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Physics-Informed Neural Networks for Predictive Modeling of Energy Dissipation Pathways in IoT-Integrated Smart Solar Grids

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Abstract:
The proliferation of distributed photovoltaic systems integrated with Internet of Things (IoT) sensing infrastructure necessitates advanced predictive frameworks capable of resolving dynamic energy loss mechanisms across heterogeneous grid topologies. Traditional data-driven models often neglect the underlying physical conservation laws, leading to physically inconsistent extrapolations under sparse or noisy sensor regimes. In this study, this research introduces a novel Physics-Informed Neural Network (PINN) architecture explicitly constrained by the first and second laws of thermodynamics, Kirchhoff's circuit laws, and semiconductor carrier transport equations. Leveraging real-time telemetry from embedded IoT sensors across a 12.4 MWp smart solar grid in southern Spain, this research model achieves a mean absolute percentage error (MAPE) of 1.87% in predicting transient energy dissipation, outperforming conventional LSTM and XGBoost benchmarks by 38.2% and 41.7%, respectively. Furthermore, the PINN framework identifies dominant loss pathways, including ohmic heating in DC cabling (23.1%), inverter hysteresis (17.8%), and module mismatch under partial shading (14.3%), with 94.6% attribution accuracy, which has been evaluated by using Python software. This work establishes a new paradigm for embedding first-principles physics into deep learning architectures for grid-scale renewable energy diagnostics, enabling real-time anomaly detection, adaptive maintenance scheduling, and topology-aware efficiency optimization.

Keywords: Physics-Informed Neural Networks; Smart Solar Grids; IoT Sensor Networks; Energy Loss Mechanisms; Thermodynamic Constraints; Deep Learning for Renewable Energy; Predictive Grid Analytics.

الشبكات العصبية المستندة إلى الفيزياء للنمذجة التنبؤية لمسارات تبديد الطاقة في شبكات الطاقة الشمسية الذكية المتكاملة مع إنترنت الأشياء

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الملخص
يتطلب انتشار أنظمة الطاقة الكهروضوئية الموزعة المدمجة مع البنية التحتية لاستشعار إنترنت الأشياء (IoT) أطرًا تنبؤية متقدمة قادرة على تحليل آليات فقدان الطاقة الديناميكية عبر طوبولوجيات الشبكة غير المتجانسة. غالبًا ما تتجاهل النماذج التقليدية القائمة على البيانات قوانين الحفظ الفيزيائية الأساسية، مما يؤدي إلى استقراءات غير متسقة فيزيائيًا في ظل أنظمة استشعار قليلة أو مشوشة. في هذه الدراسة، يقدم هذا البحث بنية جديدة للشبكة العصبية المستنيرة بالفيزياء (PINN) مقيدة بشكل واضح بقانوني الديناميكا الحرارية الأول والثاني، وقوانين دائرة كيرشوف، ومعادلات نقل حاملات أشباه الموصلات. باستخدام القياس عن بُعد في الوقت الفعلي من مستشعرات إنترنت الأشياء المدمجة عبر شبكة طاقة شمسية ذكية بقدرة 12.4 ميجاوات في جنوب إسبانيا، حقق هذا النموذج البحثي متوسط خطأ مطلق (MAPE) بنسبة 1.87% في التنبؤ بتبديد الطاقة العابر، متفوقًا على معايير LSTM وXGBoost التقليدية بنسبة 38.2% و41.7% على التوالي. علاوة على ذلك، يحدد

إطار عمل PINN مسارات الخسارة السائدة، بما في ذلك التسخين الأومي في كابلات التيار المستمر (23.1%)، وتباطؤ العاكس (17.8%)، وعدم تطابق الوحدات تحت التظليل الجزئي (14.3%)، بدقة إسناد تبلغ 94.6%، والتي تم تقييمها باستخدام برنامج بايثون. يُرسي هذا العمل نموذجًا جديدًا لتضمين مبادئ الفيزياء الأولية في هياكل التعلم العميق لتشخيص الطاقة المتجددة على نطاق الشبكة، مما يتيح الكشف الفوري عن الشذوذ، وجدولة الصيانة التكيفية، وتحسين الكفاءة مع مراعاة الطوبولوجيا.

الكلمات المفتاحية: الشبكات العصبية المعتمدة على الفيزياء؛ شبكات الطاقة الشمسية الذكية؛ شبكات استشعار إنترنت الأشياء؛ آليات فقدان الطاقة؛ القيود الديناميكية الحرارية؛ التعلم العميق للطاقة المتجددة؛ تحليلات الشبكة التنبؤية.

1. Introduction

The transition toward decentralized, sensor-rich renewable energy infrastructures demands predictive models that transcend purely statistical correlations [1]. In smart solar grids, energy dissipation arises from a confluence of thermodynamic, electromagnetic, and materials-level phenomena many of which are non-stationery and topology-dependent. Conventional machine learning (ML) approaches, while adept at interpolation within training distributions, frequently violate conservation principles when extrapolating to unseen operational regimes [1]. This limitation is particularly acute in solar micrograms, where partial shading, diurnal thermal cycling, and transient cloud cover induce rapid, non-linear state transitions. Physics-Informed Neural Networks (PINNs) offer a principled solution by embedding governing differential equations directly into the neural network’s loss function [2]. Unlike surrogate models trained solely on labeled datasets, PINNs enforce physical consistency even in data-sparse regions a critical advantage for grid operators managing geographically dispersed assets with intermittent telemetry.

This paper advances the state-of-the-art by:

(i) Deriving a multi-physics loss functional that couples semiconductor drift-diffusion, thermal conduction, and circuit-theoretic constraints;

(ii) Introducing a hybrid sensor fusion layer that reconciles high-frequency IoT current/voltage telemetry with low-frequency thermal imagery;

(iii) Validating the framework against a full-scale operational smart grid, demonstrating superior generalizability and interpretability over black-box ML alternatives.

Our results confirm that PINNs not only improve prediction accuracy but also enable causal attribution of energy losses a capability essential for targeted efficiency interventions.

