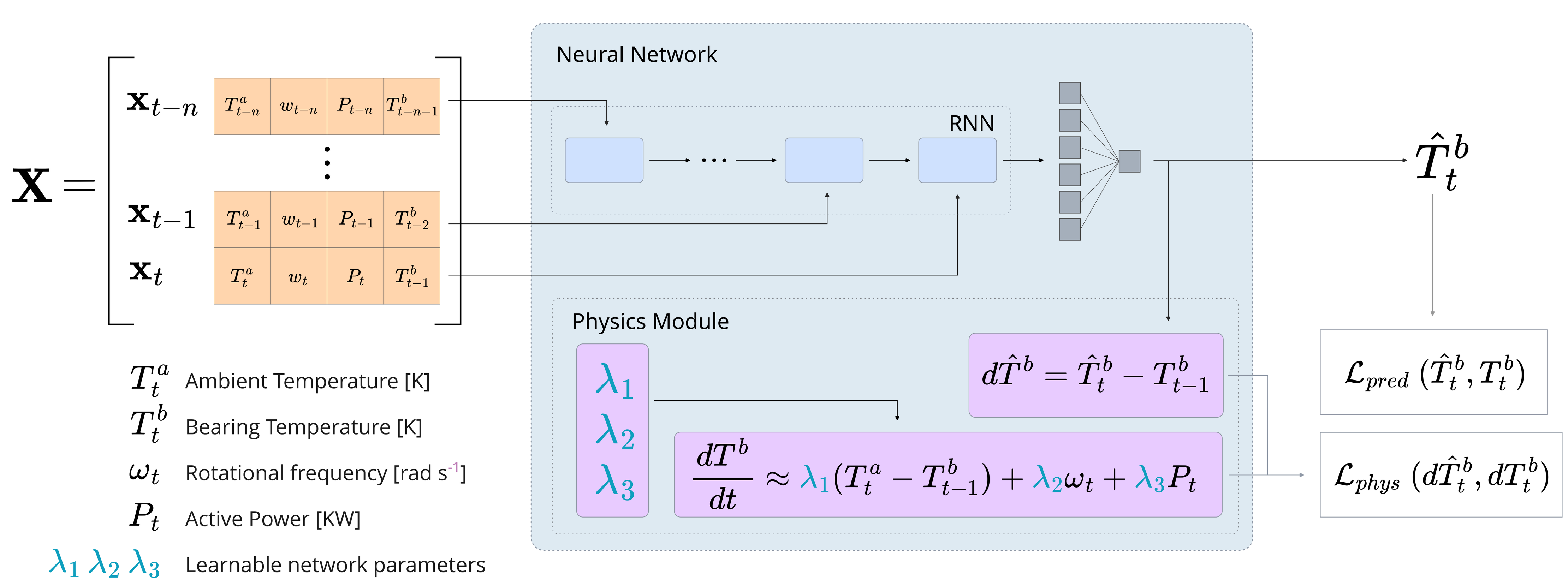
**WHY?** Leverage flexibility of ML models while assuring physical plausibility.
**HOW?** Only partial knowledge of physics in system; unknowns are treated as learnable parameters.
**DIFFICULTIES?** Aggregated time intervals allow only approximation of gradient.
**WHY NOWCASTING?** Wind speed as main driver of bearing temperature is difficult to predict; Nowcasting allows to neglect wind speed and use measured rotor speed.

## The Model

**Prediction component:** LSTM with current and lagged wind turbine states as input and current bearing temperature as output.
**Physics component**: Mathematical model of bearing temperature gradient. Physical unknowns (e.g. overall thermal conductivity, friction coefficient) are treated as learnable neural network parameters.

The model simultaneously learns to nowcast temperature and to solve equation, which acts as soft constraint for model predictions.

