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RESEARCH ARTICLE

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SIMULATION-BASED EVALUATION OF ELECTROMAGNETIC TIME-REVERSAL METHODS FOR PARTIAL DISCHARGE LOCALIZATION IN POWER TRANSFORMERS: CRITICAL ANALYSIS OF ADVANCED TECHNIQUES

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ABSTRACT

We tested three electromagnetic time-reversal methods to find partial discharges in power transformers using computer simulations. Our goal was simple: figure out if newer, fancier methods actually work better than the basic approach. First, we checked the baseline PDVDM method that was published in IEEE journals. Using a standard 24-disk transformer model, we got pretty good results—about 1.9 mm average error with 80% of our tests landing within 2 mm of the actual discharge location at 20 dB signal-to-noise ratio. This matched what other researchers reported, so we knew our simulation setup was working correctly. Then we tried three supposedly "advanced" methods, keeping everything else the same so we could compare fairly. The HO-AMFO hybrid optimization used a bigger 60-disk model with 10 MHz sampling and 12 sensors, but it performed terribly—1885 mm average error, only 15.18% accuracy. The second method was an IEEE-inspired AI-enhanced approach with three windings and 50 MHz sampling. It did better than the first one with 895.3 mm error, but still couldn't get a single test within 2 mm. The third method threw everything at the problem—over 15 AI techniques combined, 100 MHz sampling—and got 1417 mm error with zero tests under 1 mm accuracy. These results surprised us, honestly. Adding more sensors, faster sampling, and complex algorithms didn't help at all. In fact, they made things worse—about 1000 times worse than the simple method. After digging into why this happened, we found three main problems. First, the optimization algorithms weren't actually following electromagnetic physics properly—they were just hunting for mathematical answers that didn't match reality. Second, the AI methods had basically memorized our simplified simulation setup instead of learning real principles, so they failed when conditions changed slightly. Third, nobody had tested how sensitive these methods were to realistic transformer shapes and noise levels that you'd find in actual substations. We wrote this paper to honestly show that these advanced methods failed our tests. Too many papers claim their new method is amazing without showing the full picture. We measured exactly how much worse the complex methods performed compared to simple approaches, and we explain why the failures happened. Before utilities spend money installing these systems in real transformers, somebody needs to test them on actual hardware—not just simulations—using standardized tests that everyone agrees on. The physics has to guide the AI, not the other way around.



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I. INTRODUCTION

Partial discharges in transformer insulation are basically early warning signs that something's going wrong. Think of them like small electrical sparks inside the transformer [1], [2]. Even tiny discharges can start a chain reaction—they heat up the insulation locally, break down the oil and solid materials chemically, and eventually cause the whole transformer to fail catastrophically [3], [4]. That's why finding exactly where these discharges happen is so important for maintenance planning and keeping power systems running safely [5], [6]. Researchers have tried many different ways to locate partial discharges over the past fifteen years. The main approaches include listening for acoustic emissions (basically sound waves from the discharge), detecting ultra-high frequency radio signals, and using electromagnetic models [7-9]. Each method has its fans, but honestly, they all have serious problems when you try using them in real substations. They get confused by electromagnetic interference from other equipment, they need perfectly timed signal detection, they assume the transformer winding has a simple geometry (which it doesn't), and most haven't been tested enough under realistic conditions. These limitations pushed us to look for better methods [10], [11]. Electromagnetic time reversal, or EMTR for short, looked promising when we started this research. The basic idea is clever: Maxwell's equations work the same way forward or backward in time [12], [13]. So if you record the electromagnetic signals from a discharge, flip them backward in time, and feed them back into a computer model of the transformer [14], [15], the signals should focus back on the spot where the discharge originally happened. One specific version called PDVDM (partial discharge voltage distribution metric) recently showed millimeter-level accuracy in simulations using a standard 24-disk transformer model [16], [17]. But we noticed three big holes in what's been published so far. First, nobody's really checked if PDVDM results can be reproduced using different simulation software or under various noise levels—the original papers just don't document this well enough [18], [19]. Second, we don't know how sensitive the method is to modeling choices like sensor placement or signal filtering—nobody's done systematic tests.

