Physics Informed Neural Networks for Thermal Insulation Material Ageing Estimation

Joel Pino[1], Ibai Ramirez[1], David Pardo[2,5,6], Mikel Sanz[3,5,6] **Jose I. Aizpurua** [4,6]

1 Mondragon University, Electronics & Computer Science Department, Loramendi 4, Mondragon, 20500, Spain

2 University of the Basque Country (UPV/EHU), Department of Mathematics, Leioa, 48080, Spain

3 University of the Basque Country (UPV/EHU), Department of Physical Chemistry, Leioa, 48080, Spain

4 University of the Basque Country (UPV/EHU), Department of Computer Science and Artificial Intelligence, San Sebastian, 20018, Spain

5 Basque Centre for Applied Mathematics, Bilbao, 48009, Spain

6 Ikerbasque, Basque Foundation for Science, Bilbao, 48011, Spain

joxe.aizpurua@ehu.eus

Transformers are key components for the reliable operation of the grid. The thermal insulation material aging is a key transformer failure mode, which is generally tracked by monitoring the hotspot temperature (HST) [1]. However, HST measurement is complex and costly, usually estimated from indirect measurements. Existing HST estimation methods focus on space-agnostic thermal models and provide worst-case estimates [1]. This work presents a spatio-temporal model for transformer HST and insulation material ageing estimation, using a Physic Informed Neural Network (PINN) approach to improve prediction accuracy and obtain spatio-temporal resolution. Fig. 1 shows the overall framework.

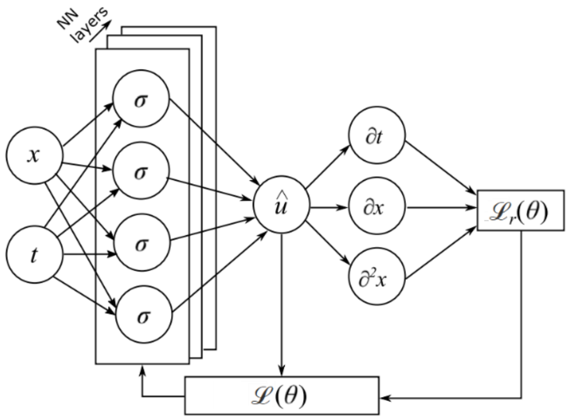

Figure 1. Overall PINN framework.

The PINN framework in Fig. 1. is trained by minimizing a loss function, $\mathcal{L}(\theta)$, defined as follows:

$$\mathcal{L}(\theta)=\mathcal{L}_0(\theta)+\mathcal{L}_b(\theta)+\mathcal{L}_r(\theta) \quad (1)$$

where $\mathcal{L}_0(\theta)$, $\mathcal{L}_b(\theta)$, and $\mathcal{L}_r(\theta)$ denote loss terms corresponding to initial conditions (IC), boundary conditions (BC), and the residual of the partial derivative equation (PDE), defined as follows:

$$\mathcal{L}_0(\theta)=\frac{1}{N_0}\sum_{i=1}^{N_0}|\overline{u}(x_i,0)-u(x_i,0)|^2 \quad (2)$$

$$\mathcal{L}_b(\theta)=\frac{1}{N_b}\sum_{i=1}^{N_b}|\overline{u}(x_i,t_i)-u(x_i,t_i)|^2 \quad (3)$$

$$\mathcal{L}_r(\theta)=\frac{1}{N_r}\sum_{i=1}^{N_r}|r(x_i,t_i)|^2 \quad (4)$$

where N_0, N_b and N_r are the number of IC, BC, and residue points, respectively, $x,t\in\mathbb{R}$ are position and time, respectively, $u(x,t)$ and $\overline{u}(x,t)$ denote the known and estimated solution, and finally $r(x,t)$ denotes the residual of PDE:

$$r(x,t)=\frac{1}{\alpha}\frac{\partial\overline{u}(x,t)}{\partial t}-\frac{\partial\overline{u}(x,t)}{\partial x^2}-\frac{1}{k}q(x,t) \quad (5)$$

where $\alpha=k/\rho c_p$ is the thermal diffusivity given in [m^2/s], k is the thermal conductivity [W/mK], ρ is the density in [kg/m^3], c_p is the specific heat capacity [J/kgK], $\overline{u}(x,t)$ is the estimated transformer oil temperature in Kelvin [K], and $q(x,t)$ represent the rate of heat generation in [W/m^3] defined as follows:

$$q(x,t)=P_0+P_K(t)-h\big(\overline{u}(x,t)-T_a(t)\big) \quad (6)$$

where $T_a(t)$ is the ambient temperature given in Kelvin [K], P_0 denotes the no-load losses in [W] and $P_K(t)$ is the load losses in [W] defined as follows:

$$P_K(t)=K(t)^2\mu \quad (7)$$

where $K(t)$ is the load factor in [p.u.], and μ is the rated load losses in [W].