### Physics-constrained RNN (PCRNN)

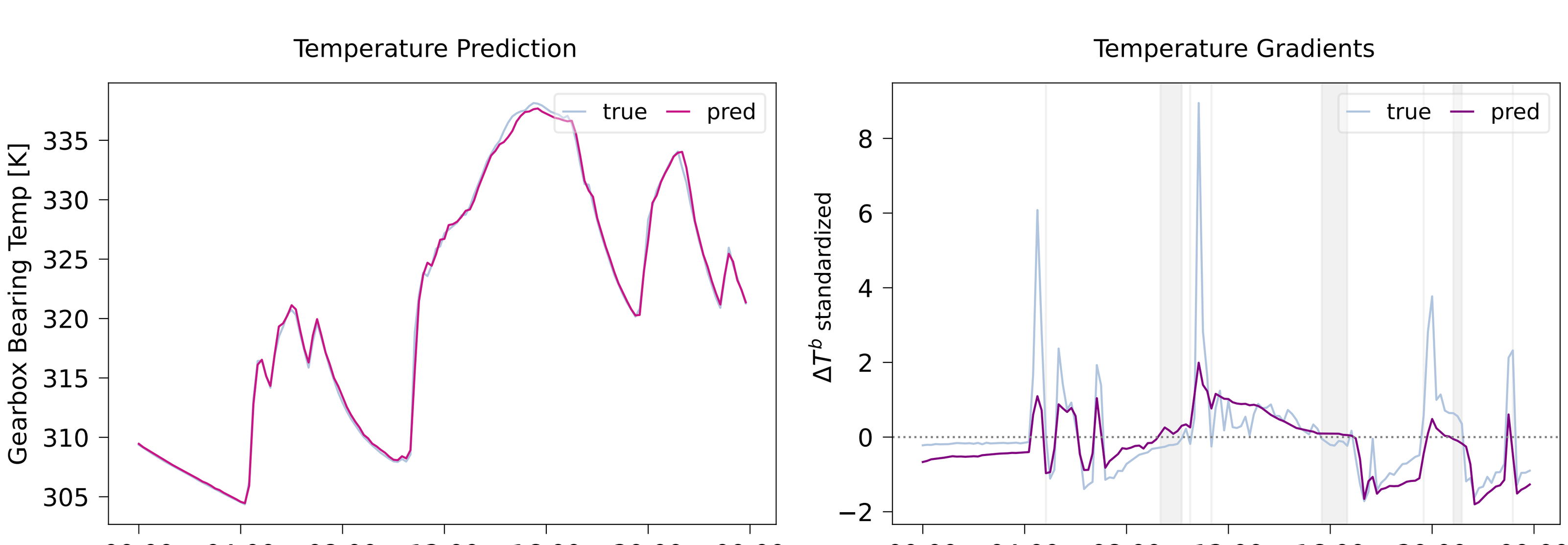



## Results

We performed experiments for three different datasets (wind farms at different locations) and different number of training turbines (1, 3, 6, 9). with data in 10 min intervals (averaged) from a SCADA system. Full year 2022 is used for training, 2023 for testing. Results are averaged over 10 runs, convergence tests over 50 runs. Baselines for comparison: standard RNN without physics, physics-based linear model.

### Prediction Performance

PCRNN offers competitive prediction performance and manages to approximate temperature change patterns.




Temperature prediction (left), PCRNN internal physics module temperature deltas and true temperature deltas (right). Deltas are standardized; different magnitudes are explained by dimensionless values inside the model. Crucial are the temperature change patterns, which the PCRNN manages to approximate. Grey areas show steps where model and true deltas differ in direction.

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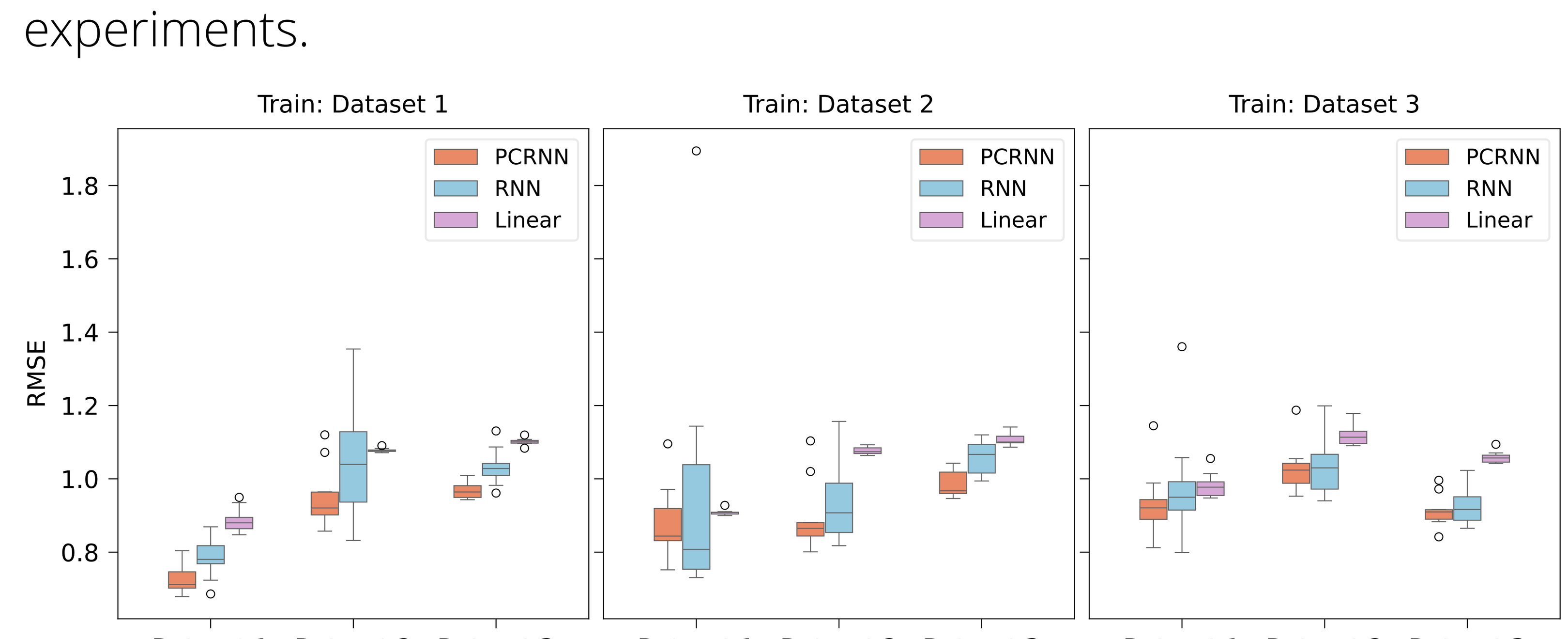
### Generalization