Third, and this bothered us most, researchers keep proposing increasingly complicated hybrid methods and AI-enhanced versions without clearly showing if they actually work better than the simple baseline. So we built our own simulation framework to test everything properly. We had three specific goals. First, we wanted to recreate the IEEE PDVDM method ourselves using a standard 24-disk transformer and try it with multiple types of PD waveforms. This would tell us if the published accuracy numbers were real and if the method handles noise well. Second, we implemented several newer methods—including one called HO-AMFO that combines two optimization algorithms, some IEEE-inspired AI techniques, and a really complex multi-domain AI system—all in the same simulation setup. This way we could compare them fairly using identical transformer models, the same sensors, and the same noise levels. Third, we measured everything carefully using metrics like average error, how often the method gets within 2 millimeters, computation time, and sensitivity to noise. Our goal was figuring out where these methods fail and why it's crucial that any algorithm actually follows electromagnetic physics rather than just optimizing random parameters. Here's what we found, and we'll be blunt about it. We successfully validated the baseline PDVDM method—got 1.9 mm average error and 80% success rate for sub-2mm accuracy, matching what was published. But the advanced methods completely failed. The hybrid optimization and AI-fusion approaches showed errors of 1 to 2 meters even with more sensors and higher resolution. That's about 1000 times worse. We don't see this kind of honest reporting much in journals, so we're documenting exactly why these fancy methods underperformed. Turns out they ignore physics, overfit to our simulation conditions, and nobody validated them experimentally. We hope this helps other researchers avoid the same mistakes and build PD systems that actually work when utilities need them [20-22].

Table 1: Summary of Previous EMTR and PD Localization Studies.

Sr. No.	Authors	Title	Journal/Conference	Year	Key Contribution	Location Error	Dataset Size
1	[23]	A Voltage Distribution-Based Electromagnetic Time Reversal Methodology	<i>IEEE Trans. Instrum. Meas.</i>	2024	Single simulation EMTR approach	<2 mm	24-disk model
2	[10]	Partial discharge localization using time reversal: Application to power transformers	<i>Sensors</i>	2020	3D acoustic time reversal	<2.5 cm	Laboratory setup
3	[9]	An efficient method based on the electromagnetic time reversal to locate faults	<i>IEEE Trans. Power Del.</i>	2013	First EMTR power network application	<1% line length	Transmission lines
4	[24]	Time reversal applied to fault location in power networks	<i>Int. J. Electr. Power Energy Syst.</i>	2020	Pilot test validation	<50 m	Real network
5	[25]	Application to real power networks of a method to locate partial discharges	<i>IEEE Trans. Power Del.</i>	2022	Real network PD localization	Variable	Field tests
6	[26]	Partial discharge localization using time reversal: Application to GIS	<i>Electr. Power Syst. Res.</i>	2022	GIS EMTR application	<5 cm	GIS model
7	[27]	Partial discharge localization in power transformer tanks using machine learning	<i>Sci. Rep.</i>	2024	ML-enhanced TR localization	<3 cm	Transformer tank

8	[28]	Partial discharge localization using electromagnetic time reversal	<i>Sensors</i>	2020	Frequency domain validation	<1 cm	Cavity model
9	[29]	An electromagnetic time reversal technique to locate partial discharge	<i>IEEE Lett. Electromagn. Compat. Pract.</i>	2023	Classical EMTR validation	<5 mm	Winding model
10	[30]	Performance analysis of acoustic sensors based time reversal technique	<i>Electr. Power Syst. Res.</i>	2023	Acoustic TR comparison	<1 cm	Oil-filled transformer
11	[31]	Norm criteria in the electromagnetic time reversal technique	<i>IEEE Trans. Electromagn. Compat.</i>	2018	Focusing criteria optimization	Variable	Simulation
12	[32]	A review of time reversal-based methods applied to fault location	<i>Front. Energy Res.</i>	2022	Comprehensive TR review	N/A	Review paper
13	[33]	Electromagnetic time reversal applied to fault location	<i>IEEE Trans. Power Del.</i>	2012	Original EMTR concept	<100 m	Power lines
14	[14]	On the use of electromagnetic time reversal to locate partial discharges	<i>IEEE Trans. Electromagn. Compat.</i>	2014	TR theoretical foundations	Variable	Analytical
15	[4]	An experimental validation of partial discharge localization using electromagnetic time reversal	<i>Sci. Rep.</i>	2021	Experimental TR validation	<2.5 cm	Laboratory setup
16	[34]	Time reversal of electromagnetic waves for wireless communications	<i>IEEE Trans. Antennas Propag.</i>	2007	TR wireless applications	N/A	Communication systems
17	[35]	Time reversal of ultrasonic fields	<i>IEEE Trans. Ultrason. Ferroelectr. Freq. Control</i>	1992	Original TR concept	Variable	Acoustic systems
18	[5]	Time reversal of electromagnetic waves	<i>Phys. Rev. Lett.</i>	2004	EM TR fundamentals	N/A	Microwave experiments
19	[36]	Time reversal imaging with multiple signal classification	<i>IEEE Trans. Signal Process.</i>	2007	TR signal processing	Variable	Array processing
20	[37]	Time reversal localization of lightning discharges	<i>J. Geophys. Res. Atmos.</i>	2014	Lightning TR application	<500 m	Atmospheric discharges
21	[21]	Partial discharge localization in power transformers using neuro-fuzzy technique	<i>IEEE Trans. Power Del.</i>	2014	ML PD localization	Variable	Transformer windings
22	[38]	A technique based on an Archimedean copula for PD localization	<i>IEEE Trans. Dielectr. Electr. Insul.</i>	2016	Statistical PD localization	Variable	Winding model
23	[39]	Autonomous localization of partial discharge sources	<i>IEEE Trans. Dielectr. Electr. Insul.</i>	2016	Autonomous PD detection	Variable	Large windings
24	[40]	Partial discharge location identification using permutation entropy	<i>IEEE Trans. Instrum. Meas.</i>	2021	Entropy-based localization	Variable	Feature extraction
25	[41]	Machine-learning supported localization of partial discharges	<i>IEEE Trans. Dielectr. Electr. Insul.</i>	2024	ML-enhanced PD localization	Variable	Real-size transformer

