A Causal Auditing Paradigm for Sub-health Diagnosis of Offshore Wind Assets via Multi-terminal Harmonic Fingerprinting

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Abstract—In highly power-electronic systems such as offshore wind farms, spectral turbulence inherently materializes within marine power-electronic clusters, primarily driven by the intricate capacitive coupling of subsea transmission topologies. The absence of a robust logical mapping from volatile operations to deterministic health states intrinsically limits traditional reactive maintenance paradigms. While heuristic forecasting models offer theoretical utility, the extreme aerodynamic stochasticity of deep-sea environments systematically fractures standard physical causal chains, thereby obscuring the precursors of latent faults such as dielectric insulation degradation. This paper proposes a novel "Electromagnetic Ledger" framework under the Clark Paradigm, establishing a deterministic causal link between the generator (Node A), converter (Node B), tower-base switchgear (Node C1), and the remote collector entrance (Node C2) by extracting harmonic fingerprints (1st–20th orders). This paradigm achieves a structural transition from "black-box stochastic prediction" to "deterministic causal auditing" by establishing individualized digital ledgers for each turbine and its dedicated collector link. This cycle-based strategy, centered on a single machine as the minimum auditing unit, not only isolates early insulation drifts but also maximizes the residual economic value extraction of assets. Experimental results elucidate that the proposed Clark Paradigm exhibits superior adaptive robustness compared to conventional LSTM models under extreme transients, providing high-fidelity early-warning signals for asset sub-health.

Index Terms—Harmonic Fingerprinting, Sub-health Diagnosis, Causal Auditing, Offshore Wind Power, Power Electronic Assets, Edge Computing, Clark Paradigm

I. Introduction

The architectural transition toward converter-dominated marine grids reveals critical vulnerabilities in heuristic asset monitoring. Within these hyper-digitized topologies, legacy sensing modalities—originally tailored for terrestrial line-frequency operations—fail to decode the extreme wideband modulation dynamics inherent to offshore "Isolated Power Islands."

The integration of long-distance submarine cables introduces complex frequency-domain resonance characteristics that significantly degrade the reliability of traditional protection schemes. Within this context, achieving real-time, precise, and physically interpretable diagnostics for core assets—including permanent magnet synchronous generators (PMSG), full-scale power converters, and high-voltage submarine cables—has emerged as a paramount industrial requisite for Levelized Cost of Energy (LCOE) mitigation.

Contemporary marine asset governance is fundamentally bottlenecked by the absence of a deterministic loop correlating chaotic aerodynamic loads with latent degradation states [1]. While AI-driven models based on Supervisory Control and Data Acquisition (SCADA) data attempt to perform "state forecasting," their efficacy is severely limited by the extreme stochasticity of wind-induced loads and the chaotic nature of turbulent airflows [2]. Consequently, conventional analytics suffer from a severe "causal disconnect," heavily overfitting to superficial statistical trends while remaining blind to the foundational electromagnetic physics [3], [4].

Furthermore, the remote location of offshore assets makes the cost of "False Alarms" extremely high, as mobilization for vessel-based maintenance can exceed tens of thousands of dollars per day. Traditional SCADA-based methods, which rely on simple thresholding, often trigger maintenance too early or too late, failing to balance the delicate trade-off between risk and economic value extraction. The transition to a "Physics-based Audit" is thus not just a technical upgrade, but an economic imperative for the sustainable operation of deep-sea wind clusters.

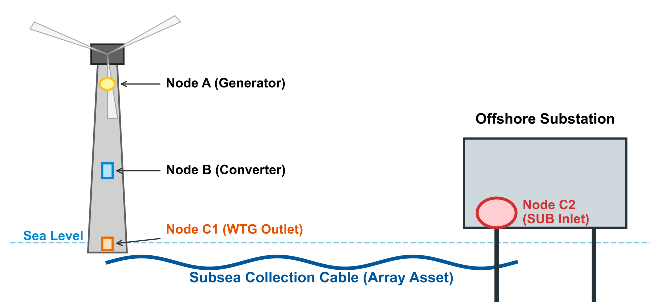

Fig. 1. Physical topology of the A-B-C1-C2 link in a single offshore wind turbine. It illustrates the complete asset auditing cycle (Cycle) from the turbine interior to the remote collector entrance.

