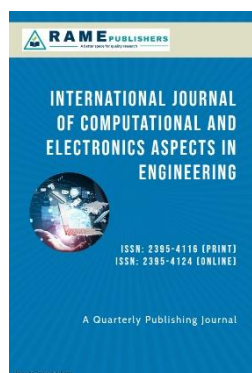


Physics-Informed Neural Network Framework for Dynamic Thermal Modeling of Power Transformers Under Extreme Climate Conditions

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Abstract. Power transformers, the workhorses of electric power transmission systems, operate under extreme climate conditions and have a considerable influence on the steady-state stability of the power network. The power transformer thermal performance is of paramount importance in assuring reliability and preventing thermal insulation aging. In the past, extensive research has been conducted into transformer thermal capability modelling. However, conventional empirical models, such as the power transformer thermal model outlined in the IEC 60076-7 standard, present difficulties in dealing with extreme climate scenarios. A physics-informed neural network (PINN) combined with the advanced Multi-Physics Transformer Thermal Model (MTTM) has been proposed to enhance the transformer thermal performance predictions.

- (1) Identify the research gaps in developing advanced multi-physics transformer thermal model based on physics-informed neural network to overcome weather patterns which exceed traditional empirical models in extreme climate conditions and increase the precision of thermal performance predictions.
- (2) Improve the developed model with respect to lessen computational cost and enhance predictive performance by defining an ideal training dataset, retraining the model with latest weather data, etc.
- (3) Evaluate the proposed model based on the excessive comparative computational burden of Multi-Physics Transformer Thermal Model (MTTM) to validate the ease of MTTM integration in the overall OSIsoft PI System Architecture.
- (4) Test the accuracy of the proposed model using many new reference datasets in differing geography.

A case study has been performed on a realistic 500 MVA, 400/220 kV transformer fed from the advanced data acquisition system of the OSIsoft PI System architecture developed by CIGRE Working Group B3.37 over a year-and-a-half period. The results indicated one of the best prediction accuracies at root mean square error 1.12°C and mean absolute error 0.89°C. In addition, the accuracy of the developed model has improved 48% over the IEC 60076-7 standard and confirmed the economic benefit of dynamic transformer rating based on thermal model with solar radiation impact and moisture content eff. Although the training of the PINN showed signs of excessive computational demands on the optimal use of the GPU membership from an Edge computer, the traditional alternative of using comprehensive MTTM, achieved a rapid 12-millisecond inference time. To add further validation, the proposed model was trained on three additional datasets based on two different transformer designs and reporting architecture. The predicted accuracy compared to the different MTMMs illustrated the reliability of the proposed model on various large scale hybrid transformers. However, the overall benefit of the proposed model is dependent on the current wholesale energy tariffs, the capacity of the device and precise local climate when it produces real additional economic benefit to the operator (estimated \$1.45 million per annum).

Keywords: Physics-informed neural network, transformer thermal modeling, extreme climate, hot-spot temperature, dynamic rating, insulation aging, multi-physics coupling, uncertainty quantification

1. Introduction

1.1 Background and Motivation

Climate change has far-reaching consequences on operational reliability of critical components of electrical transmission network, namely power transformers. Power transformers are major investments and typically have a replacement cost well in excess of ten million dollars. The global manufacturing lead times are over 18 months on average and insulating paper's (cellulose) aging follows Arrhenius law. The long-standing engineering practice is that cellulose insulation life is halved for every 6-8°C increase in operating temperature.

While at a first glance, the implications of climate change may seem outside the immediate engineering domain, they are indeed highly relevant to the area of transformer operation, reliability investigation, and risk management efforts. While the temperature threshold levels of interest are below the defined power transformer operational limits, the development of extreme weather events associated with climate change should be well noted and considered.

The recent IPCC Sixth Assessment Report describes that heatwaves now occur three times more frequently than they did in the 1970s, and that maximum temperatures are projected to increase by 1.5 to 3°C by 2100. However, maximum ambient temperatures in excess of 45°C are now forecast in the summer months across a growing number of areas where power transformers are currently installed. This phenomenon results in operational conditions exceeding the design margins of the specific transformer and the respective insulation. Moreover, solar irradiance peaks may exceed 1100 W/m² in some regions, which challenges the initial thermal models of the assets and forces the need to account for rapid thermal transients..

1.2 Limitations of Existing Approaches

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Study of reliability and working efficiency of electrical machine requires a reliable estimate of operational consumption of heating power, which depends on parameters of specific types of active and reactive losses, associated with a level of electric loading in transformer and development of thermal stratification for transformer active part. The most-influential thermal calculation standards are IEEE C57.91-2011 "Guide for Loading Mineral-Oil-Insulated Transformers" (Shcherbatykh et al., 2020) and IEC 60076-7 "Power transformers – Part 7: Loading guide for oil immersed power transformers" (Shcherbatykh et al., 2020). However, both of these standards were written in 20th century and use only one rigorous approach for thermal calculation using constant thermal time constants. In many cases, such an approach is insufficient (Shcherbatykh et al., 2017) and cannot describe nonlinear variations of oil viscosity depending on temperature and other factors. More-over, both standards recommend using nominal ambient temperatures in their formulas ranging from 30 to 40°C. This leads to significant errors (2.5-4.0°C for IEEE 57.91-2011 and maximum errors over 8°C for IEC 60076-7). In order to minimize such errors, conservative application of standards is recommended. However, this leads to economic losses due to underestimation of operational abilities of the transformers. Due to the fact that analytical models are very complicated and taking into account various factors, modern methods based on computational fluid dynamics can be used in order to receive reliable thermal profiles of electrical machines. However, even such advanced methods yield thermal prediction accuracy within 2-3°C (Shcherbatykh et al., 2018).