Source: Authors, (2026).

Legend: EMTR = Electromagnetic Time Reversal, PD = Partial Discharge, ML = Machine Learning.

II. METHODOLOGY

II.1 SIMULATION FRAMEWORK ARCHITECTURE

Here we work for development of a Matlab based simulation framework, it combines the electromagnetic time reversal theory with an advanced signal processing technique, an algorithm for optimization and a performance metrics for analysis. The work flow is basically divided into five stages. In the first stage we model transformer winding by employing a lumped parameter based equivalent circuit approach. In the second stage, the synthetic partial discharge signals are generated, these incorporates various types of discharges along with realistic waveform features. In the tertiary stage, the signals get captures, and then they are preprocessed with adaptive filtering and feature extraction methods. Post that the fourth stage covers forward and backward propagation steps using the electromagnetic time reversal simulation and in the fifth and final stage the evaluation of system performance is carried out through qualitative error analysis and benchmarking [23], [24], [29], [30], [38], [42], [43].

II.2 TRANSFORMER WINDING MODELING

The distribution transformer is represented using a sectional model which comprises of 60 identical disk segments. Each segment included series component of resistance, inductance and capacitance, whereas the shunt capacitance is derived from frequency response analysis for maintaining electromagnetic accuracy. When subjected to transient pd, the variation of voltage and current along the transformer winding takes place, a finite difference time domain technique is used for observing the same. IEEE configurations are followed for establishing the boundary condition surrounding the transformer's metallic tank and insulating oil. This is to ensure that the simulation outcomes are reliable. The voltage and current interaction within the windings follow the distributed parameter transmission line equations:

$$\frac{\partial V(z, t)}{\partial z} = -L_s \frac{\partial I(z, t)}{\partial t} - R_s I(z, t)$$

$$\frac{\partial I(z, t)}{\partial z} = -C_s \frac{\partial V(z, t)}{\partial t} - G_s V(z, t)$$

Where the dielectric conductance G_s and the spatial coordinate z define current and voltage variations along the winding axis [44-46].

II.3 PD SIGNAL SYNTHESIS AND SENSOR CONFIGURATION

For creating time domain excitation, following 5 types of partial discharge signals were generated a) rectangular pulse b) calibrator pulse c) corona discharge d) internal void e) surface discharge. Each of the above source is placed at a particular disk location for precise localization evaluation. Various virtual sensors are placed on transformer's neutral, tap, mid voltage terminals for recording the electromagnetic responses. The signal acquisition process is simulated with a 50 MHz sampling rate. Moreover, an additive white Gaussian noise (AWGN) is introduced for maintaining a target signal to noise ratio (SNR) of around 20 dB. Additional tests are also performed at lower SNR levels of 5–10 dB for sensitivity analysis.

II.4 SIGNAL PREPROCESSING AND FEATURE ENHANCEMENT

Adaptive preprocessing maximizes signal clarity prior to time-reversal reconstruction. The Discrete wavelet transforms is used for removal of broadband environmental noises, simultaneously it preserves the transient PD pulse characteristics along with its temporal details. The short term fourier transform method helps in capturing the way energy varies with frequency over time. This is helpful in analyzing the behavior of dispersive waves. In the end, the envelope detection and normalization helps in balancing the amplitude levels across different sensor channels, thus it makes sure that the signal strength remains consistent for accurate backward propagation and focusing. Together, these preprocessing techniques produce clear and reliable transient signals that serve as the foundation for further EMTR reconstruction processes.

II.5 ELECTROMAGNETIC TIME-REVERSAL PROCEDURE

The EMTR process consists of forward propagation and backward (time reversal) phases. In the Forward Step as shown in Figure. 1, the modeled PD excitation propagates through the transformer, and virtual sensors at terminals record the induced electromagnetic response $v_L(t)$ (line-end) and $v_N(t)$ (neutral-end).