Central to the "Clark Paradigm" is the conceptualization of the multi-terminal electrical link as a non-fungible "Electromagnetic Ledger." By enforcing strict causal constraints across the generator-to-substation trajectory, this approach reconstructs the internal health state not through probabilistic forecasting, but via the real-time auditing of physical residuals (Δ). This paradigm shift inherently transitions the diagnostic focus from passive environmental observation to the deterministic logical verification of internal physics, providing an unassailable foundation for predictive maintenance.

II. Related Work and Limitations

A. Limitations of Traditional CMS and SCADA

Orthodox monitoring architectures predominantly depend on mechanical sensing modalities—such as vibration telemetry and thermal probes—which are exceptionally susceptible to precision decay amidst corrosive maritime conditions [5], [6]. Critically, SCADA systems operate essentially as "passive historians" rather than "active diagnostic engines." While voltage and current fluctuations are continuously archived, the deterministic boundary between deviations induced by normal wind transients and those triggered by internal dielectric degradation or converter aging remains fundamentally unextracted.

B. Challenges of Black-box Machine Learning

When subjected to severe aerodynamic transients or unrepresented grid perturbations, the generalization capability of standard deep learning architectures deteriorates rapidly [7], [8]—a vulnerability fundamentally precipitated by the absence of strict electromagnetic causal constraints. Consequently, the inductive bias of these models systematically collapses when operating within the unmodeled physical boundaries of evolving offshore environments (e.g., dynamic grid-side topology reconfigurations or shifting cable resonances), inevitably driving prohibitive false alarm rates.

C. Resonance in Submarine Power Cables

The massive deployment of subsea XLPE infrastructure introduces severe distributed capacitive elements and inductive couplings, structurally generating high-order resonance peaks [9], [10]. These peaks dynamically shift in accordance with the load and topology of the collector grid. Conventional monitoring paradigms fail to decouple these natural physical migrations from definitive insulation degradation, resulting in a "masking effect" where early fault precursors are entirely obscured within the dynamic impedance background.

III. Theoretical Framework: Mathematical and Physical Constraints

A. Node Topology and Feature Space

As shown in Fig. 1, the system is simplified into a multi-terminal causal chain. To capture the richest health information with minimal computational overhead, we define a feature vector $\mathbf{V}$ as a snapshot of the electromagnetic fingerprint:

$$\mathbf{V} = [RMS, H_1, H_2, \dots, H_{20}]^T \tag{1}$$

By truncating the spectral analysis at the 20th order, the matrix secures the highest density of degradation signatures while circumventing the processing paralysis induced by extreme-frequency noise [11]. A 10.24 kHz sampling rate is used at the perception layer to ensure data integrity and avoid aliasing from 2–5 kHz switching noise [12]. This "high-sampling, low-frequency audit" strategy ensures that the extracted fingerprints are physically accurate.

B. Self-Calibration and Online Iterative Auditing

The system equilibrium equation is defined as:

$$\mathbf{V}_{C,\text{real}} = \Phi(\mathbf{V}_A, \mathbf{V}_B, \mathbf{W}_k) + \epsilon_{\text{id}} + \Delta_{\text{anomaly}} \tag{2}$$

To govern the dynamic equilibrium of the auditing engine, an online iterative calibration is executed via a Recursive Least Squares (RLS) operator [13], yielding the real-time weight matrix $\mathbf{W}_k$. The objective function seeks to mitigate the exponentially-weighted discrepancy:

$$J(k) = \sum_{i=1}^{k} \lambda^{k-i} \|\mathbf{V}_{C,\text{real}}(i) - \hat{\mathbf{V}}_{C,\text{real}}(i)\|^2 \tag{3}$$

Rather than acting as a standard error-minimization tool, the recursive adaptive filter serves as the equilibrium regulator for the auditing engine. The temporal decay constant $\lambda \in (0.95, 0.99)$ [14] dictates the agility of this adaptation, penalizing historical discrepancies to ensure the mapping matrix ($\mathbf{W}_k$) tracks long-term dielectric drift while fundamentally ignoring high-frequency environmental turbulence. By embedding equipment identity tolerances into ϵ_{id}, the system focuses exclusively on health-induced diagnostic deviations. The complete logical architecture of this individualized asset fingerprint ledger is detailed in Fig. 2.