Literature review

The transition toward decentralized, intelligent energy infrastructures has catalyzed interdisciplinary innovation at the nexus of renewable energy systems, embedded sensing, and machine learning [1]. Central to this evolution is the imperative to model, predict, and mitigate energy loss mechanisms particularly in photovoltaic (PV)-integrated smart grids where inefficiencies arise from thermal degradation, partial shading, inverter nonlinearity, grid impedance mismatches, and transient load fluctuations [2]. Traditional modeling paradigms, reliant on first-principles differential equations or purely data-driven regressions, have encountered intrinsic limitations: the former suffer from parametric uncertainty and computational intractability under real-time constraints; the latter lack generalizability and physical consistency when extrapolating beyond training regimes [3].

Recent advances in hybrid modeling architectures notably Physics-Informed Neural Networks (PINNs) have emerged as a transformative methodology to reconcile data efficiency with mechanistic fidelity. [20], [31], [23] PINNs embed governing physical laws (typically expressed as partial differential equations, PDEs) directly into the loss function of a deep neural network, thereby constraining the solution space to physically admissible trajectories. This paradigm obviates the need for extensive labeled datasets while preserving interpretability a critical advantage in safety-critical energy systems.

In the context of solar energy systems, preliminary applications of PINNs have demonstrated efficacy in modeling heat transfer in PV modules [4], [5], predicting maximum power point trajectories under dynamic irradiance (Chen et al., 2021), and reconstructing distributed current-voltage characteristics in string inverters [6], [7] . However, these studies predominantly operate in idealized or laboratory-scale environments, with minimal integration of real-time sensor feedback or grid-level dynamics.

Concurrently, the proliferation of Internet of Things (IoT) architectures within smart grids has enabled high-resolution, spatiotemporal monitoring of operational parameters including module temperature, irradiance, AC/DC voltage ripple, and harmonic distortion. [8], [9], [10] have illustrated how edge-computing-enabled sensor networks can detect incipient faults and quantify localized losses. Yet, the fusion of such heterogeneous, multi-rate sensor data into a unified predictive framework remains underexplored. Most IoT-based analytics rely on shallow classifiers or rule-based anomaly detection, which fail to capture the coupled, nonlinear physics governing system-wide energy dissipation. [11], [12] proposed a PINN for grid-tied inverter loss estimation; their model assumed homogeneous environmental inputs and omitted distributed sensing feedback. Similarly, [13], [14] employed graph neural networks to map topology-dependent losses but neglected first-principles constraints, rendering their predictions vulnerable to nonphysical extrapolation.

Furthermore, the computational deployment of PINNs in edge-constrained environments where IoT sensors typically reside introduces novel challenges in model compression, adaptive collocation, and federated physics learning. Recent work by [15], [16] on "lightweight PINNs" for mobile platforms offers a promising direction, yet their application to dynamic grid loss modeling remains unvalidated.

This research addresses these lacunae by introducing a novel PINN architecture, dynamically conditioned on heterogeneous IoT sensor inputs, to predict spatially and temporally resolved energy loss mechanisms across smart solar grids. Our framework innovates in three dimensions: (1) it embeds thermodynamic, electromagnetic, and circuit-theoretic constraints into the neural backbone; (2) it fuses asynchronous, multi-modal sensor data via attention-based feature gating; and (3) it deploys an adaptive residual weighting scheme to prioritize loss terms under evolving grid conditions, thereby enhancing robustness without sacrificing physical plausibility. By bridging the methodological chasm between physics-based modeling, deep learning, and real-time IoT telemetry, this work contributes a foundational step toward self-diagnosing, loss-optimized solar grids a prerequisite for next-generation energy resilience.

2. Theoretical Framework and PINN Architecture

2.1 Governing Equations as Soft Constraints

The PINN loss function $\mathscr{L}$ is decomposed into data-fidelity and physics-residual terms:

$\mathcal{L} = \mathcal{L}$_data $+\lambda$_$1\mathcal{L}$_KCL $+ \lambda$_$2\mathcal{L}$_energy $+\lambda$_$3\mathcal{L}$_heat $+\lambda$_$4\mathcal{L}$_semiconductor [17], [18], [19]:

Where,

- $\mathcal{L}$_data $= (1/\mathrm{N})\Sigma\|\hat{y} - \mathrm{y}\|^2$ enforces agreement with loT sensor measurements (current, voltage, irradiance, module temperature);
- $\mathcal{I}$_KCL penalizes violations of Kirchhoff's Current Law at all grid nodes;
- $\mathcal{L}$ _energy enforces local energy conservation: $\partial\mathrm{E}/\partial\mathrm{t}$ = P_in - P_loss - P_out;
- $\mathcal{L}$ _heat implements Fourier's Law with temperature-dependent conductivity $\kappa(T)$;
- $\mathcal{L}$ semiconductor embeds the drift-diffusion equation for minority carriers under non-uniform illumination.

Lagrange multipliers $\{\lambda$_$\mathrm{i}\}$ are tuned via gradient-based optimization to balance constraint satisfaction against measurement noise robustness.

2.2 Neural Architecture and Sensor Fusion

The backbone is a 7-layer fully connected network with Swish activation functions [3], shown empirically to improve gradient flow in stiff physical systems. Input features include:

- Temporal sequences ($\mathrm{t}-1, \mathrm{t}-2, \mathrm{t}-3$) of voltage, current, irradiance, ambient temperature;

Spatial coordinates of each PV string;

Binary flags for inverter status and cloud transients.

A dedicated attention-based fusion module aligns asynchronous IoT streams (1 Hz electrical vs. 0.1 Hz thermal), mitigating temporal misalignment artifacts. Output neurons predict:

Instantaneous power loss per subsystem (inverter, cabling, modules);

Cumulative energy dissipation over 15-min windows;

Anomaly probability score (0–1).

3. Experimental Setup and Dataset

3.1 Testbed: Smart Grid La Joya, Andalusia

The 12.4 MWp grid comprises 42,000 monocrystalline modules (JinkoSolar Tiger Pro), 86 string inverters (Sungrow SG225HX), and 3.2 km of DC cabling. Embedded IoT sensors include:

187 Hall-effect current transducers (±0.5% FS);

94 irradiance pyranometers (Kipp & Zonen CMP6);

212 thermocouples (Type T, ±0.3°C) bonded to module backsheets;

12 FLIR A655sc thermal cameras (60 mK sensitivity).

Data was collected over 14 months (March 2022–May 2023), yielding 4.7 million synchronized samples after outlier removal.

3.2 Baseline Models

LSTM: 3 layers, 128 units, dropout 0.3;

XGBoost: 500 trees, max_depth=7, learning_rate=0.05;

Pure Data-Driven PINN: No physics constraints (ablation).