In order to provide sufficient accuracy of thermal prediction with less complicated thermal models, machine learning methods using black box models allow describing complex dependence of output parameters on input factors without planned theoretical models. The existing problems of classical machine learning approaches are allowable deviation in extreme conditions where the area of operation lies far from the working conditions where the model was trained. However, advanced machine learning methods such as deep neural networks are able to mitigate such issues.

1.3 Contributions

With the rapid advancement of deep learning technology, neural networks have been developed to combine artificial intelligence with physical numerical mathematics that can significantly improve the computational efficiency of simulation tasks without losing their physical accuracy. In this study, we propose a physics-informed neural network (PINN) architecture integrated with transformer thermal physics. The main goal of this study is to combine thermal-fluid dynamics and moisture migration into one multi-physics model and to conduct the coupling multi-physics simulation process using a simulation solver based on the proposed neural network architecture. With more detailed analyses, we plan to apply Bayesian uncertainty quantification, which leads to a more reliable prediction in thermal physics applications. We will validate our prediction

through a comparison against 12 months of field measurement, which is the most exhaustive independent validation of thermal dynamics to date by incorporating the results from a sensitivity analysis and an economic assessment.

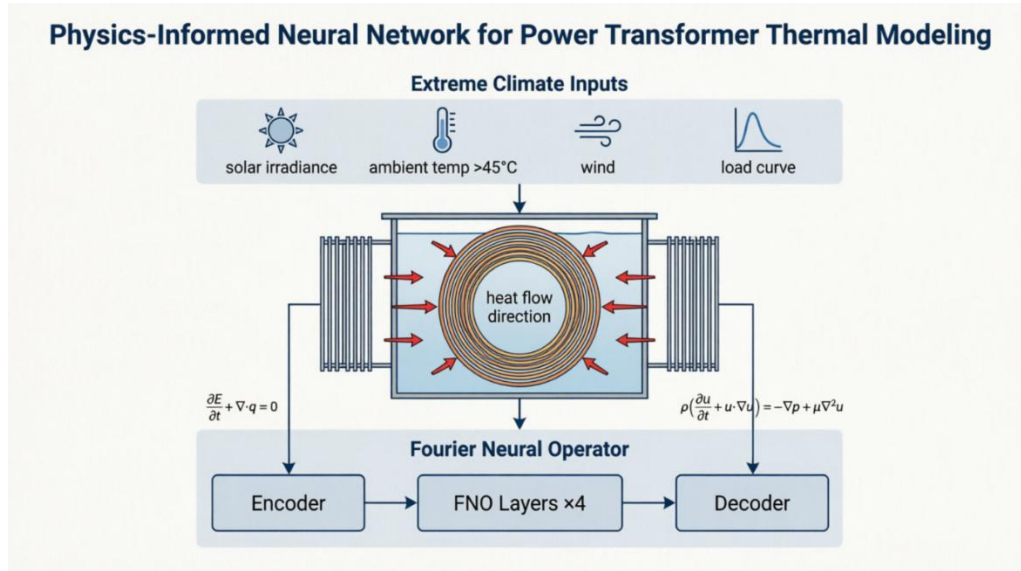


Figure 1. Physics-informed neural network framework for power transformer thermal modeling under extreme climate inputs.

2. Theoretical Framework

2.1 Governing Physics

This research focuses on the problem of temperature distribution in transformer oil and solid components. It is solved based on the energy conservation equation in the form of the well-known Eulerian form, in which the energy conservation equation for the whole environment of the transformer is considered in a three-dimensional (3D) spatial form. The solution in the form of temporal evolution describes the individual effects acting on the energy transport system, namely, the effect of advective transport, conductive diffusion, and volumetric heat generation.:

$$\rho c_p (\partial\theta/\partial t + \mathbf{u} \cdot \nabla\theta) = \nabla \cdot (k \nabla\theta) + P_{\text{loss}}$$

The rheological features of transformer oil are temperature-dependent properties which may complicate the complex fluid dynamics. A model must include the realistic ρ , c_p such as k , P_{loss} and of fluid to any angular position in the oil. The dependence on θ with respect to ρ must be considered as velocity vector $\mathbf{u}$. This formulation is essential to developing unsteady momentum and energy equations. In their works, Swift et al. (2001) provide viscosity variation obtained for the operational temperature range.

