KTH ROYAL INSTITUTE OF TECHNOLOGY

Use of physics-informed neural networks for ageing prediction and lifetime extension of wind farm components

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Introduction

- Project overview
- What are Physics-Informed Neural Networks (PINNs)?
- Our work on analysis of thermal behavior of power transformers using PINNs
  - Description
  - Results
- Current work description:
  - Degradation of materials: Cellulose insulation degradation
  - Functional mechanical properties: identification critical wind farm components
  - How long can wind farms live?

Project Overview

Main Goal: Develop a new physics-based machine learning system for the circular reuse of power components.

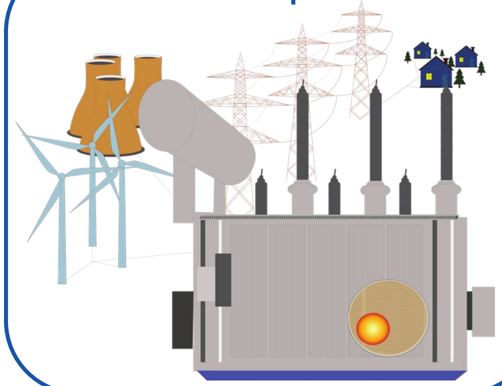
Objectives:

- Estimate component’s ageing rate close to the end of its lifetime using Physics-Informed Neural Networks (PINNs)
- Reuse parts of non-reusable components for repair parts
- Better utilization of already existing assets:
  - Accomplish better material utilization;
  - Contribute to the development of circular industry, improve the sustainability of system design, and reduce pollution caused by the manufacturing process.

Project Overview

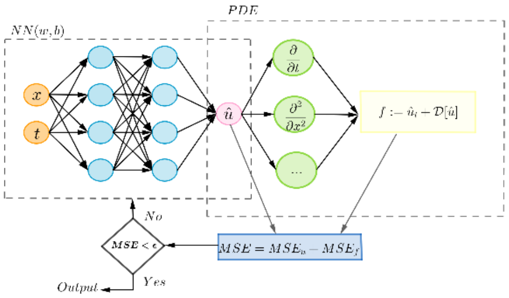
Data

Power components



Type of data: Top-oil temperature, ambient temperature, load factor, degree of polymerization, etc.

Physics-based machine learning



Physics-Informed Neural Networks: Solution of PDE, Discovery of PDE

Maintenance

Physics-Informed Neural Networks (PINNs)[1]

Data-driven solutions to PDEs

$$u_t + \mathcal{D}[u] = 0, \;\; x \in \Omega, \;\; t \in [0, n]$$

- $u(x, t)$ is the latent hidden solution;
- $\mathcal{D}[\cdot]$ is a nonlinear differential operator;
- The domain Ω is a subset of $\mathbb{R}^d$.

Forward problem

Given some fixed parameters λ, what is the solution $u(x, t)$?

Data-driven discovery of PDEs

$$u_t + \mathcal{D}[u; \lambda] = 0, \;\; x \in \Omega, \;\; t \in [0, n]$$

- $u(x, t)$ is the latent hidden solution;
- $\mathcal{D}[\cdot; \lambda]$ is a nonlinear differential operator parametrized by λ;
- The domain Ω is a subset of $\mathbb{R}^d$.

Inverse problem

What are the best parameters λ of the PDE that describe the data?

[1] M. Raissi, P. Perdikaris, G.E. Karniadakis, ”*Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations*”.

Physics-Informed Neural Networks (PINNs)

Data-driven solutions to PDEs

$$u_t + \mathcal{D}[u] = 0,\ \ x \in \Omega,\ \ t \in [0, n]$$

Set the function:

$$f \coloneqq u_t + \mathcal{D}[u]$$

Minimise the mean squared error loss:

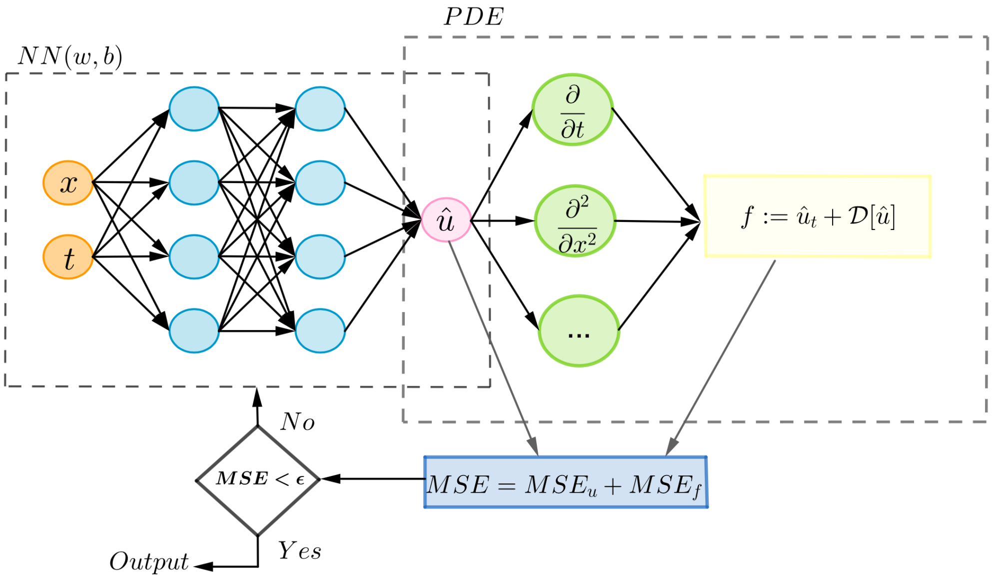
$$MSE = MSE_u + MSE_f$$

$$MSE_u = \frac{1}{N_u} \sum_{i=1}^{N_u} \left| \hat{u}(x_u^i, t_u^i) - u^i \right|^2$$

Number of **initial and boundary training data**

$$MSE_f = \frac{1}{N_f} \sum_{i=1}^{N_f} \left| f(x_f^i, t_f^i) \right|^2$$

Number of **collocation points**



PINNs: Yes or No?

Advantages

- Good approximations both with large and small datasets
- No curse of dimensionality
- Robust to noisy data
- Does not require a discretization grid to calculate solutions

Disadvantages

- Extensive computation time for training the neural network
- No proof that the model gives the optimal solution
- Difficulty to handle large parameters involved in the equation

Previous work

- Analysis of the thermal distribution in power transformers
- Focus on the temperatures that the oil in the tank experiences
- Conventional dynamic thermal models do not conserve energy and do not provide temperature distributions

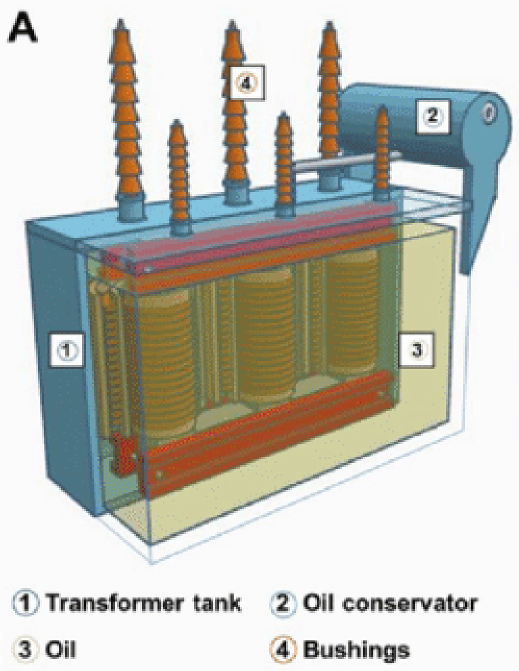
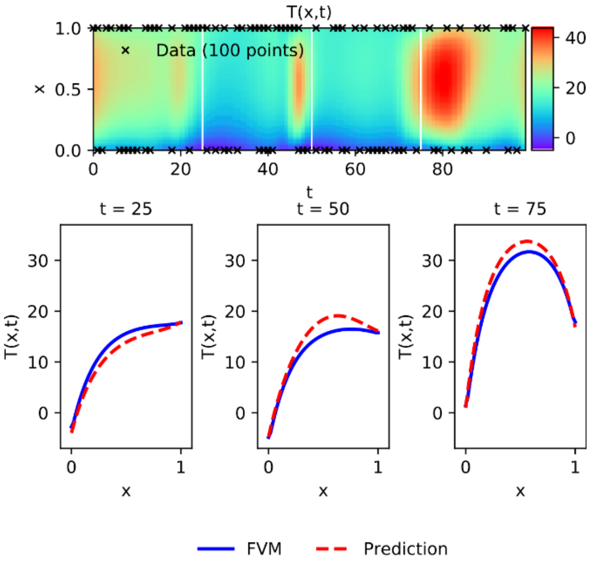