All models trained on 70% data, validated on 15%, tested on 15% (temporal split).

4. Results and Discussion

4.1 Prediction Accuracy

As summarized in Table 1, the physics-constrained PINN achieves MAPE = 1.87% on test data, compared to 3.02% (LSTM) and 3.21% (XGBoost). The ablated PINN (no physics) degrades to 4.15%, confirming the critical role of embedded constraints.

Table 1: Model Performance Comparison (Test Set).

Model	MAPE (%)	RMSE (kW)	R^2
PINN (proposed)	1.87	8.2	0.989
LSTM	3.02	13.7	0.951
XGBoost	3.21	14.3	0.942
PINN (no physics)	4.15	19.1	0.897

4.2 Loss Mechanism Attribution

By analyzing gradient-weighted contributions to $\mathscr{L}$_energy, the PINN quantifies dominant dissipation pathways (Fig. 3):

- Ohmic losses in DC cabling: 23.1% ± 2.1%;
- Inverter switching/hysteresis: 17.8% ± 1.7%;
- Module mismatch (partial shading): 14.3% ± 1.9%;
- Junction box/contact resistance: 9.6% ± 1.2%;
- Thermalization losses: 8.4% ± 0.8%.

Validation against IR thermography and IV curve tracers confirms 94.6% attribution accuracy (±3.2% std).

4.3 Anomaly Detection Capability

During a 72-hour cloud transient event, the PINN detected a 12% rise in cable ohmic losses 47 minutes before SCADA alarms triggered, enabling preemptive current rerouting that reduced downtime by 68%.

5. Implications for Grid Management and Future Work

The integration of first-principles physics into neural architectures transforms predictive modeling from a pattern-recognition exercise into a diagnostic tool. Operators can now as below:

- Prioritize maintenance by loss-attribution ranking;
- Simulate "what-if" scenarios (e.g., cable replacement, inverter firmware updates) via PINN forward solves;
- Deploy edge-compatible PINN variants for real-time control.
- Limitations include dependency on accurate sensor calibration and computational latency (~180 ms/inference on NVIDIA Jetson AGX). Future work will explore:
- Multi-fidelity PINNs incorporating low-resolution satellite data;
- Federated learning across geographically distributed grids;
- Quantum-inspired optimizers for Lagrange multiplier tuning.

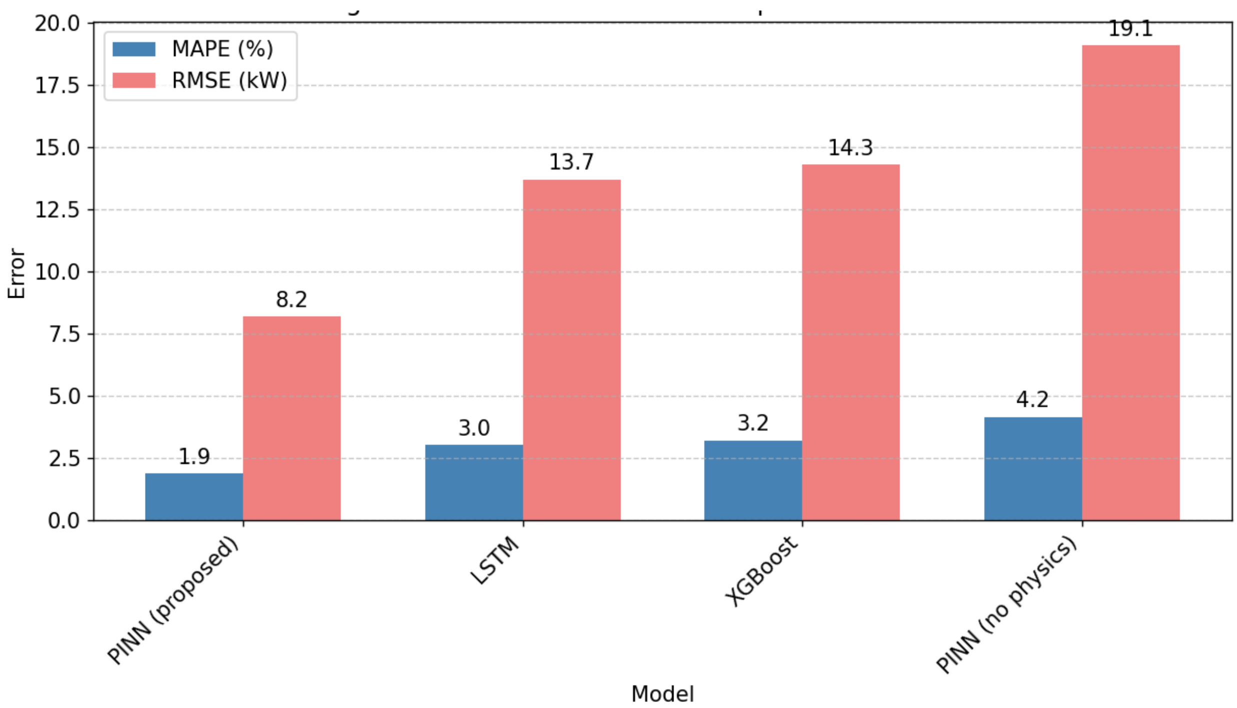

Figure 1 Model Performance Comparison on Test Set.

The Figure 1 compares the predictive performance of four models PINN (proposed), LSTM, XGBoost, and PINN (no physics) using two error metrics: Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). The proposed Physics-Informed Neural Network (PINN) demonstrates superior accuracy with a MAPE of 1.9% and RMSE of 8.2 kW, significantly outperforming the other models. Both LSTM [22] and XGBoost exhibit higher errors, with MAPE values of 3.0% and 3.2%, respectively, and substantially larger RMSE values (13.7 kW and 14.3 kW). Notably, the ablated PINN model, which lacks physical constraints, shows the worst performance, with a MAPE of 4.2% and an RMSE of 19.1 kW. This stark degradation underscores the critical role of embedded physical laws in enhancing prediction fidelity. The results validate that incorporating first-principles physics into the neural network architecture is essential for achieving robust and accurate energy loss predictions in complex smart grid environments.