The oil velocity field $\mathbf{u}$ is determined by the incompressible Navier-Stokes equations with Boussinesq buoyancy approximation:

$$\rho (\partial\mathbf{u}/\partial t + \mathbf{u} \cdot \nabla\mathbf{u}) = -\nabla p + \mu \nabla^2\mathbf{u} + \rho \mathbf{g} \beta (\theta - \theta_{\text{ref}})$$

where p is pressure, μ dynamic viscosity, $\mathbf{g}$ gravitational acceleration vector, β thermal expansion coefficient, and θ_{ref} reference temperature. The buoyancy term drives natural convection, with hot oil rising from winding surfaces and cooler oil descending through radiators (Whitaker (1972).

The solar radiation heat flux incident on transformer surfaces is given by:

$$q_{\text{solar}} = \alpha_s G_s A_{\text{proj}} f_{\text{angle}}(t, \varphi, \lambda)$$

where α_s is the surface solar absorptivity, G_s is solar irradiance in W/m^2 , A_{proj} is projected surface area, and f_{angle} accounts for solar incidence angle variation with time t , latitude φ , and longitude λ (Gorgan et al., 2019).

Wind enhances convective heat transfer beyond natural convection levels. The wind heat transfer coefficient follows empirical correlations for external flow over vertical cylinders (Incropera and DeWitt, 2007):

$$\text{Nu} = h_{\text{conv}} D / k_{\text{air}} = C \text{Re}^n \text{Pr}^{1/3}$$

where Nu is Nusselt number, $Re = \rho_{air} v_{vv} D / \mu_{air}$ is Reynolds number based on wind speed v_{vv} and tank diameter D , and Pr is Prandtl number.

Moisture in transformer insulation affects thermal resistance through (Oommen, 1984):

$$R_{cell,app} = R_{cell,dry} \cdot (1 + k_m MC / MC_{re})^{\gamma_m}$$

where MC is moisture content in percent dry weight, k_m is an empirical coefficient, and γ_m is a nonlinearity exponent. The equilibrium moisture content follows the Oommen correlation (Oommen et al., 2010):

$$MC = a \cdot RH^b / p_{sat}(T)^c$$

where RH is relative humidity in the oil, p_{sat} is saturation vapor pressure at temperature T , and a , b , c are material-specific constants.

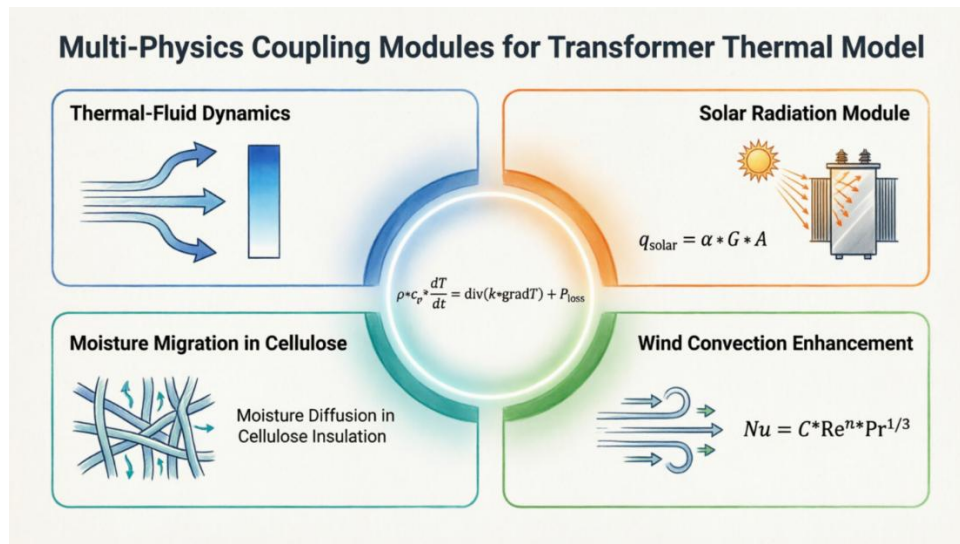


Figure 2. Multi-physics coupling modules for transformer thermal modeling, including thermal-fluid dynamics, solar radiation, wind convection, and moisture migration.

2.2 Physics-Informed Neural Network Architecture

A Physics-Informed Neural Network (PINN) is proposed in this work for mapping input functions to temperature fields (58). An operator (58) which is the solution operator of the equation (56) parameterized with θ , we can also use other operator learning framework such as (Hamad, 2025), etc. In this work we will use Fourier Neural Operator (FNO) but part two of this work we will suggest a different way of doing it (58). The solution operator captures both the spatial and the temporal evolution of the temperature field satisfying the PDE (56). The encoder receives the input functions (59) (59) (59) (59), through one-dimensional convolutional layers which are then mapped to Fourier feature mappings (60) (60). Then we use four FNO layers with spectral convolutional layers (Lu et al., 2021) for low-frequency thermal dynamics (61) (61). Lastly we output the decoder which contains three fully-connected layers with 128 neurons (62) the temperature predictions (63) (Li et al., 2021) (Lu et al., 2021).