The convergence of the proposed PINN approach has been enhanced by the implementation of the Residual-Based Attention (PINN-RBA) scheme [2]. Moreover, spatio-temporal HST values were estimated based upon PINN predictions, which were validated using fiber optic sensor (FOS) measurements, and additionally, the spatio-temporal transformer ageing model was inferred. The top oil temperature (TOT) and HST are considered mobile across the transformer geometry. Accordingly, the estimated spatio-temporal winding temperature, $\overline{w}(x,t)$, is defined as follows:

$$\overline{w}(x,t)=\overline{u}(x,t)+\Delta h(t) \quad (8)$$

where $\Delta h(t)$ is the HST rise over TOT, which is defined in IEC 60076-7 standard [2]. Using the spatio-temporal winding temperature in (8) along with the ageing acceleration factor of the insulation paper [1], the spatiotemporal ageing at time and position x, t, can be defined as follows:

$$\overline{v}(x,t)=2^{(\overline{w}(x,t)-98)/6} \quad (9)$$

The proposed approach was validated with a distribution transformer operated on a floating photovoltaic power plant. Fig 2. shows transformer oil temperature predictions of the proposed RBA-PINN scheme.

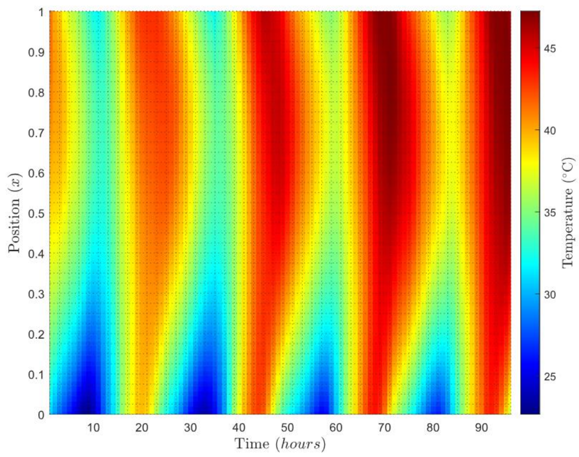

Figure 2. RBA-PINN prediction.

Fig 3. shows the obtained prediction errors with respect to the numerical solution. RBA-PINN obtains small deviations with a maximum error of 2.8 °C near the IC $(t = 0)$ and the half of the spatial dimension $(x = 0.5)$.

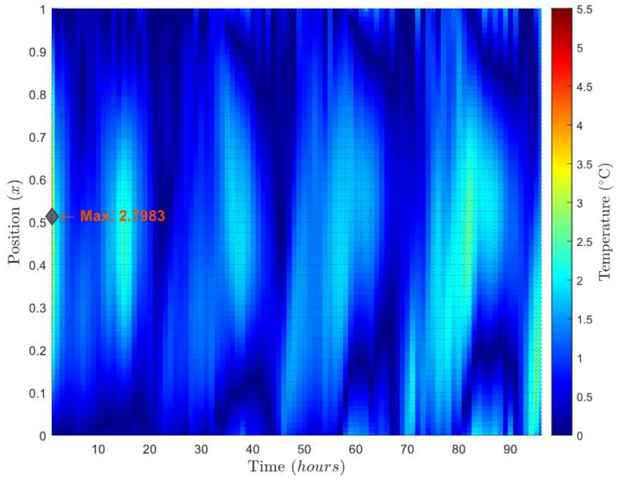

Figure 3. Prediction error of RBA-PINN.

Fig. 4. shows the obtained HST results from spatio-temporal winding temperature estimations based on the PINN-RBA predictions integrated in Eq. (8).