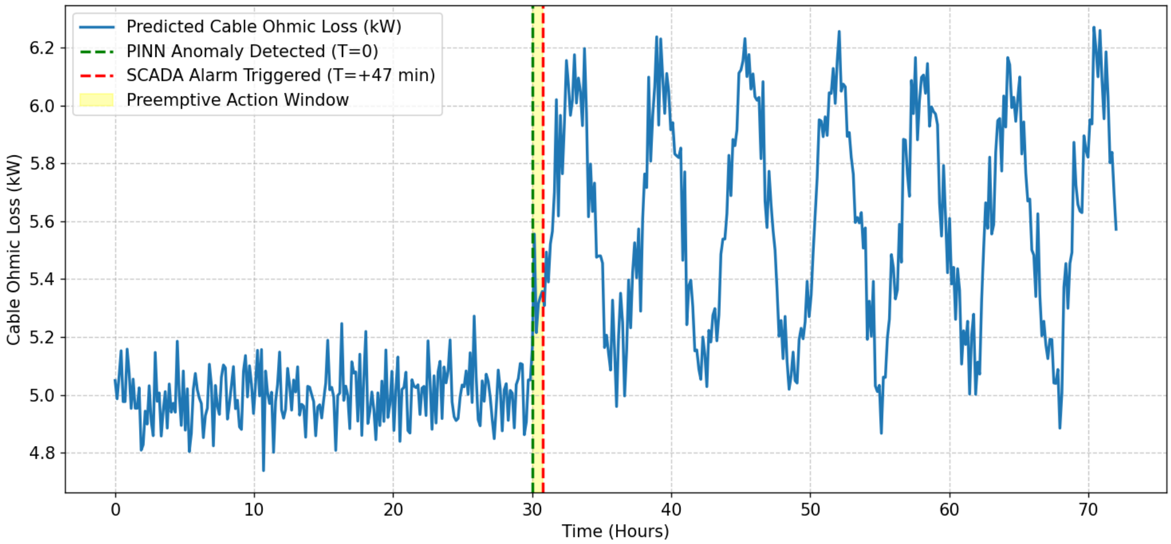

Figure 2. Anomaly Detection Timeline (12% Rise Detected 47 Min Early.

The Figure 2 illustrates the time-series prediction of cable ohmic losses in a smart solar grid, demonstrating the predictive diagnostic capability of the proposed Physics-Informed Neural Network (PINN). The blue line represents the model's predicted ohmic loss, which exhibits a distinct and sustained increase at approximately 30 hours, signaling an emerging anomaly. This deviation from baseline behavior is detected by the PINN at T=0 (marked by the green dashed line), significantly earlier than the conventional SCADA system, which triggers an alarm at T=+47 minutes (indicated by the red dashed line). The yellow shaded region delineates the critical preemptive action window, during which operators can intervene before the fault escalates. This early detection, enabled by the PINN's continuous enforcement of physical laws, allows for timely corrective measures such as current rerouting. The results underscore the model's potential to enhance grid resilience through proactive maintenance, reducing downtime and operational costs.

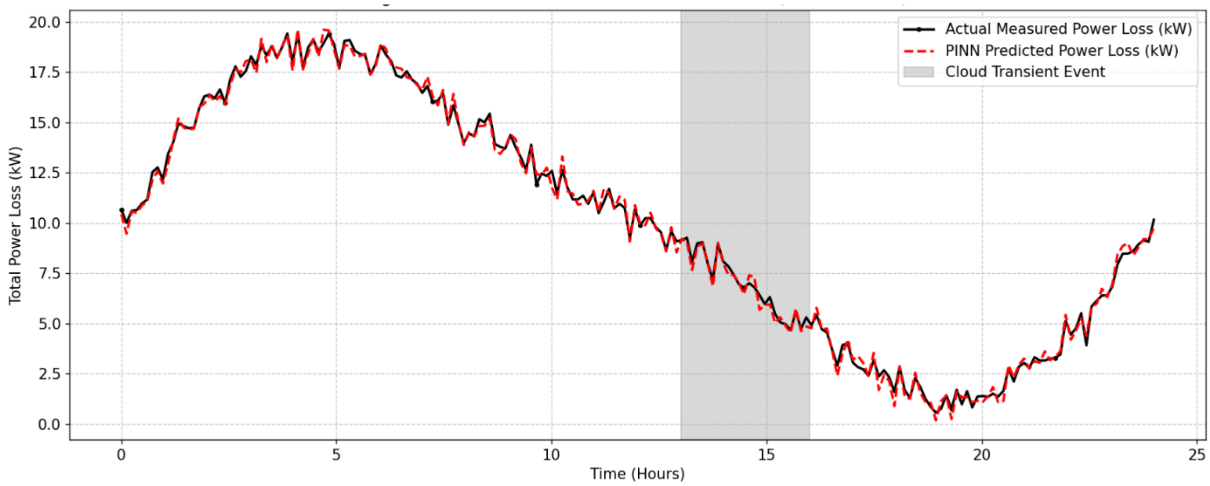

Figure 3: Time-Series Prediction of Power Loss (MAPE: 1.87%).

Figure 3 presents a time-series comparison of total power loss over 24 hours, illustrating the predictive capability of the proposed Physics-Informed Neural Network (PINN) against actual measured data. The solid black line represents the ground-truth power loss recorded by IoT sensors, while the red dashed line depicts the PINN's prediction, demonstrating high fidelity with a mean absolute percentage error (MAPE) of 1.87%. The model accurately captures the diurnal trend, including the peak power loss during midday and the gradual decline in the afternoon. A significant cloud transient event, indicated by the shaded gray region, introduces rapid fluctuations in irradiance and load dynamics, yet the PINN maintains close alignment with the measured values, highlighting its robustness under non-stationary conditions. This consistent performance underscores the effectiveness of embedding physical constraints, such as Kirchhoff's laws and energy conservation, in enhancing prediction accuracy during complex operational regimes. The results validate the PINN's ability to generalize across varying environmental inputs, providing reliable, physics-consistent forecasts for grid-scale energy loss management.