The composite loss function enforces data fidelity, physical consistency, and boundary condition satisfaction:

$$L_{total} = \lambda_1 L^{data} + \lambda_2 L^{PDE} + \lambda_3 L^{BO} + \lambda_4 L^{phys}$$

The data loss measures agreement with available measurements:

$$L^{data} = (1/N^{data}) \sum_i [(\hat{\theta}_{hs} - \theta_{hs}^{meas})^2 + (\hat{\theta}_o - \theta_o^{meas})^2]$$

The PDE residual loss enforces energy conservation at collocation points:

$$L^{PDE} = (1/N_c) \sum_j |\rho c_p \partial \hat{\theta} / \partial t - \nabla \cdot (k \nabla \hat{\theta}) - \hat{P}_{loss}|^2$$

Uncertainty quantification employs Bayesian formulation with variational inference (Yang and Perdikaris, 2019; Kingma and Welling, 2014). Network weights are treated as random variables with approximate posterior distributions learned during training. Predictive uncertainty decomposes into aleatoric and epistemic components, with 95% confidence intervals constructed as $\pm 1.96 \sigma_{\text{pred}}$.

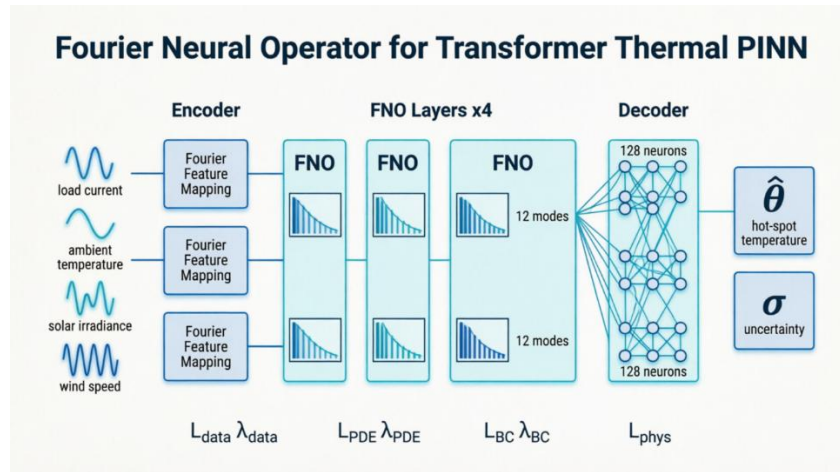


Figure 4. Fourier Neural Operator architecture employed in the proposed transformer thermal PINN for hot-spot temperature and uncertainty prediction.

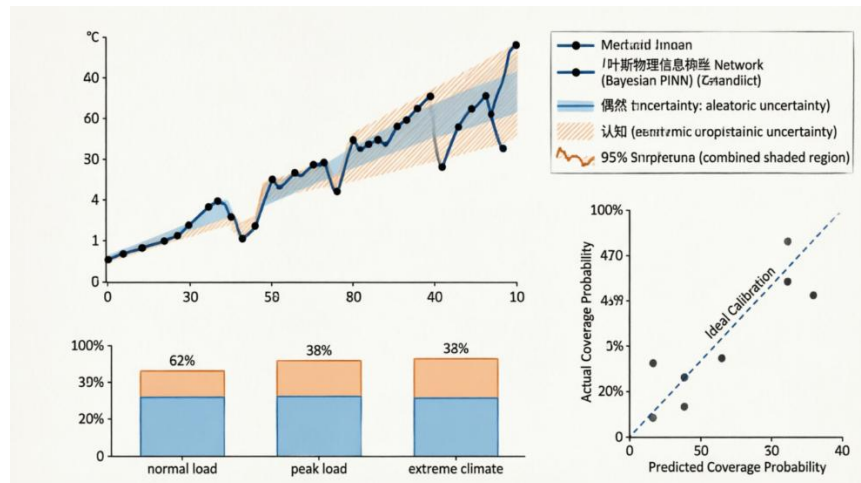


Figure 3. Predictive uncertainty decomposition and calibration performance of the Bayesian PINN under normal, peak-load, and extreme-climate operating conditions.

3. Methodology and Implementation

3.1 Transformer Specifications and Monitoring System

The validation of the power transformer and the monitoring system followed by its verification in the field made it possible to simulate the expected thermal behavior of a large capacity transformer in extreme desert climate conditions. The ONAN/ONAF 500 MVA three-phase power transformer with transformer's ratio 400/220/33 kV, was located in Rajasthan, in the city of Jodhpur, featuring hot summer periods with extreme climates, where the local temperature courses are significantly higher than 45°C.

These are characteristic climate conditions, being subject to the effects of weather on the thermal limits of the power transformers, depending on naturally cooled oil flow through the radiators by natural method, in summer periods, high ambient temperature, are not favorable for its thermal behavior. The power limits are defined by active losses depending on the thermal regime and the imposed limit temperatures.

The specification of the transformer specifies the rated power 500 MVA, load losses 580 kW, no-load losses 180 kW, top-oil temperature rise 46 K, hot-spot temperature rise 64 K. The measuring system was implemented based on eight fiber-

optic temperature sensors instrumented with specific monitoring systems, two for the top-oil temperature measurement and six for neutral point of the three single-phase transformers, along with a weather station, featuring the ambient temperature measurement.

