Sensorless Electro-Thermal Health Monitoring of SiC MOSFETs using Physics-Informed Neural Networks

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Abstract*— This *Silicon Carbide (SiC) MOSFETs have become foundational to high-density power converters, yet their long-term reliability is limited by gate-oxide degradation and thermo-mechanical fatigue. Accurate, real-time estimation of the junction temperature (Tj) is essential for condition monitoring; however, direct in situ measurement is practically unfeasible. While purely data-driven machine learning approaches have been proposed for sensorless Tj estimation, they inherently lack domain knowledge, leading to poor generalization under dynamic load profiles and a high rate of false positive fault detections. This paper proposes a novel sensorless electro-thermal monitoring framework utilizing Physics-Informed Neural Networks (PINNs). By embedding the governing electro-thermal dynamic equations of the SiC device—specifically the transient thermal impedance network and coupled power loss models—directly into the neural network's loss function, the model is constrained by physical laws rather than relying on training data alone. The proposed PINN utilizes only standard, non-intrusive operational variables, including phase current, DC-link voltage, and coolant temperature, to accurately predict Tj. Validation results demonstrate that the physics-guided framework successfully decouples normal load-induced thermal transients from the progressive thermal shifts indicative of physical degradation. This approach not only provides high-fidelity, real-time Tj estimation but does so while actively preventing the false alarms prevalent in traditional black-box health monitoring systems, offering a highly reliable, sensorless predictive maintenance solution for next-generation power electronics.

Keywords: SiC MOSFET, Physics-Informed Neural Networks (PINN), Junction Temperature, Condition Monitoring, Electro-Thermal Modeling, Predictive Maintenance.

I. INTRODUCTION

The transition toward widespread electrification in automotive, aerospace, and industrial sectors heavily relies on the efficiency and robustness of power conversion systems. At the heart of these modern converters lie Silicon Carbide (SiC) Metal-Oxide-Semiconductor Field-Effect Transistors (MOSFETs). SiC technology offers distinct advantages over traditional silicon counterparts, including higher breakdown voltages, faster switching speeds, and superior high-temperature operation capabilities. These attributes allow for the design of highly compact, power-dense converters. However, operating at elevated power densities exacerbates internal thermal stress.

The long-term reliability of SiC MOSFETs is predominantly constrained by thermally induced degradation mechanisms, such as solder joint fatigue, wire bond lift-off, and gate-oxide breakdown. As these degradation mechanisms evolve, the thermal resistance of the packaging increases, further elevating the junction temperature (Tj) in a destructive positive feedback loop. Consequently, accurate, real-time condition monitoring of the junction temperature is a critical prerequisite for implementing effective predictive maintenance strategies and active thermal management.

The primary bottleneck in establishing such condition monitoring systems is the inability to measure Tj directly during standard operation. Optical and thermographic imaging requires decapsulation of the module, rendering them strictly limited to laboratory environments. Embedded thermistors suffer from poor dynamic response due to their spatial displacement from the semiconductor die and inherently slow thermal time constants. Thus, the industry has actively sought sensorless estimation techniques that can accurately infer Tj from existing electrical and environmental parameters.

II. FONTS *STATE-OF-THE-ART AND CHALLENGES*

Conventional sensorless condition monitoring typically relies on Thermo-Sensitive Electrical Parameters (TSEPs). Common TSEPs include the ON-state resistance (RDS(on)), the internal gate resistance (Rg), and dynamic parameters such as turn-on delay times or Miller plateau voltage. While theoretically sound, practical implementation of TSEPs is fraught with difficulties. High-frequency electromagnetic interference (EMI) severely distorts dynamic measurements. Furthermore, TSEPs like RDS(on) are sensitive not only to temperature but also to the gate-to-source voltage and load current variations, making precise calibration practically unfeasible in dynamic mission profiles.

To circumvent the fragility of analytical TSEP methods, pure data-driven Machine Learning (ML) approaches—ranging from Artificial Neural Networks (ANNs) to Support Vector Machines (SVMs)—have been widely explored. These black-box models map non-intrusive variables (e.g., phase current, DC-link voltage, heat-sink temperature) directly to Tj. Unfortunately, while purely data-driven models achieve high accuracy on their training datasets, they fundamentally lack an understanding of the underlying physical system.