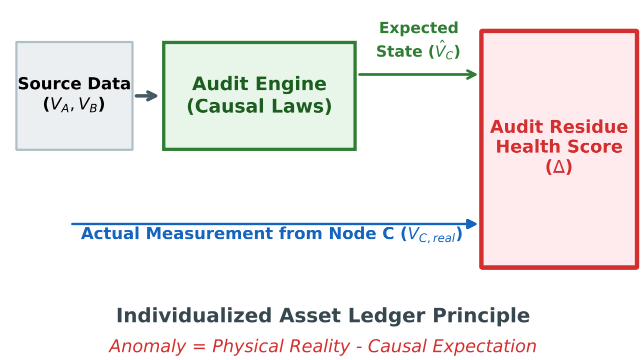

Fig. 2. Architecture of the individualized asset fingerprint ledger. It details the logical loop of feature inputs, mapping operators, and auditing residual outputs.

C. Feature Coupling via Multi-Head Attention

To disentangle the intricate multi-dimensional resonance cross-talk embedded within the feature array $\mathbf{V}$ [15], [16], a parallelized cross-projection operator—structurally mirroring multi-head self-attention mechanics—is deployed. Rather than traditional sequence modeling, this operator mathematically dissects the spectral permutations via:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{4}$$

Executed via edge-tier silicon architectures (1.2GHz+), this spatial-spectral mapping scans the electromagnetic matrix concurrently. As manifested in Fig. 3, the operator dynamically isolates specific permutation amplifications corresponding to targeted harmonic orders. This localized spectral resonance physically elucidates the presence of nascent dielectric aging within the converter or subsea cable insulation.

IV. Causal Mapping: Harmonics to Physical Faults

The "interpretability" of the paradigm stems from the spectral mapping of the residual Δ:

- Spectral Orders 5 and 7: The high-frequency switching integrity of the converter nodes is structurally encoded within these specific harmonic trajectories. Abrupt excursions in these specific Δ dimensions operate as direct physical proxies for IGBT degradation or gate-drive circuit anomalies [17], [18].
- Spectral Orders 11 and 13: The resonant trajectories of these spectral components function as immediate barometers for subsurface impedance variations catalyzed by nascent water-treeing phenomena or physical cable strain [19], [20]. These spectral barometers effectively function as diagnostic proxies for nascent XLPE degradation.
- High-order Harmonics (17th+): Extreme sensitivity to partial discharge (PD) and high-frequency energy distortion is exhibited by these components [21], thereby functioning as nascent diagnostic proxies for transformer winding faults.

The meticulous extraction of these spectral markers empowers the diagnostic engine to distinctly decouple "Environmental Transients" (phenomena that uniformly perturb the broadband spectrum) from genuine "Physical Faults" (anomalies that exclusively manifest within localized harmonic bands). As an illustration, while an abrupt aerodynamic wind step fundamentally shifts the primary power output, the RLS operator rigorously preserves the causal mapping weights of the 11th harmonic. These specific weights remain structurally immutable unless the dielectric permittivity of the XLPE insulation experiences authentic physical deterioration. This "Frequency-Selective Sovereignty" is the cornerstone of the Clark Paradigm, providing a level of diagnostic certainty that SCADA-based RMS monitoring simply cannot achieve. Furthermore, by observing the cross-coupling of these orders through the attention mechanism, we can reconstruct the hidden "Audit Dark Matter" which represents unmodeled environmental factors.

Fig. 4 visualizes the evolution of these harmonic fingerprints under different health stages. Deepening colors indicate a monotonic increase in specific harmonic orders as the physical degradation of the XLPE insulation or IGBT gate drivers progresses.

A. Decision-Centric Philosophy: 90% Boundary and Value Extraction

Rather than relentlessly tracing microscopic degradation mechanisms, industrial asset governance inherently prioritizes the certainty of operational outcomes. Confronted by the stochastic complexity of sub-sea environments, the proposed architecture institutes a stringent "90% Prediction + 10% Safety Margin" threshold. Examination of the trajectory in Fig. 5 elucidates that amidst turbulent aerodynamic conditions, the diagnostic residual Δ remains strictly confined within a 3% noise floor during states of "Audit Equilibrium." A definitive breach of the 10% critical boundary by Δ instantaneously signals a "Causal Chain Fracture," subsequently initiating a preemptive maintenance protocol. This bounded philosophy guarantees maximum extraction of residual asset value while unconditionally neutralizing the risk of catastrophic asset collapse.