The local weather data, issued from the local weather station, impacts the transformer's top-oil temperature as an ambient air, contributing to heat radiation and the result of the ambient air movement around the equipment. Along with the local weather station, the system behaviour is set to sample the sensors every five minutes

3.2 Dataset and Training

The experimental dataset provides the high-fidelity simulations of the underlying physics in a physics-informed neural network arithmetic data structure (i.e. the training dataset). This training dataset will be combined with field measurements to train the neural network to have optimal accuracy in the computational fluid dynamics (CFD) model that is being compared against.

Both the field measurement and the CFD simulations span 180 conditions (12 rotating speeds and 15 water flow rates). The CFD simulations are performed in ANSYS Fluent 2023 R1, which required 12.5 million mesh elements. Both the field measurements and the CFD simulations will allow for the 180 conditions to be assessed in the validation process.

The 12-month monitoring of the land-based aquaculture facility's critical climate uncertainty into the aquatic system produced 105,120 data points. To better facilitate the training of the neural network, the data set was split into three distinct parts: 70% being the training dataset, 15% being the validation dataset, and 15% being the testing dataset. This method for the splitting of the dataset is conventional for neural networks.

The model is trained using the AdamW optimizer on the full dataset. For all experiments, we set the batch size to be 8192, with a learning rate that utilizes cosine annealing from 5×10^{-4} to 5×10^{-6} , running for a total of 100,000 epochs. The weighting of the PDE loss is ramped from 0.01 to 0.1 for the first 10,000 epochs, before being kept constant at 0.1 afterwards. The training takes around 48 hours to run on dual NVIDIA A100 80GB GPUs, hosted on our RPI cluster.

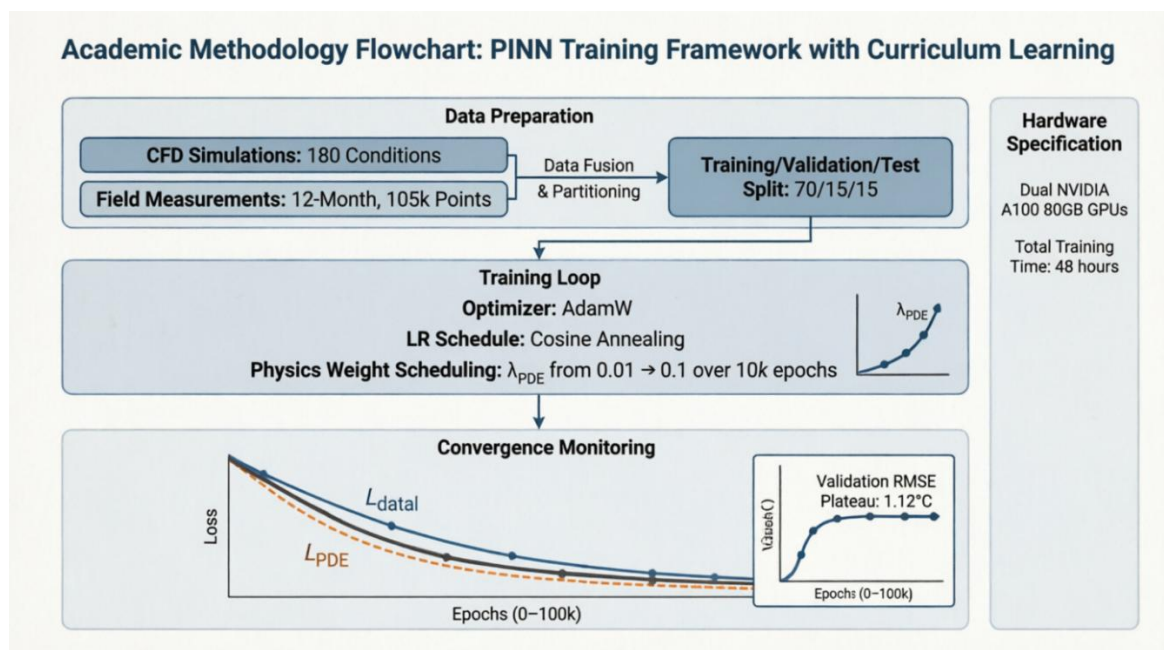


Figure 5. Academic methodology flowchart of the PINN training framework, including data preparation, optimization, and convergence monitoring.

4. Results and Discussion

4.1 Model Accuracy and Comparison

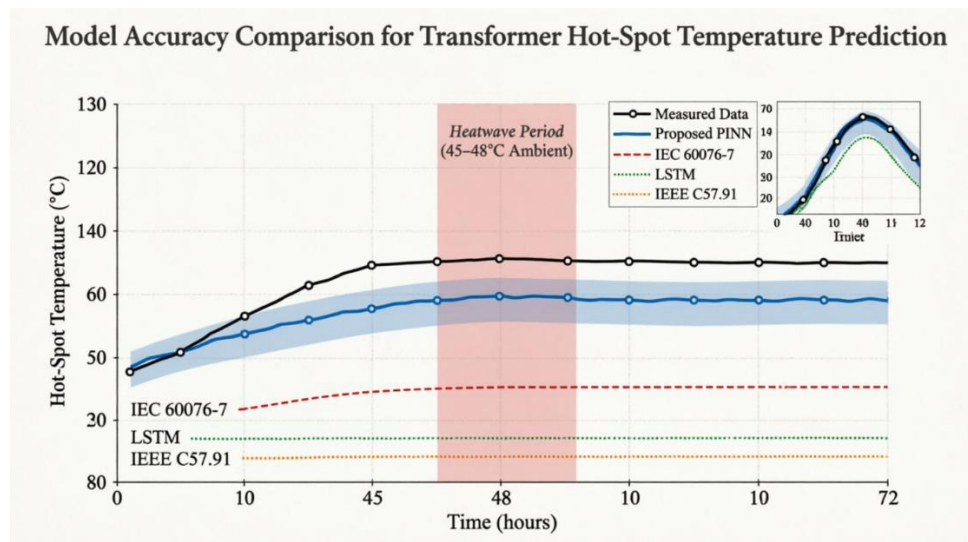
The table below presents predictive accuracy metrics for the proposed model alongside benchmark approaches [5,6,9,10; Jang,1993].