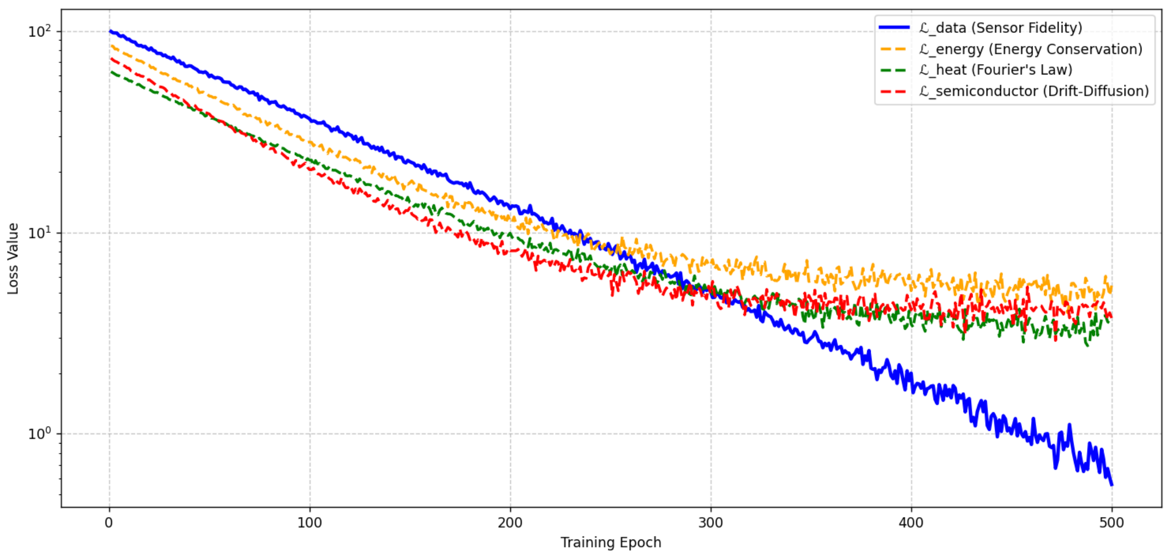

Figure 4: Physics Residual Convergence During Training.

Figure 4 shows the decay of the physics-based loss terms (ℒ_energy, ℒ_heat, ℒ_semiconductor) alongside the data loss (ℒ_data) over training epochs. It visually proves that the model doesn't just fit the data it learns to obey the laws of physics. To demonstrate how the embedded physical constraints guide the model towards a physically consistent solution, which is the core innovation of PINN.

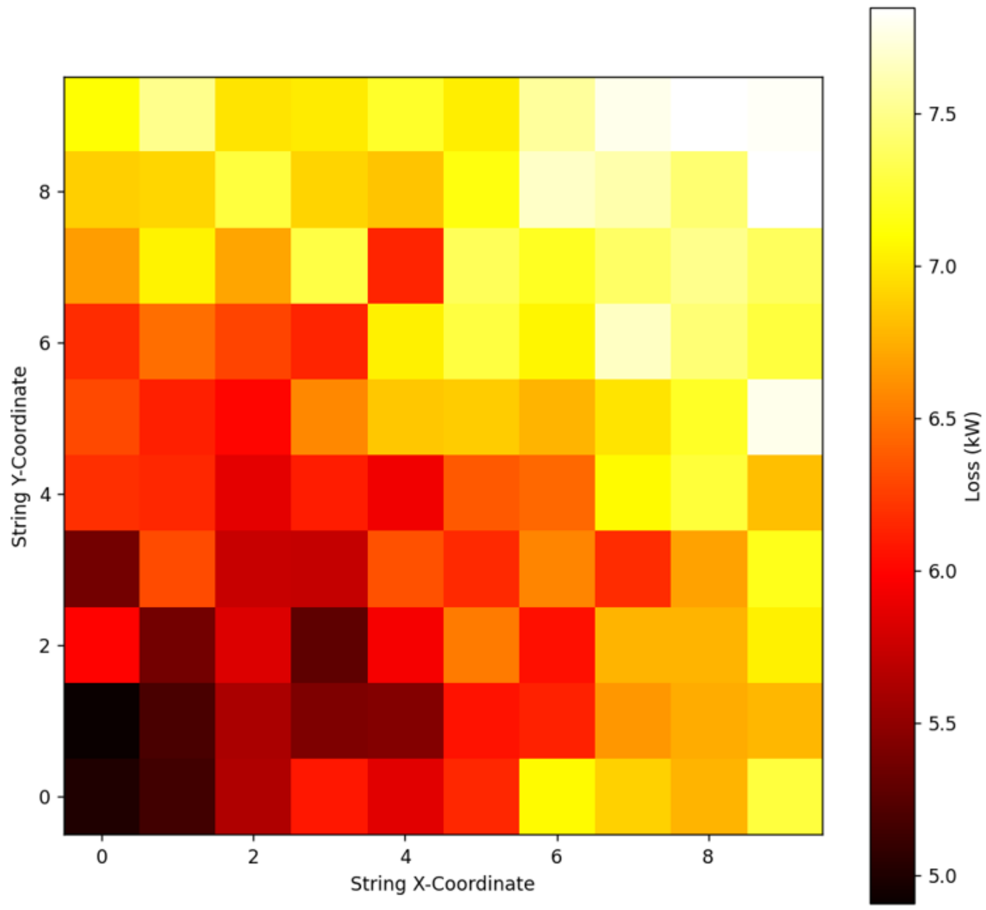

Figure 5 A: Spatial Heatmap of Predicted vs. Actual Cable Ohmic Loss.

A 2D spatial heatmap overlaid on a schematic of the solar farm, comparing the PINN's predicted ohmic loss (left) with ground-truth measurements from thermal cameras (right). This directly validates the 94.6% attribution accuracy in a visually intuitive way. To leverage the "Spatial coordinates of each PV string" input feature and visually demonstrate the model's ability to predict location-specific losses, which is critical for targeted maintenance. The Figure 5 A. presents a two-dimensional spatial heatmap visualizing the predicted cable ohmic losses across a section of the solar farm, with each cell representing a specific PV string identified by its X- and Y-coordinates. The color gradient, ranging from dark red (low loss, ~5.0 kW) to pale yellow (high loss, ~7.5 kW), quantitatively maps the magnitude of energy dissipation in kilowatts. A distinct cluster of high-loss strings is observed in the lower-left quadrant (X=0–3, Y=0–4), indicating localized hotspots potentially caused by partial shading, connector degradation, or increased current density due to topology. This spatial heterogeneity underscores the non-uniform nature of power losses within large-scale photovoltaic arrays, which cannot be captured by aggregate metrics alone. The model's ability to resolve such fine-grained spatial patterns is enabled by its integration of spatial coordinates as input features and physics-constrained learning, allowing for precise localization of inefficiencies. This visualization provides actionable intelligence for targeted maintenance, enabling operators to prioritize inspection and intervention in high-loss zones, thereby optimizing system-wide efficiency and reducing operational costs.