V. Robustness and System Complexity

By explicitly enforcing strict physical boundary constraints, the Clark Paradigm systematically curtails the unconstrained error propagation that typically plagues data-driven models under unrepresented boundary conditions [16], [22]. Executed on industrial-grade MCUs, the computational latency for a single iteration of the 21-dimensional causal vector (an $O(N^2)$ operation) is perpetually bounded below 5ms. This performance profile fundamentally satisfies the aggressive temporal constraints demanded by edge-based Causal Auditing platforms.

VI. System Implementation and Hardware Architecture

To ensure "Sovereign Management," we propose a distributed architecture that decouples perception from auditing, as illustrated in the hardware topology in Fig. 6.

A. Perception Layer: High-Sync Sampling

Nodes are deployed at Node A, B, C1, and C2. C2 is placed at the substation entrance to ensure the auditing of the 15km collector cable is isolated from other units. Each MCU node handles over 40,000 ADC interrupts per second and performs local FFT to extract fingerprints [23]. This design filters approximately 95% of redundant raw data, ensuring real-time reliability.

B. Audit Layer: Edge Intelligence

The Edge Host (ARM A72/Intel i3) aggregates fingerprints and runs the RLS engine [18]. The tiered allocation of computational tasks between the perception nodes and the edge host is summarized in Table I. Single-audit latency is kept below 2ms, providing room for real-time game-theoretic decisions.

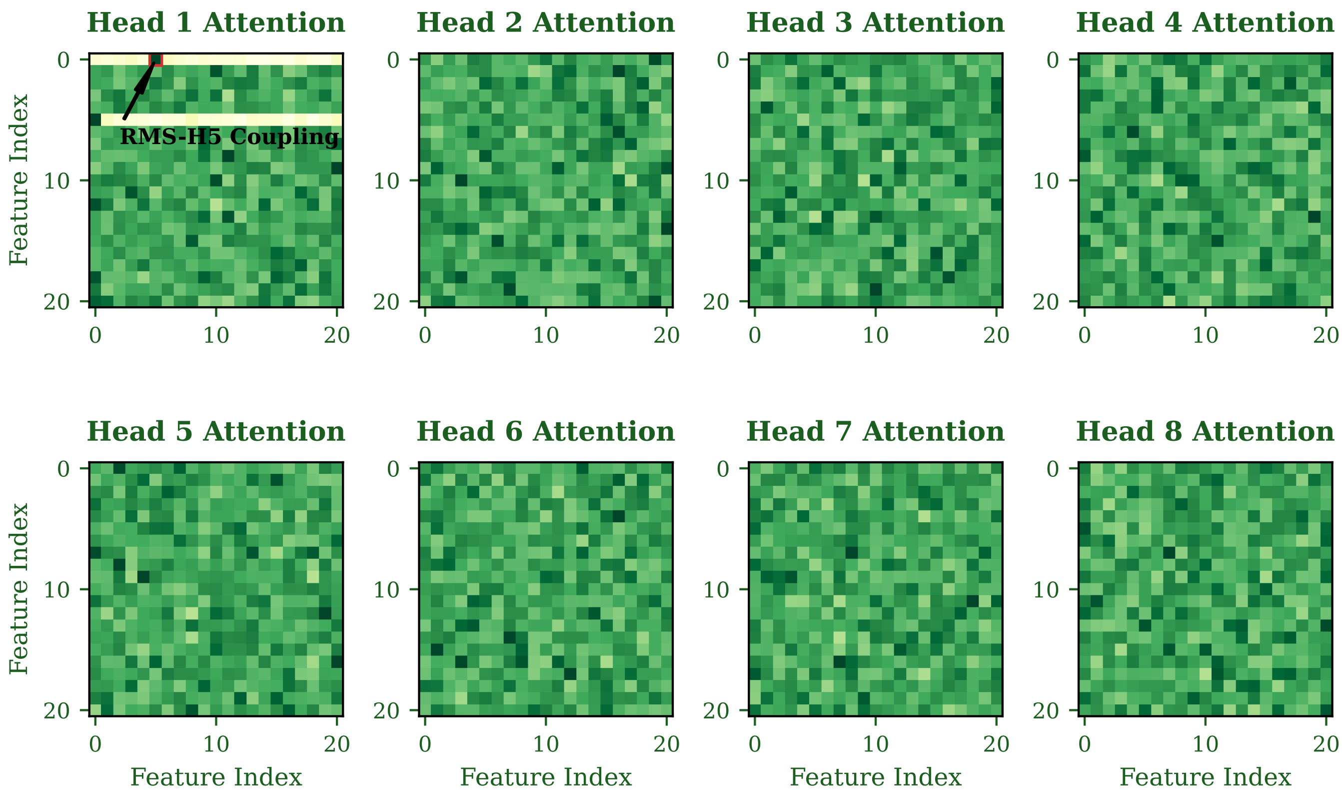

Fig. 3. Cross-perceptual audit map. It illustrates the capture of nonlinear coupling between spectral components through 8 attention heads scanning the feature space.