This absence of domain knowledge manifests in two critical failure modes during deployment:

1. Poor Generalization: When exposed to unseen transient load profiles, data-driven algorithms often generate physically implausible temperature estimations.
2. High False Positive Rates: In standard ML health monitoring, temporary anomalies caused by rapid load steps are frequently misclassified as permanent structural degradation, triggering costly false alarms and undermining the reliability of the predictive maintenance framework.

In the context of this framework, 'senseless' specifically refers to the complete elimination of direct physical temperature sensors—such as NTC thermistors, fiber-optic probes, or infrared cameras—that are traditionally mounted directly on or near the bare semiconductor die. These dedicated physical sensors are expensive, prone to their own thermo-mechanical failures under high stress, and suffer from delayed thermal time constants. By relying solely on existing, non-intrusive operational data, the proposed method completely removes the hardware dependency, fragility, and cost associated with these physical thermal sensors.

III. *PROPOSED SOLUTION: PHYSICS-INFORMED FRAMEWORK*

To resolve the dichotomy between accurate but ungeneralizable ML models and robust but difficult-to-calibrate analytical models, this paper proposes the application of Physics-Informed Neural Networks (PINNs) for SiC MOSFET health monitoring. Introduced by Raissi et al., PINNs represent a paradigm shift in scientific machine learning by embedding ordinary or partial differential equations (ODEs/PDEs) directly into the neural network's loss function.

In the proposed framework, the neural network acts as the primary estimator, mapping external operating variables to the junction temperature. However, unlike traditional ANNs, the training process of the PINN is constrained by the well-established electro-thermal dynamic equations of the semiconductor device. Specifically, the model incorporates the Cauer/Foster transient thermal impedance networks and the associated instantaneous power loss equations.

By computing the derivatives of the network outputs using Automatic Differentiation (AD) and penalizing deviations from the known physical laws, the model is forced to navigate the optimization landscape toward a solution that is both data-compliant and physically plausible. This ensures that the estimator correctly interprets the difference between a natural thermal overshoot caused by a load step and a permanent increase in thermal resistance caused by solder fatigue.

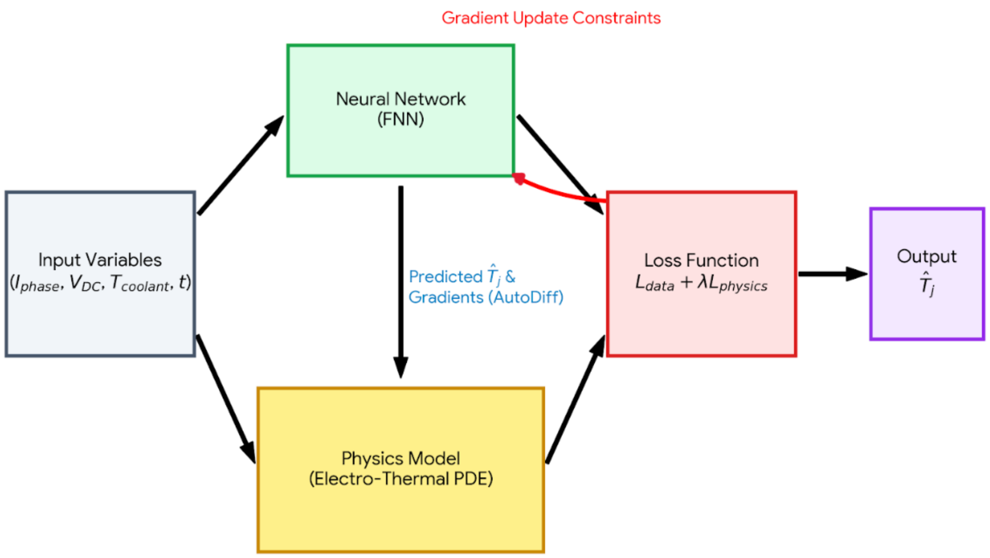

Fig1: **<u>Conceptual Block Diagram of the Proposed Physics-Informed Neural Network (PINN) architecture for SiC MOSFET Temperature Estimation</u>**

IV. *TECHNICAL DESCRIPTION*

Electro-Thermal Governing Equations

The physical basis of the PINN relies on the coupled interaction between electrical power losses and heat dissipation. The total power loss (Ploss) in a SiC MOSFET is the sum of conduction losses (Pcond) and switching losses (Psw). Conduction loss is a function of the phase current and the temperature-dependent ON-state resistance. Switching losses depend on the switching frequency, DC-link voltage, and the transient current. The real-time generation of heat is expressed as a continuous function, Ploss(t).