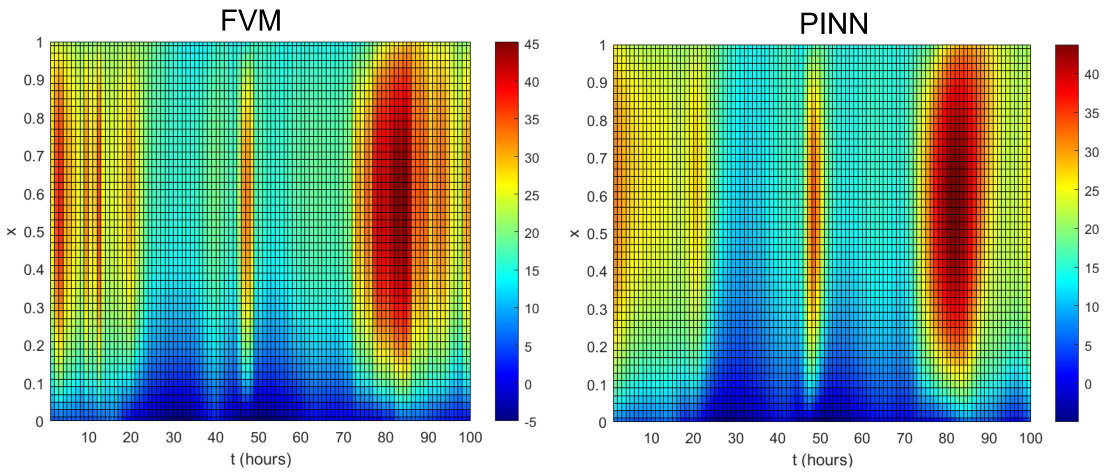
Figure taken from "Jusner, Paul & Schwaiger, Elisabeth & Potthast, Antje & Rosenau, Thomas. (2021). Thermal stability of cellulose insulation in electrical power transformers – A review. Carbohydrate Polymers. 252. 117196. 10.1016/j.carbpol.2020.117196."

Results

PINN: $t = 0 - 100$



FVM vs PINN



- $N_u = 100$
- $N_f = 10000$
- 4 hidden layers, 50 neurons
- L2 Error u: 1.45e-01
- L2 Error T_o: 2.59e-02

Current focus

Defining component ageing

Degradation of materials

Functional mechanical ware-off

- Cellulose insulation degradation
- Create a model for cellulose degradation using PINNs
- Correlation of Degree of Polymerization (DP) and ageing rate

- Identify critical wind farm components
- How often do these components fail?
- What is the cause of the failure and how it can be prevented?

Conclusions

Discussion

- Potential in using PINNs in the circular reusage of power transformers:
  - Analysis on the thermal distribution
  - Monitoring aging and thermal behavior of the transformer's insulation paper
  - Perform fault characterization in wind farms to estimate how longer they could live
- Preliminary results on cellulose degradation
- Further analysis and results on advantages and disadvantages of PINNs

Future Work

- Working on improving the degradation of cellulose model that we have
- Expand the analysis of degradation and failure of components to wind farms components to understand how long they could live
- Analyze how important is the impact of physics on the model performance and final result
- Compare performances of physics-based and non-physics-based ML

Thank you!

Questions?

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Project Sponsors:

VINNOVA

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Papers:

- F. Bragone, K. Morozovska, T. Laneryd, M. Luvisotto, and P. Hilber, “Physics-informed neural networks for modelling power transformer’s dynamic thermal behaviour,” in 2022 Power Systems Computation Conference (PSCC), pp. 1–7, 2022.
- T. Laneryd, F. Bragone, K. Morozovska, and M. Luvisotto, “Physics informed neural networks for power transformer dynamic thermal modelling,” in 10th Vienna International Conference on Mathematical Modelling, pp. 1–6, 2022.
- O. W. Odeback, F. Bragone, T. Laneryd, M. Luvisotto, and K. Morozovska, “Physics-Informed Neural Networks for prediction of transformer's temperature distribution”, in IEEE ICMLA 2022 (accepted).
- F. Bragone, K. Oueslati, T. Laneryd, M. Luvisotto, and K. Morozovska, “Physics-Informed Neural Networks for Modeling Cellulose Degradation in Power Transformers”, in IEEE ICMLA 2022 (accepted).