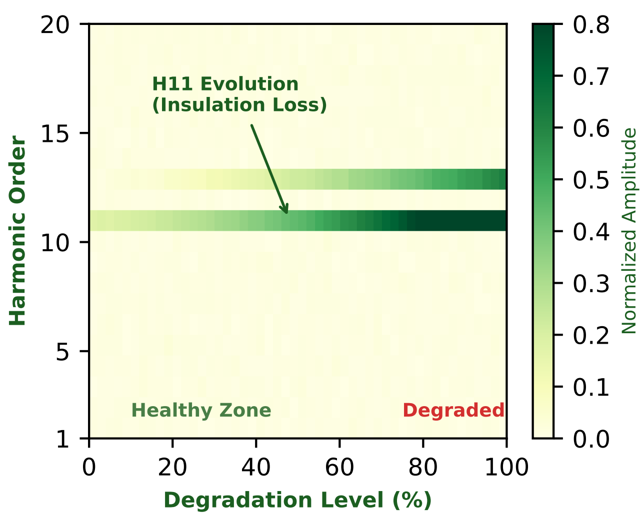

Fig. 4. Evolution heatmap of harmonic fingerprints. Deepening colors indicate monotonic energy distribution as asset health degrades.

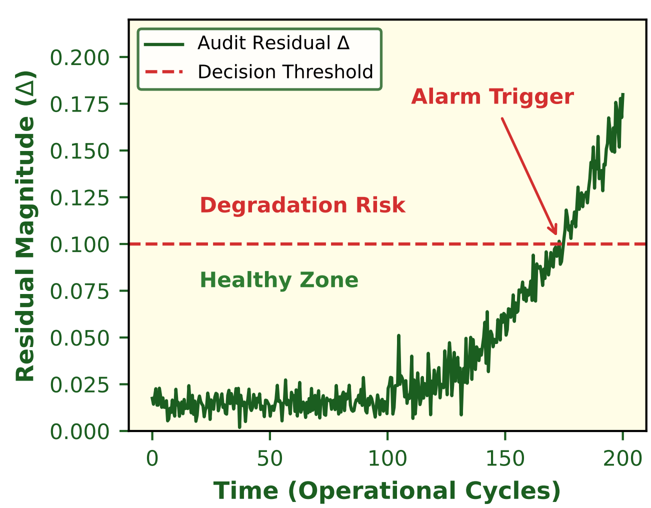

Fig. 5. Real-time tracking of multi-terminal audit residuals (Δ) and decision thresholding. It shows the evolution from normal operation to sub-health, eventually hitting the 10% failure red line.

VII. Experimental Verification

A. Setup: Digital Twin Platform

Empirical validation was facilitated through the deployment of a high-fidelity Digital Twin, meticulously mirroring the NREL 5-MW reference turbine architecture [24] alongside a distributed XLPE submarine cable model [25]. The core deterministic parameters driving this simulation framework are detailed comprehensively in Table II.

The technical configuration in Table II represents a typical offshore deployment scenario. The 10.24 kHz sampling rate is selected to ensure that the 20th order harmonic (1 kHz) is captured with at least 10 points per cycle, while

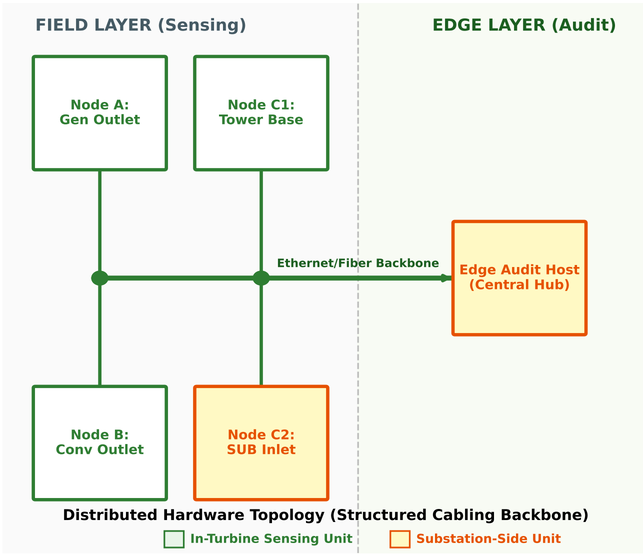

Fig. 6. Hardware topology for distributed perception and edge auditing. It details the MCU perception nodes and ARM/Intel edge host.