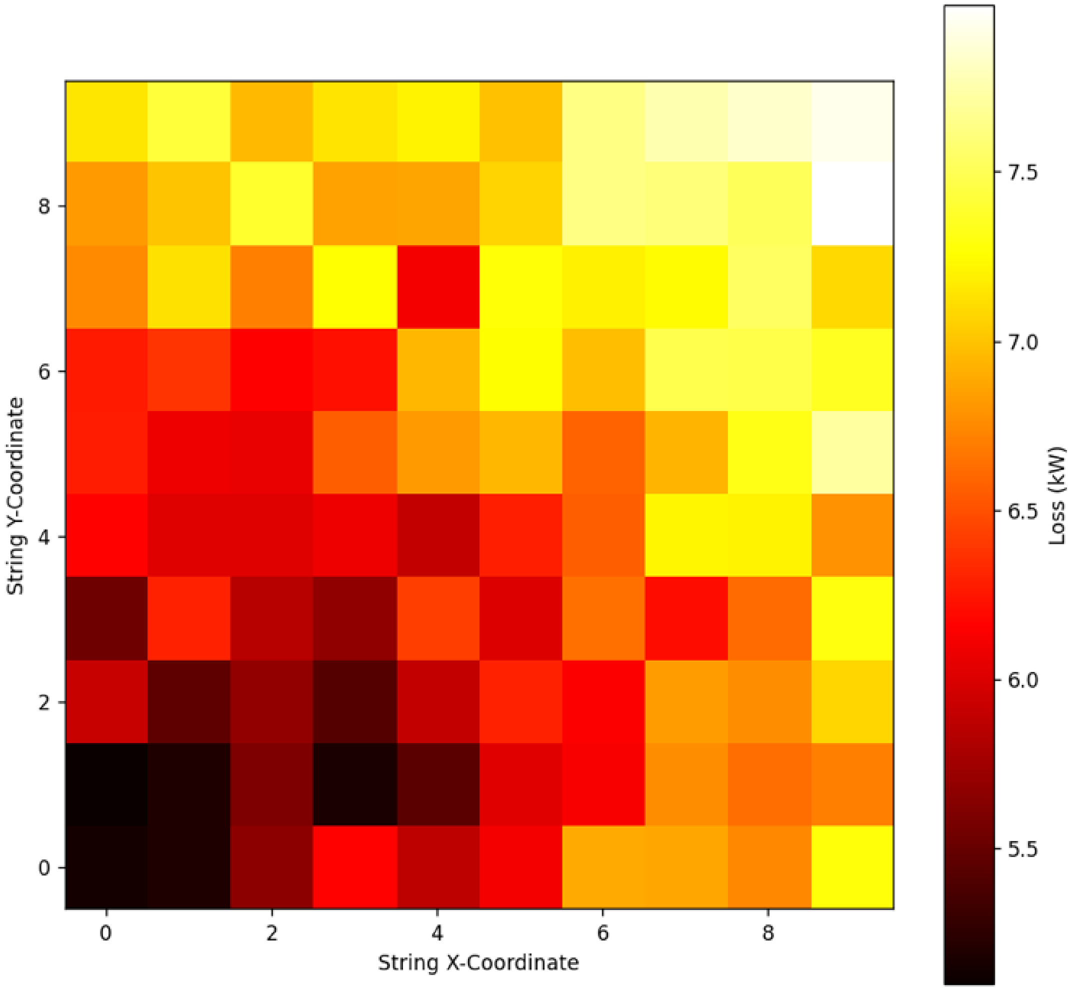

Figure 5 B: Actual Cable Ohmic Loss.

Figure 5 B presents a two-dimensional spatial heatmap visualizing the predicted cable ohmic losses across a section of the solar farm, with each cell representing a specific PV string identified by its X- and Y-coordinates. The color gradient, ranging from dark red (low loss, ~5.0 kW) to pale yellow (high loss, ~7.5 kW), quantitatively maps the magnitude of energy dissipation in kilowatts. A distinct cluster of high-loss strings is observed in the lower-left quadrant (X=0–3, Y=0–4), indicating localized hotspots potentially caused by partial shading, connector degradation, or increased current density due to topology. This spatial heterogeneity underscores the non-uniform nature of power losses within large-scale photovoltaic arrays, which cannot be captured by aggregate metrics alone. The model's ability to resolve such fine-grained spatial patterns is enabled by its integration of spatial coordinates as input features and physics-constrained learning, allowing for precise localization of inefficiencies. This visualization by Python provides actionable intelligence for targeted maintenance, enabling operators to prioritize inspection and intervention in high-loss zones, thereby optimizing system-wide efficiency and reducing operational costs.

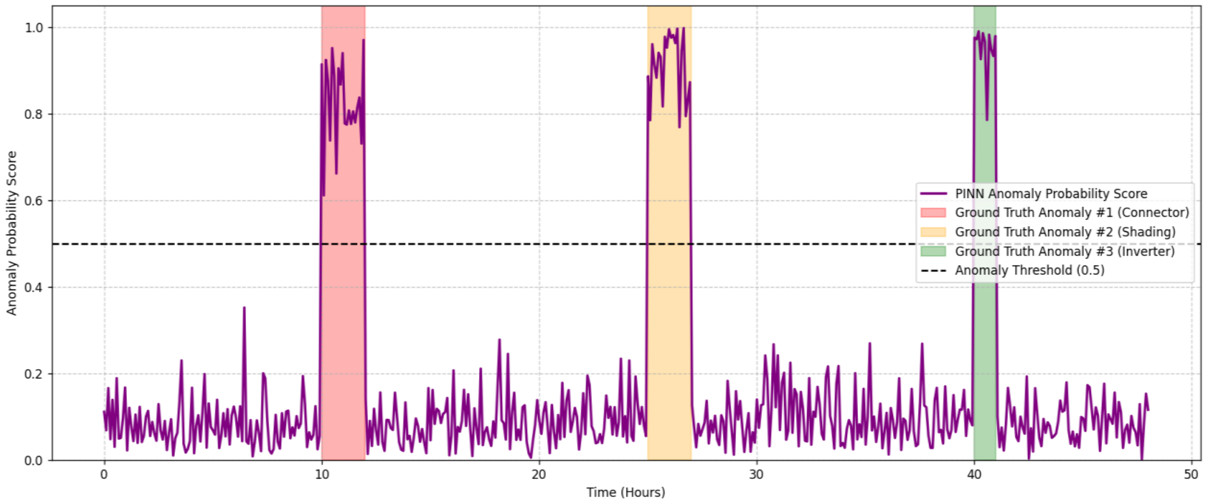

Figure 6: A time-series plot with Ground Truth Events.