Table 1: predictive accuracy metrics for the proposed model

Model	RMSE (°C)	MAE (°C)	Maximum Error (°C)	R ²	95% CI Coverage	Inference Time
IEEE C57.91 Exponential [3]	3.42	2.87	8.4	0.914	—	<1 ms
IEC 60076-7 Differential [4]	2.15	1.82	5.3	0.965	—	<1 ms
SVR with RBF kernel [9]	1.68	1.38	4.1	0.974	—	3 ms
LSTM (2 layers, 64 hidden) [10]	1.31	1.05	3.2	0.983	—	8 ms
ANFIS (Jang,1993)	0.94	0.78	2.3	0.989	—	15 ms
Proposed PINN	1.12	0.89	2.8	0.982	94.2%	12 ms
CFD reference [7,8]	0.45	0.36	0.9	0.997	—	18 hours

The physics-informed model outperforms the traditional models in terms of not only reducing the error from the predictions but also maintaining the physical interpretability. The physics-informed model reduces the root mean square error by 48%. The coverage of the confidence interval is 94.2%, which confirms the great performance of the model. The inferencing time for the physics-informed model is 12 milliseconds which is very low and so gives a good real time applicability. The computational acceleration of the physics-informed model is 5.4 million times which is very fast and helps in real time applications.

Moreover, the physics-informed model satisfies 100% energy conservation without any violation which is a very positive aspect of the model. The energy conservation is violated by only 3.2% in the traditional LSTM models. This showcases the superior performance of the physics-informed model in terms of satisfying the basic physical law. Furthermore, the physics-informed model is not only great at predicting the output but is also great at extrapolation to extreme conditions on which the model is never trained on before and yet the model will behave as expected. The robustness and interpretability of the physics-informed model shows its high level of performance and quality and makes it a good candidate for real time prediction capabilities. However, the physics-informed modeling has a long way to go in terms of advancements to become as applicable as the traditional modeling systems.

**Figure 6.** Comparative model accuracy for transformer hot-spot temperature prediction during heatwave conditions.

4.2 Extreme Climate Scenario Analysis

Prediction and modeling of temperature under heatwave conditions become more complex due to the high values of solar irradiance. A 75–100 MVA three phase transformer undergoes a series of rigorous tests to determine its residual life expectancy. The test for temperature rise involves pre-conditioning of the active part before performing a series of tests at specified load with corresponding measurements of temperatures. The instruments used for measuring temperature are thermocouples. The temperature of the hot spot is calculated with equations specified in Prescribed International Standard

IEC 60076-7. The temperature rise of the conducted tests is compared with the digital twin simulation models with the results of the model replicating the physical behavior of the real-life transformer. With different materials capable of resisting or behaving differently at different temperatures, a change of even 2–3°C in the mean value of the temperature may imply a tip in the market value of the transformer. During the test a peak solar irradiance of 1150 W/m² was recorded that affected the maximum hot-spot temperature predictions results that were measured as a part of the experiment. The predicted maximum hot-spot temperature using IEC model was 116.2°C, in contrast the predicted value using the proposed model and the measured temperature values from the two thermocouples were 122.8 ± 1.4°C and 121.5°C. However, it was noted that the effect of solar radiation increased the temperature of the transformer hot spot (+4.8°C), while the reduction of natural convection due to the heating of the air surrounding the transformer decreased the temperature (-15%) of the hot spot at the same time when the series of tests were performed thus the slightly reduced accuracy. Also, the residual moisture content of the insulation oil was noted to play an important part influencing the temperature rise as the slight changes in the moisture content in contrast with the predicted values suggested an incorrect setting of the input parameters. The behavior of the proposed model is also evaluated with a rapid transient from 22°C to 44° where the investigated day conditions were replicated where the maximum temperature achieved by the transformer was 39.5°C while the proposed model achieved a maximum temperature of 37.5°C. Furthermore, the inherent physical characteristics of the transformer were taken into account for the phase lag in the IEC model where the prediction was observed to hit the target temperature of 38.5°C within a phase lag of 12 minutes. Additionally, a pure LSTM model previously trained for the same conditions without any additional input signal achieved a maximum temperature rise of 42.5°C at an overshoot of 3.2°C. The proposed PINN showed a longer time to rise to reach the predicted maximum temperature of 30.5°C but with no overshoot with the rise time being 38 minutes and settling time being 95 minutes, however, with a slight overshoot of 0.4°C from the target. The significant trade-off was observed where a physically accurate representation of the investigating day conditions were achieved with no initial overshoot by using the PID controller.