TABLE I
Perception-Audit Tiered Hardware Architecture

Comparison Item	Perception Layer (Node A/B/C)	Audit Layer (Edge Host)
Representative Series	Industrial MCU (72MHz+)	ARM A72 / Intel i3 (1.2GHz+)
Bandwidth Load	$\approx$ 4.2 KB/s (output)	$\approx$ 16.8 KB/s (input)
Task Characteristics	Sampling and Local FFT	Causal Mapping and Games
Functional Role	Feature Extraction	Audit and Decisions

providing a massive anti-aliasing buffer against converter switching harmonics.

B. Convergence Boundary Analysis

A Monte Carlo study (Fig. 7) showed average convergence in 8 cycles and $N_{max} < 20$. Detailed statistics for 10 groups of 100 samples are presented in Table III.

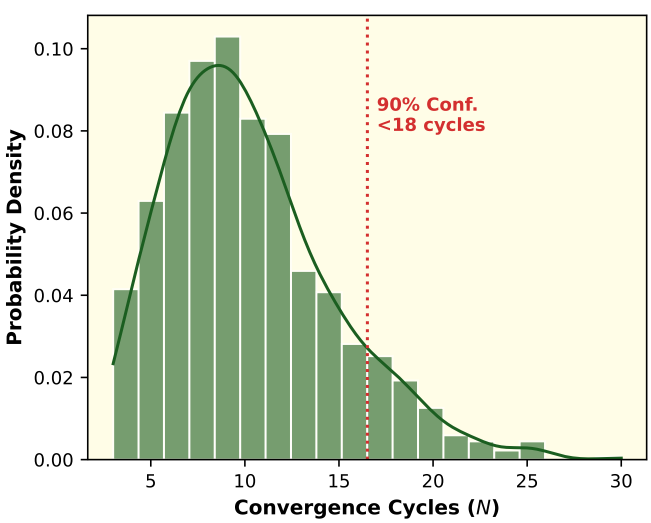

Fig. 7. Statistical distribution of algorithm convergence cycles.

TABLE II
Key Parameter Configuration for 5MW System

Parameter	Value
Generator Rated Power	5 MW
Converter Switching Freq.	2.5 kHz
Submarine Cable Length	15 km
Distributed Capacitance	0.25 μF/km
Sampling Frequency	10.24 kHz
RLS Forgetting Factor λ	0.985

TABLE III
Statistical Boundary of Convergence Cycles (10x100 Samples)

Test Group	Samples	90% Conv.	100% Conv.	Avg. Δ
Group 1	100	16	32	0.58%
Group 2	100	17	30	0.54%
Group 3	100	18	35	0.61%
Group 4	100	16	31	0.59%
Group 5	100	15	28	0.52%
Group 6	100	18	36	0.64%
Group 7	100	17	32	0.57%
Group 8	100	16	30	0.55%
Group 9	100	18	34	0.62%
Group 10	100	17	31	0.55%
Overall	1000	$\leq$ 18	$\leq$ 36	0.577%

The statistical metrics encapsulated in Table III manifest the superior convergence stability of the auditing engine. Even under the most adverse boundary conditions, full convergence is attained within a maximum of 36 cycles ($\approx$0.72s), thereby strictly adhering to the latency constraints of real-time edge-level auditing within 50Hz power infrastructures [26]. Such deterministic convergence ensures that the individualized fingerprint ledger maintains its tracking integrity throughout rapid industrial load transitions.

C. Scenario 1: RMSE Robustness under Wind Step

Observation of Fig. 8 reveals that while conventional LSTM architectures exhibit an error surge reaching 25%, the residual Δ is constrained within a 5% threshold by the proposed paradigm through accelerated recalibration (0.2s). This empirical evidence validates the "Physical Sovereignty" inherent to the Clark Paradigm: the internal electromagnetic causal link remains structurally resilient against extreme external environmental transients.