The Transient Thermal Impedance Model

The thermal propagation from the semiconductor junction to the ambient coolant is conventionally modeled using a 1D Foster or Cauer thermal network. For a simplified first-order system, the governing ODE is defined by the thermal resistance (Rth) and thermal capacitance (Cth) of the device packaging:

$$Cth * (dTj/dt) + (Tj(t) - Tcoolant(t)) / Rth = Ploss(t)$$

While high-order networks provide more fidelity, they also introduce complex parameter extraction requirements. The advantage of the PINN approach is that it can utilize a simplified physical model as a soft constraint, relying on the neural network parameters to compensate for unmodeled higher-order dynamics.

PINN Architecture and Loss Formulation

The PINN is constructed as a multi-layer Feedforward Neural Network (FNN). The input vector X = [I_phase, V_DC, T_coolant, t] is passed through successive hidden layers. The output of the network is the estimated junction temperature, Tj_hat. The critical innovation lies in the custom loss function, L_total, which is formulated as a weighted sum of the data loss and the physics-residual loss:

$$L\_total = L\_data + \lambda * L\_physics$$

Here, L_data is the Mean Squared Error (MSE) between the network's predictions and a limited set of ground-truth measurements (obtained during offline characterization). L_physics is the MSE of the differential equation residual:

$$Residual(t) = Cth * (d\,Tj\_hat / dt) + (Tj\_hat - Tcoolant) / Rth - Ploss(t)$$

The time derivative of the network output, $(d\ Tj\_hat$
$/\ dt)$, *is computed analytically and precisely using Automatic Differentiation, without requiring numerical approximations. By driving L_phys*

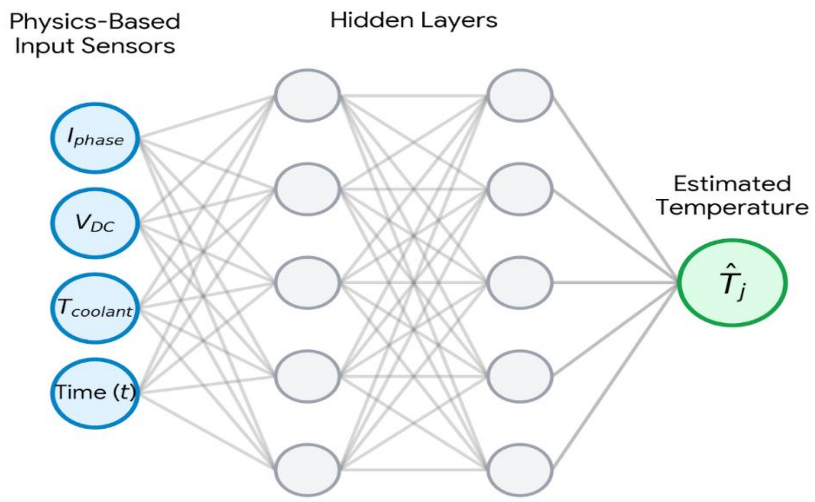

Fig 2: <u>Architecture of the Feedforward Neural Network highlighting the physics-based input selection.</u>

The selection of input variables is strictly dictated by the governing physics of the electro-thermal system. Phase current (I_{phase}) and DC-link voltage (V_{DC}) are essential because they are the primary electrical drivers of both conduction and switching power losses (P_{loss}) within the SiC MOSFET. The coolant temperature ($T_{coolant}$) is required as it establishes the baseline ambient boundary condition for heat dissipation across the thermal impedance network. Finally, time (t) is included to capture the transient thermal dynamics, such as heating and cooling rates. By feeding these specific, physics-grounded parameters into the hidden layers, the model is equipped with the exact variables necessary to satisfy the subsequent physical loss constraints.