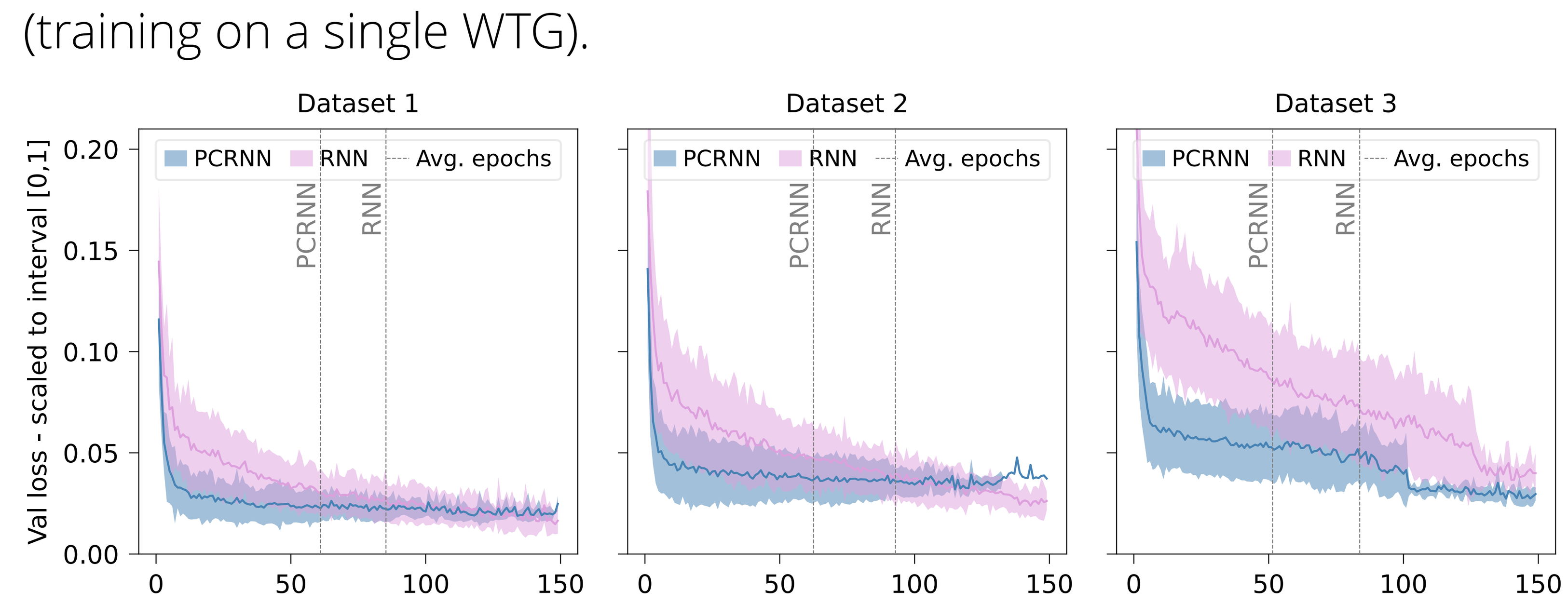
PCRNN performs better on unseen datasets/turbines in a majority of experiments.




Performance on data from unseen turbines, training set size of 6 turbines.

### Convergence

PCRNN converges on average approx. 20 - 30 epochs faster than RNN (training on a single WTG).




Average convergence for different datasets (scaled to [0,1]).

Code available at: `github.com/jxnb/pcrnn-wtg`