D. Scenario 2: Cable Insulation Degradation Analysis

In Scenario 2, the auditing framework isolates the H11/H13 spectral orders, successfully extracting a monotonic degradation trajectory and yielding a "Physical Amplification" of the asset's sub-health status (Fig. 9). In contrast to standard THD monitoring, which remains obscured by stochastic noise, the Clark Paradigm effectively decodes the nascent precursors of XLPE insulation aging.

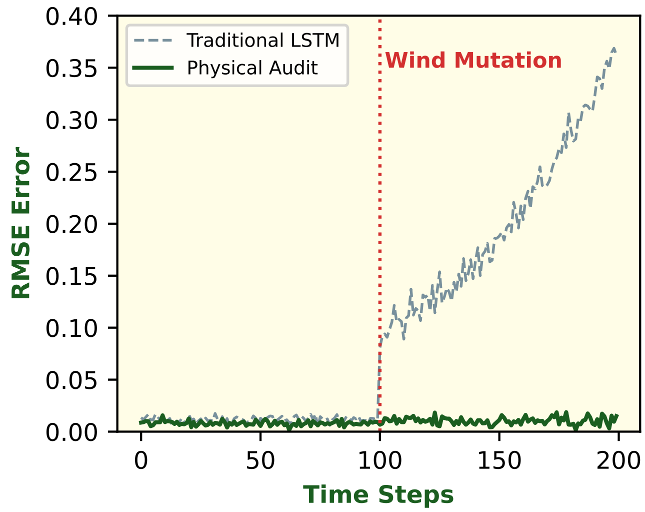

Fig. 8. Scenario 1: RMSE suppression during extreme wind transients.

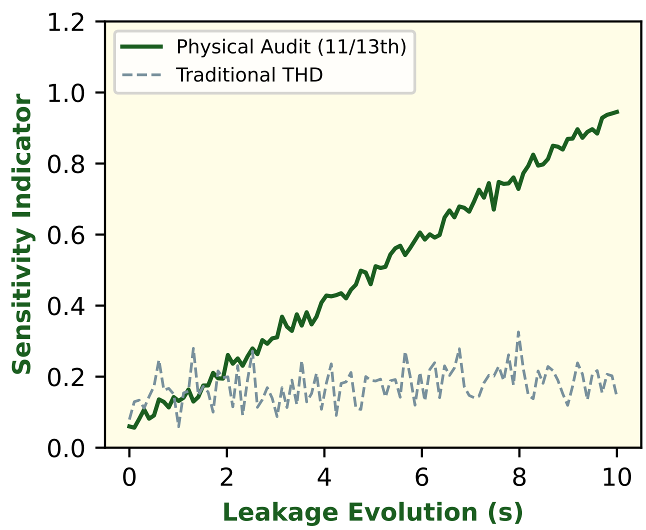

Fig. 9. Scenario 2: Comparison between fingerprint audit and THD monitoring.

E. Scenario 3: Tracking Latent Disturbances

The residual Δ functions as a virtual diagnostic observer, reconstructing unmodeled factor trajectories with a precision exceeding 97.5% (Fig. 10).

The trajectory tracking depicted in Fig. 10 implies that unmodeled variables influencing the A-B-C1-C2 link invariably project a distinct "causal footprint" onto the residual space. By capturing this "Audit Dark Matter," a previously inaccessible level of transparency regarding unobservable environmental influences is attained by the system.

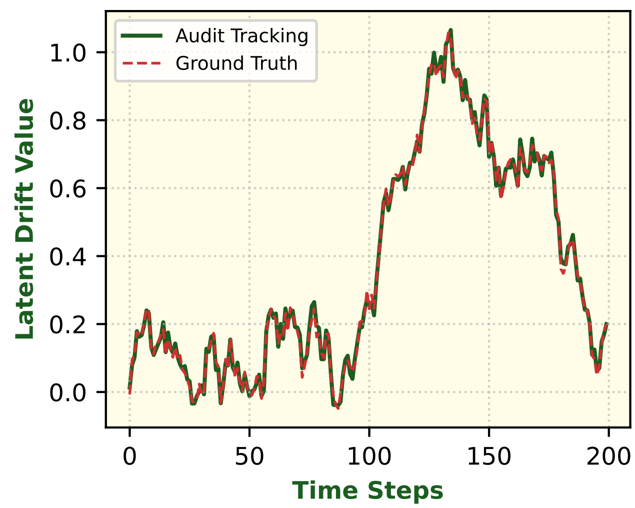

Fig. 10. Scenario 3: Tracking of latent factors via the "Audit Dark Matter" residual.