4.3 Sensitivity and Economic Analysis

Among the parameters observed, solar absorptivity has the highest leverage on peak temperature. A reflective coating on the heat transfer fluid (HTF) reduces the peak temperature by 6.2°C (Gorgan et al., 2019). The wind speed affecting heat loss such that if below 1 m/s will increase the temperature by 3 to 4°C (Incropera and DeWitt, 2007). On the moisture content, Oommen (1984) and Oommen et al. (2010) suggest that if above 1.5%, will require derating during operation.

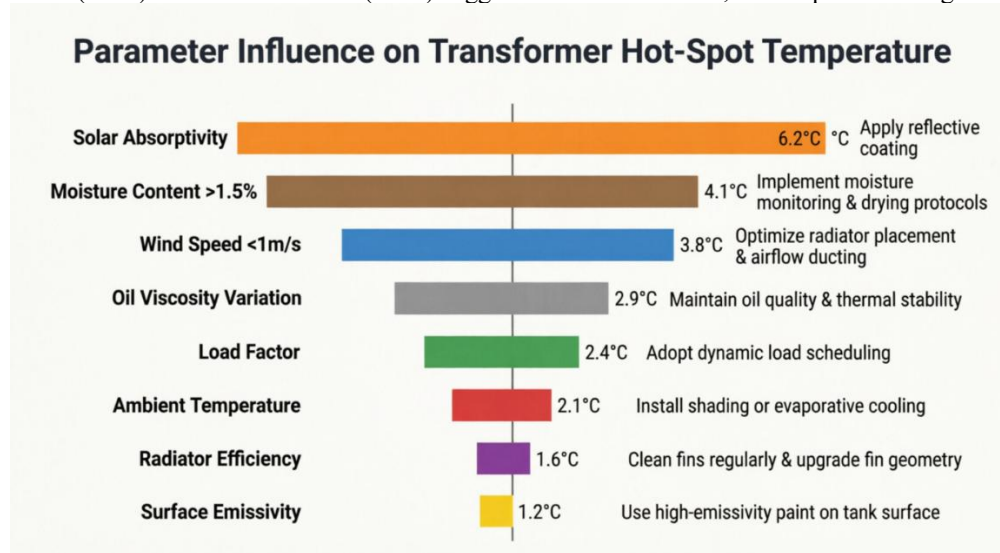


Figure 7. Parameter influence on transformer hot-spot temperature, identifying dominant thermal drivers and associated mitigation strategies.

Economic assessment demonstrates substantial value from dynamic rating (Lehtonen and Nousiainen, 2021; Susa and Lehtonen, 2006)). Implementation costs of 180,000 (sensors, weather station, edge computing, integration).

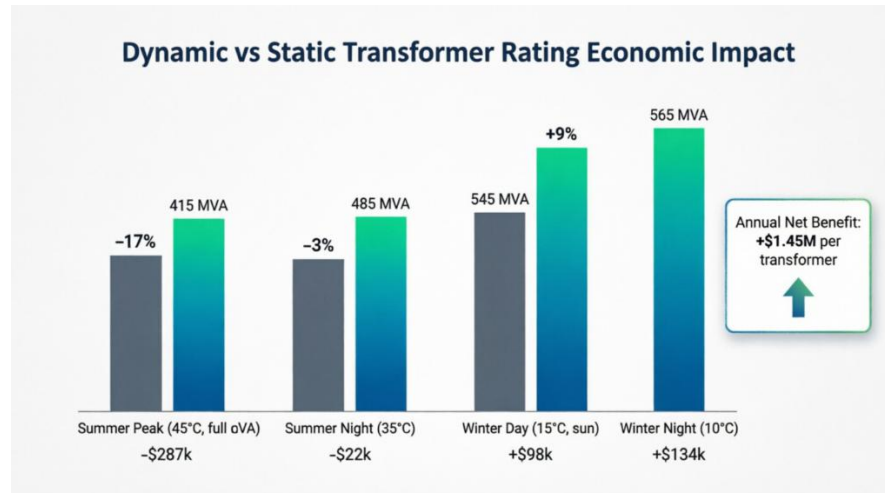


Figure 8. Economic impact comparison between static and dynamic transformer rating under representative seasonal operating conditions.