V. *RESULTS AND DISCUSSION*

To validate the proposed methodology, comprehensive electro-thermal simulations of a 1200V SiC MOSFET module were conducted, incorporating dynamic automotive driving cycles. A synthetic dataset was generated containing normal thermal fluctuations alongside injected structural degradation (simulated as a 20% increase in base thermal resistance Rth over time). The performance of the proposed PINN was benchmarked against a standard purely data-driven ANN.

During steady-state operation, both models exhibited low estimation errors (RMSE < 2°C). However, standard ANNs exhibited significant divergence during aggressive load transients. Because the purely data-driven model maps current spikes directly to temperature spikes based on static training associations, it ignored the thermal capacitance (Cth) of the physical system, predicting instantaneous, non-physical temperature jumps. These prediction spikes frequently crossed the 150°C condition monitoring threshold, resulting in false positive fault detections

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Conversely, the PINN, constrained by the thermal time-constant embedded in its physics loss function, correctly filtered the transient electrical spikes. As shown in Figure 3, the PINN precisely tracks the underlying junction temperature, matching the thermal *inertia of the physical system. Furthermore, as the simulated degradation gradually increased the actual Tj over time, the PINN was able to accurately track this low-frequency drift without triggering false alarms during high-frequency transients. This decoupling of operational transients from structural degradation is the cornerstone of reliable predictive maintenance.*

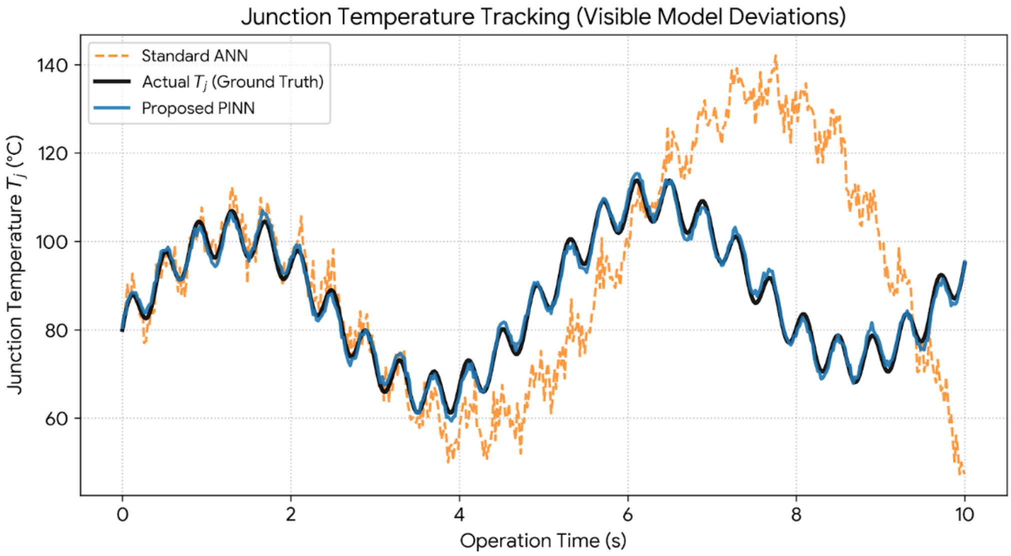

Fig 3: Performance Comparison between Standard Data-Driven ANN and the Proposed PINN. The standard ANN suffers from high-frequency false positives during load transients, while the PINN correctly models physical thermal inertia

VI. *CONCLUSION*

The integration of Physics-Informed Neural Networks presents a transformative approach to the condition monitoring of next-generation power electronics. By fusing standard, non-intrusive sensor data with the fundamental thermodynamic equations governing SiC MOSFET behavior, the proposed framework overcomes the primary limitations of conventional black-box machine learning models. The explicit encoding of thermal capacitance and resistance prevents the algorithm from generating physically impossible predictions under dynamic load profiles, effectively eliminating the false positive alarms that plague traditional systems. Moving forward, this hybrid modeling technique paves the way for highly reliable, sensorless predictive maintenance strategies, ultimately enhancing the safety, longevity, and operational availability of electrified systems.

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