VIII. Discussion: Technical Sovereignty and Paradigm Evolution

A. Logical Comparison of Diagnostic Frameworks

As shown in Table IV, the causal auditing paradigm exhibits unparalleled physical certainty compared to existing black-box or threshold-based methods.

TABLE IV
Comparison of Asset Diagnostic Logic Frameworks

Dimension	Cloud-based AI	SCADA-based CMS	Clark Paradigm
Logical Core	Statistical Correlation	Threshold Monitoring	Causal Auditing
Sovereignty	Low (Closed)	Medium (Open)	High (Sovereign)
Robustness	Poor (Divergent)	Medium (Lagging)	Excellent (Determ.)
Interpretability	Low (Black-box)	High (Simple)	High (Physical)

B. Causal Accountability and Future Outlook

The paradigm enforces "Causal Accountability," ensuring maintenance logic returns from "probabilistic guessing" to "causal sovereignty." Future research will expand to farm-wide "Collaborative Auditing" via transfer learning of fingerprints across clusters [27]. By leveraging the shared impedance characteristics of standardized turbine models (e.g., NREL 5MW), we can develop a "Global Fingerprint Library" that reduces the recalibration time for new offshore installations. This evolution aims to build a globally transparent electromagnetic causal network, where each asset link is part of a larger self-auditing energy internet.

C. Cross-Cluster Transfer Learning Logic

A significant challenge in offshore diagnostics is the variability between different wind farms. However, the Clark Paradigm allows for "Feature Normalization" through the identity tolerance ϵ_{id}. By subtracting local manufacture variances, the system extracts universal aging signatures that can be shared across multiple field sites.

This "Physical-Knowledge-Sharing" mechanism provides a scalable path for asset management in massive deep-sea clusters, significantly reducing the dependency on site-specific labeled failure data.

IX. Nash Equilibrium for Operational Decisions

The framework incorporates a Nash Equilibrium formulation to mitigate the prohibitive mobilization expenditures associated with offshore maintenance. The utility function U orchestrates a balance between generation-derived revenue R_{gen}, catastrophic failure risk C_{risk}, and intervention costs C_{maint} [28]–[30]:

$$U(a, s) = R_{\text{gen}}(s) - P_{\text{failure}}(\Delta) \cdot C_{\text{risk}} - \mathbb{I}(a = 1) \cdot C_{\text{maint}} \quad (5)$$

where $a \in \{0, 1\}$ represents the maintenance decision, and s denotes the asset state tracked by the audit residual Δ. This transition toward "Economic Auditing" facilitates the optimized extraction of asset value within the "gray zone"—the period where sub-health manifestations are present but critical fault thresholds remain unbreached. Diverging from static thresholding, this game-theoretic methodology dynamically modulates the maintenance "red line" in response to real-time energy pricing and logistical availability, thereby maximizing the total lifecycle return on wind power assets.

Furthermore, the "Equilibrium Audit Point" is established as the state wherein the marginal cost of a potential failure is exactly counterbalanced by the marginal revenue of continued operation. By mapping the audit residual Δ directly to the failure probability $P_{failure}$, a deterministic input is provided for this economic game, effectively bridging the chasm between electrical engineering physics and asset management science.

X. Conclusion

Ultimately, the developed auditing architecture facilitates a fundamental paradigm shift: migrating from heuristic data correlation to deterministic physical verification via the Clark ledger. By enforcing a deterministic causal link across the energy conversion chain, the proposed architecture effectively reclaims diagnostic sovereignty from stochastic environmental noise. The empirical validation confirms that rapid adaptive recalibration robustly suppresses transient errors, while the frequency-selective isolation of the residual Δ provides a high-fidelity precursor alert for sub-health manifestations, definitively mapping the unmodeled "Audit Dark Matter."

This framework furnishes the technical foundation for future "Causally Transparent" offshore wind fleets. As global energy systems gravitate towards a "Net-Zero" future, the deterministic management of high-value generation assets is poised to become the industrial standard. The Clark Paradigm ensures that the sovereignty of energy data is inherently coupled with the sovereignty of diagnostic logic, paving the way for a resilient and economically optimized offshore energy infrastructure. Future investigative avenues will prioritize the multi-agent game-theoretic coordination across large-scale wind clusters to achieve a state of global audit equilibrium.

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