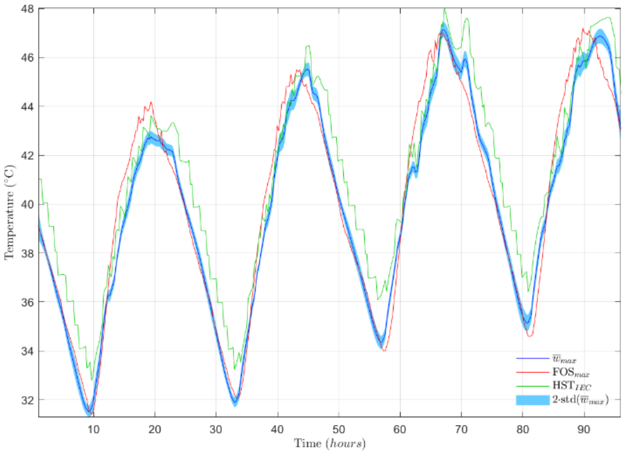

Figure 4. HST estimation and validation.

Fig. 5 shows the HST prediction errors, calculated through the relative error, $e_u = (u - \overline{u})/u$, where u refers to the ground truth, FOS_{max} in this case, and $\overline{u}$ represents the estimates, *i.e.* HST_{IEC} and $\overline{u}_{max}$.

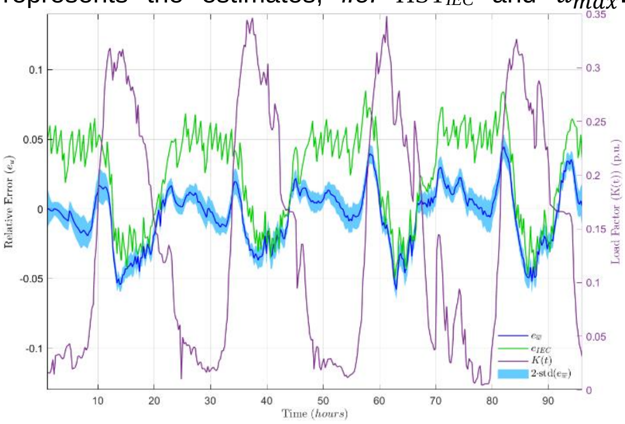

Figure 5. HST relative error.

Fig. 6 shows the instantaneous ageing estimations of the insulation material from HST results via Eq. (9). Finally, Fig. 7 shows the ageing estimate errors with respect to the FOS measurements for the proposed RBA-PINN and IEC models.

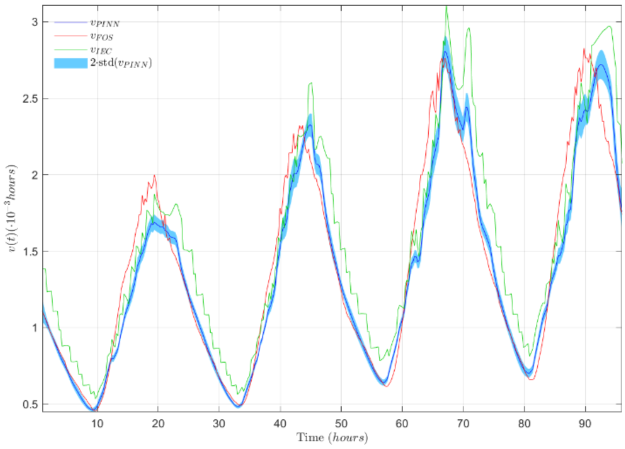

Figure 6. Instantaneous ageing estimation.

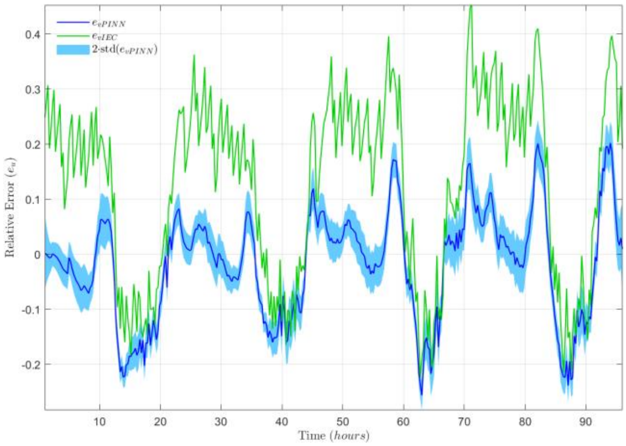

Figure 7. Ageing estimation error and validation.

Fig. 7 confirms that the ageing estimation error of the proposed solution is lower than engineering-standard based ageing estimation methods.

The obtained results contribute to the current transformer health management practice through a spatiotemporal definition of the HST and insulation ageing equation. The implementation of the PINN model for the transformer insulation heating enabled the design of an accurate and efficient surrogate mode, which can be used in further decision-making processes. Future work will consider the extension of the model to higher dimensions. The complete details of the presented study can be found in [3].

References

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