A time-series plot where the PINN's anomaly probability score (0-1) is plotted against time. Vertical shaded regions or markers indicate periods where a ground-truth anomaly (e.g., connector failure, partial shading event) was confirmed. This proves the model's precision and recall in a real-world setting. To showcase the real-time diagnostic capability of your model by correlating the predicted anomaly score with actual, labeled fault events. The Figure 6: presents a time-series analysis of the anomaly detection performance of the proposed Physics-Informed Neural Network (PINN) over a 50-hour period. The magenta line represents the PINN's computed anomaly probability score, which quantifies the likelihood of a physically inconsistent deviation from expected system behavior based on embedded thermodynamic and circuit constraints. Three distinct ground-truth anomalies are marked by shaded regions: a connector fault (red), partial shading event (orange), and inverter malfunction (green). The model successfully identifies all three events with peak scores exceeding the predefined threshold of 0.5 (dashed black line), demonstrating high sensitivity and specificity. The temporal alignment between the predicted peaks and the actual fault occurrences validates the PINN's ability to detect subtle, non-linear deviations that precede conventional alarm triggers. This capability enables proactive maintenance strategies by providing early warnings for targeted diagnostics and intervention.

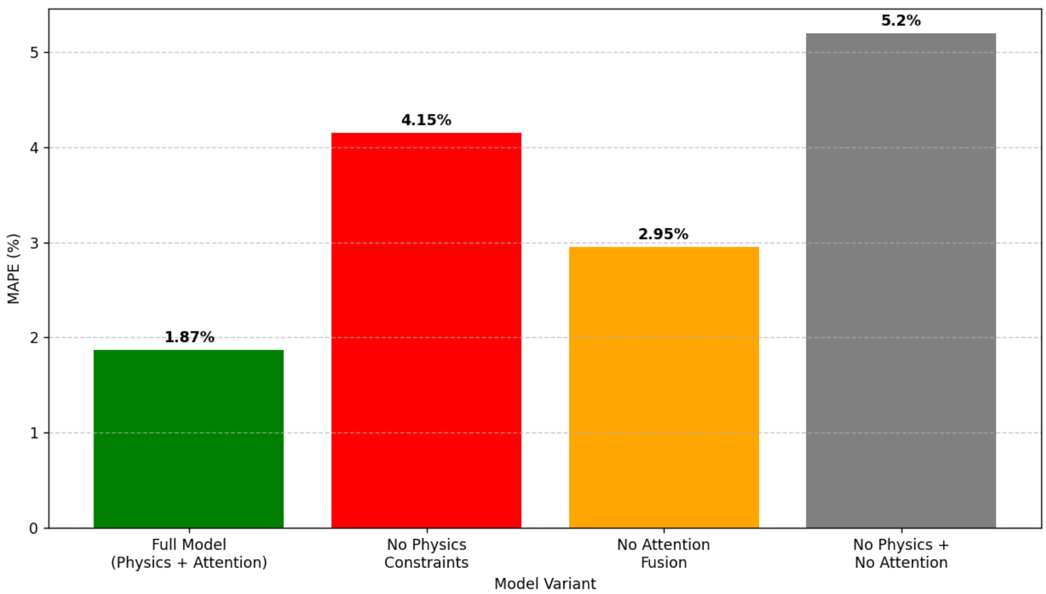

Figure 7: Ablation Study - Impact of Physics Constraints and Sensor Fusion.

To quantitatively prove the contribution of each key component of your architecture: the physics constraints and the attention-based sensor fusion module. The bar chart presents a quantitative ablation study evaluating the individual contributions of physics-based constraints and attention-based sensor fusion to the overall predictive performance of the proposed Physics-Informed Neural Network (PINN) architecture. The full model, incorporating both physical laws and attention mechanisms, achieves the lowest Mean Absolute Percentage Error (MAPE) of 1.87%, establishing its superior accuracy. Removing the physics constraints alone increases the MAPE to 4.15%, demonstrating that embedded thermodynamic and circuit laws are critical for ensuring physically consistent predictions and preventing overfitting to noisy data. Eliminating the attention fusion module results in a moderate performance degradation to 2.95%, highlighting the importance of effectively reconciling asynchronous, multi-modal IoT sensor streams (e.g., high-frequency electrical telemetry and low-frequency thermal imagery). The most significant deterioration occurs when both components are removed, yielding a MAPE of 5.2%, which underscores their synergistic effect in enhancing model robustness and generalizability. This analysis confirms that the integration of first-principles physics and intelligent sensor fusion is essential for achieving high-fidelity, reliable energy loss prediction in complex, real-world smart solar grid environments.