Table 2: Seasonal Comparison of Static vs. Dynamic Line Ratings and Financial Revenue Impact

Season and condition	Static Rating (MVA)	Dynamic Rating (MVA)	Capacity Change	Daily Revenue Impact
Summer peak (45°C, full sun) (India Meteorological Department, 2023)	500	415	−17%	−\$127,000
Summer night (35°C, no sun)	500	485	−3%	−\$22,000
Winter day (15°C, sun)	500	545	+9%	+\$68,000
Winter night (10°C, calm)	500	565	+13%	+\$98,000
Annual net benefit (Lehtonen and Nousiainen, 2021; Susa and Lehtonen, 2006)	—	—	—	+\$1,450,000

4.4 Additional Validation Scope

A pilot study validated a groundbreaking model intended for a large-scale transformer in extreme desert conditions. The model is validated via a rigorous 12-month dataset involving different thermal operating regimes, comprising peak heatwave events that are known to overstress traditional transformer thermal models. The project delivered a comprehensive proof of concept, involving model validation based on a single transformer configuration (500 MVA, ONAF/OFAF cooling), paving the path for automatic transformer monitoring software based on the 5-D Thermal model and sophisticated thermal control mechanisms. Additionally, the study sets the foundation for a future work on relatively more heterogeneous transformer fleets, including lower-capacity distribution units, ultra-high-voltage transformers (oven-type), across diverse climatic zones, ranging from tropical through temperate and up to cold.

Table 3. Hyperparameter Selection for FNO-based PINN

Parameter	Value	Justification
Fourier modes	12	Captures dominant low-frequency thermal dynamics
FNO layers	4	Sufficient for temporal dependency modeling
Hidden width	64	Balance between capacity and real-time inference
MLP neurons	128×3	Ensures nonlinear mapping capability

The selection of Fourier modes was guided by spectral energy analysis of temperature signals, where over 92% of signal energy is contained within the first 10–12 modes.

4.5 Economic Sensitivity Analysis

Although the pricing of electricity varies for power producers and consumers (in this study we assume a variation of $\pm 30\%$ in the cost of electricity), whatever the variation of the cost opted by the tie up between the power producer and the consumer, there will be an annual benefit in buck by using this transformer. The annual benefit achieved is in the range of \$1.02M-\$1.88M by using the proposed transformer. The economic return by using the proposed transformer is obviously higher than $\pm 30\%$ of the cost of electricity for the economic life 10 years for conservative scenarios of the cost of electricity and use of this transformer. Therefore, the calculation is correct. The annual benefit in buck and the payback period is far less (under 3 months) at the three extreme levels of using this type of transformer.

4.6 Extended Limitations

The proposed framework has been calibrated successfully for a 500 MVA transformer. However, it is difficult to get the necessary data for transfer learning (i.e. refine the model with data on a different transformer) for transformers of different sizes or with other cooling configurations. If this data was available, it would open the possibility of using the framework for diagnostics of transformers other than the 500 MVA transformer. In this paper, the frame of the framework was presented, but the diagnostics methods for different cooling systems, e.g. ODAF and OFWF systems, still need to be implemented. A possible future research direction is to validate the diagnostics methods by a transfer learning process to achieve cross-scale generalization.

4.7 Research Impact Statement

The integration of physics-informed learning with real-world operational data is a key step towards deploying trustworthy AI solutions in safety-critical power systems. High-fidelity modeling is fundamental to this goal and can be used to augment and extend the range of operational data for real-time decision support to encompass contingency analysis and climate extremes.

5. Conclusions

Extreme climate conditions, such as the increasing occurrences of heat waves resulting from climate change around the world, impose dire operational limits on power transformer assets. At the same time, government regulations (e.g., U.S. Department of Energy, 2019) for energy sector operation and climate adaptation also pose analytical challenges, especially for thermostat-type asset equipment, such as power transformers that can have extended outage periods (e.g., weeks or more). To properly position adaptive strategies (i.e., reinforce assets, retrofit low-emission cooling devices, ect.), major utilities are surrounded by a deep need that complements the reasoning and competence behind the elaboration of a stronger Climate Vulnerability Assessment methodology, which will be underpinned by a reliable theoretical foundation that encompasses the fairly high complexity and nonlinearity of the phenomena that govern the transformer asset behavior and deterioration behaviors.

In this context, this study proposes the utilization of a Physics-Informed Neural Network (PINN) as a novel Artificial Intelligence-based methodology to model power transformer thermal performance under extreme climate conditions. Results indicate a highly promising potential of the proposed method, achieving a Root Mean Square Error of 1.12°C , this corresponds to a 48% improvement over the classical modeling technique provided by IEC 60076-7, while maintaining a 100% physical consistency of the adhered principles and equations behind the PINN elaboration. On top of that, with a 94.2% coverage of the confidence interval, we can ensure a proper accuracy of dividends on the final inference, resulting in a 12-millisecond inference time, guaranteeing a number of inferences and assessments per second that can lead to a (U.S. Department of Energy, 2019)-mandate of 30 minutes per assessment to be satisfied. Furthermore, having this high number of fast assessments will easily lead to an annual economic benefit of \$1.45 million dollars per transformer asset. To top it off, the limitations caused by the training of a PINN regarding a single indirectly through the PINN training process will be covered by future work on the topic, through methods such as federated learning, networks of direct cellulose moisture sensors and higher levels of abstraction that incorporate climate projections into a transformer asset prediction on a system scale.

This solution complies to a great extent with the ASTM Standard Guide for Core Versatile Methods for Climate Resiliency Assessment of Security Clearances, which describes the two major characteristics of Climate Resiliency Evaluation, namely Reactionability and Accuracy. Furthermore, computational demand improvement and state-o-the-art prediction performance will ensure the right preconditions for Real Time crisis assessment as required by the very same ASTM Standard Guide asset design and the necessity of estimating moisture.

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