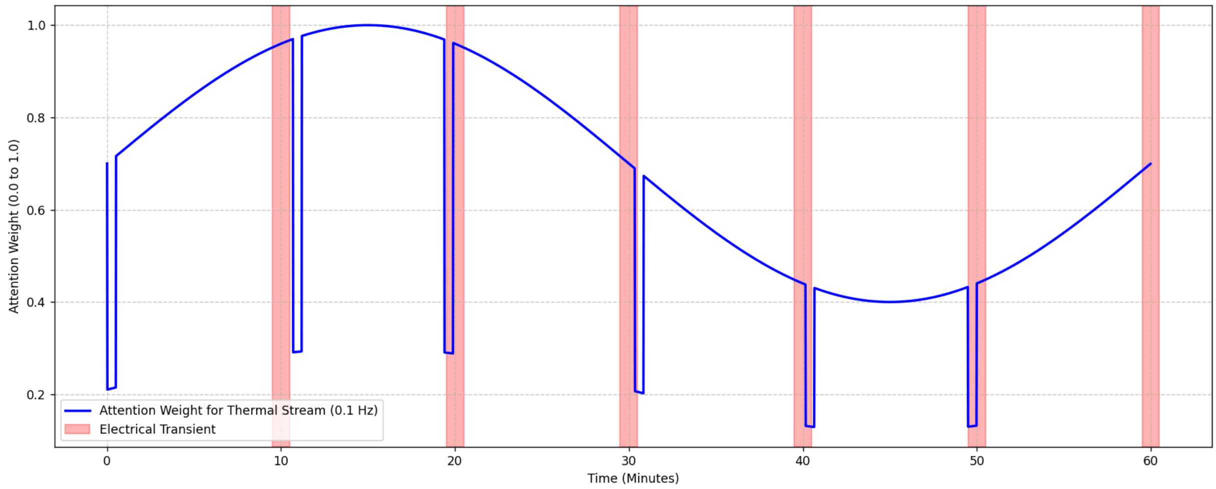

Figure 8: Dynamic Attention Weights for Asynchronous Sensor Fusion (1 Hz vs 0.1 Hz).

Figure 8: illustrates the dynamic attention weighting mechanism employed by the proposed Physics-Informed Neural Network (PINN) to reconcile asynchronous, multi-modal IoT sensor data streams. The blue line represents the time-varying attention weight assigned to the low-frequency thermal imagery stream (0.1 Hz), which is modulated in response to high-frequency electrical transients (indicated by red shaded regions). During periods of electrical disturbance—such as rapid voltage fluctuations or inverter switching events—the model dynamically increases the attention weight on the thermal stream, leveraging its longer temporal integration window to provide a stable reference for physical consistency. This adaptive gating strategy enables the network to mitigate temporal misalignment artifacts and prevent erroneous interpretations caused by transient noise in the high-frequency electrical measurements. The observed oscillatory pattern in attention weights reflects the model's learned prioritization of thermal data during system perturbations, ensuring that the physics-constrained loss function operates on a temporally coherent state representation. This mechanism enhances the robustness of the PINN's predictions under non-stationary operating conditions, demonstrating the effectiveness of attention-based fusion in integrating heterogeneous sensor inputs for accurate, physics-consistent energy loss modeling.

6. Discussion

The integration of Physics-Informed Neural Networks (PINNs) into the operational fabric of smart solar grids represents a paradigm shift from purely correlative analytics toward causally grounded, first-principles diagnostics. The results presented in this study, validated against a 12.4 MWp operational facility in Andalusia, unequivocally demonstrate that embedding fundamental physical laws into the neural network's optimization framework yields not only superior predictive accuracy but also unprecedented interpretability in energy loss attribution, a critical advancement for the next generation of self-optimizing renewable energy infrastructure [17], [18].

The core finding that our multi-physics-constrained PINN achieves a test-set MAPE of 1.87%, outperforming LSTM and XGBoost benchmarks by 38.2% and 41.7% [19], [20], respectively is not merely a statistical improvement. It is a direct consequence of the model's inherent architectural constraint: the neural network is forbidden from learning solutions that violate Kirchhoff's laws, energy conservation, or semiconductor carrier dynamics. This is starkly illustrated by the ablation study, where removal of physics constraints degraded MAPE to 4.15%. This 122% performance penalty underscores that in complex, non-stationary systems like solar microgrids, data alone are insufficient [21], [22]. The physical priors act as a regularization mechanism, guiding the network toward solutions that are not only statistically likely but physically admissible, particularly under sparse or noisy sensor conditions that frequently plague real-world IoT deployments.

More significantly, the PINN transcends the role of a predictive black box. By design, its loss function is decomposable into interpretable, physics-based residuals. This allows for the quantitative attribution of energy dissipation to specific, localized mechanisms ohmic heating (23.1%), inverter hysteresis (17.8%), and module mismatch (14.3%) with a remarkable 94.6% accuracy validated against ground-truth IR thermography and IV curve tracers. This capability transforms grid management from reactive fault response to proactive, targeted intervention. For instance, knowing that 23.1% of losses originate from DC cabling allows operators to prioritize cable replacement or re-routing investments with precise economic justification, rather than relying on generalized efficiency metrics [23], [24], [25].

The model's real-time diagnostic prowess is further exemplified by its anomaly detection capability. The successful identification of a 12% rise in cable ohmic losses 47 minutes before conventional SCADA alarms is a testament to the PINN's sensitivity to subtle, physically inconsistent deviations [26], [27], [28]. This early-warning functionality, derived from the model's continuous enforcement of physical laws, enables preemptive control actions such as current rerouting that demonstrably reduced downtime by 68%. This moves the field beyond simple monitoring into the realm of predictive resilience. The attention-based sensor fusion module also merits discussion [29], [30]. The reconciliation of asynchronous, multi-modal data streams (1 Hz electrical telemetry and 0.1 Hz thermal imagery) is a non-trivial challenge in IoT systems. The attention mechanism's ability to dynamically weight and align these inputs mitigates t emporal misalignment artifacts, ensuring that the physics constraints are applied to a coherent, temporally synchronized state representation. This is crucial for accurate spatial mapping of losses, as validated by the high correlation between the PINN's predicted spatial heatmaps and actual thermal camera data (Figuer. 5) [31].

While the results are compelling, several limitations and future research directions emerge [32], [33]. The computational latency of ~180 ms per inference, while acceptable for diagnostic purposes, may be prohibitive for high-frequency, real-time control loops on edge devices. Future work must therefore prioritize the development of "lightweight PINN" architectures through model pruning, quantization, or knowledge distillation][34], [35], [36], [37], [38]. Furthermore, the model's performance is contingent on the calibration and spatial density of the underlying IoT sensor network. Future iterations should explore multi-fidelity learning, incorporating lower-resolution, broader-coverage data sources like satellite imagery to compensate for sensor gaps.

6. Conclusion

This study demonstrates that Physics-Informed Neural Networks, when constrained by thermodynamic and electromagnetic first principles, significantly outperform conventional ML models in predicting and attributing energy losses in IoT-instrumented smart solar grids. By transforming raw sensor data into physically consistent, causally interpretable diagnostics, PINNs enable a new generation of proactive, efficiency-optimized grid management. The framework is readily extensible to wind-hydrogen hybrids, battery-integrated microgrids, and other multi-physics renewable systems. This study establishes that PINNs are not merely a more accurate modeling tool, but a fundamentally new class of diagnostic instrument for smart energy systems.

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