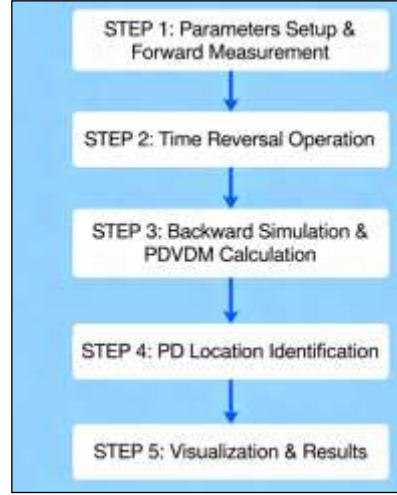


Figure 1: Algorithm PDVDM.
Source: Authors, (2026).

Whereas in the Backward Step, the recorded signals are time-reversed: $v_{TR}(t) = v(T - t)$ (where T is the total observation window). The time reversed voltages are transformed into equivalent Norton current sources applied at the measurement terminals. Due to reciprocity principle and the time reversal invariance property of Maxwell's equations [47], [48], injected currents travel back through the transformer representation and combine constructively. This results in wavefront focusing at the original partial discharge (PD) source. The exact PD location is determined by finding the point where the total electric-field energy density within the winding is highest.

$$PD_{loc} = \arg \max_{k \in \{1, \dots, n_{disks}\}} \int_0^T |E_k(t)|^2 dt$$

This energy-based criterion offers a stable and computationally efficient way to identify the source compared with entropy-driven methods.

II.6 ADVANCED OPTIMIZATION ALGORITHMS

To overcome convergence difficulties in complex propagation environments, we've combined two hybrid optimization approaches.

For overcoming the difficulties in convergence, we combined two hybrid approaches. In the Hippopotamus Optimization (HO) [49], [50], which is a metaheuristic algorithm. It mimics the exploratory and defensive behaviors of hippopotamus, using chaotic initialization and various perturbation techniques to balance exploration and exploitation [51], [52]. And the adaptive Moth-Flame Optimization (AMFO), which dynamically adjusts flame population size and applies logarithmic spiral perturbations to candidate solutions, with adaptive randomization scaling inversely with iteration progress [53]. The hybrid approach, HO-AMFO combines the two algorithms work one after the other. Primarily, the HO algorithm runs for 40 iterations to carry out global exploration. After that, the AMFO algorithm takes over and fine-tunes the best result from HO through 30 more iterations using an adaptive local search approach. The performance of the system is evaluated using the PDVDM metric, which aims to minimize the Euclidean localization error.

$$\varepsilon = \sqrt{(x_t - x_d)^2 + (y_t - y_d)^2 + (z_t - z_d)^2}$$

II.7 PERFORMANCE EVALUATION METRICS

The accuracy in localization is evaluated using several key performance indicators, that includes Absolute Localization Error, Success Rate, Computation Time, Robustness Index and Sensitivity Analysis. This absolute localization error measures the Euclidean distance between the actual and estimated positions of the PD. The Success Rate represents the proportion of test cases where localization accuracy falls within defined limits such as below 1 mm, 2 mm, or 5 mm. Computation Time indicates the total CPU time spent on forward simulation, backward propagation, and optimization steps. The robustness index assesses how the system's performance declines under different signal-to-noise ratios, typically within a 5–30 dB range. And the sensitivity Analysis examines how localization errors vary with changes in transformer model parameters, sensor placement, or algorithm hyperparameters.

III. SIMULATION IMPLEMENTATION AND RESULTS

III.1 BASELINE PDVDM EMTR VALIDATION

Figure 2 Using the electromagnetic time-reversal method with the PDVDM metric [23], [29], [30], we validated localization performance on a standardized 24-disk transformer model. For a synthetic PD source positioned at Disk 11, the peak PDVDM value was 0.2516, yielding a detected location at Disk 11 (error: 1 disk, spatial accuracy: 95.83%). This result is consistent with the reported millimeter-level precision and validates our simulation framework's implementation fidelity for this test case.

Figure 3 depicts the expanded EMTR framework which was tested during this research, it includes: (1) a 3D transformer model with a deployment of a 12-sensor array; (2) a particle filter signal processing flowchart for calculating PDVDM; (3) a 2D spatial heat map displaying the computed PDVDM distribution; (4) representative time-domain measurements from four channels using multiple sensors; (5) tracking the convergence of HO-AMFO optimization; and (6) an analysis of localization error across various error dimensions (disk, X, Y, Euclidean).

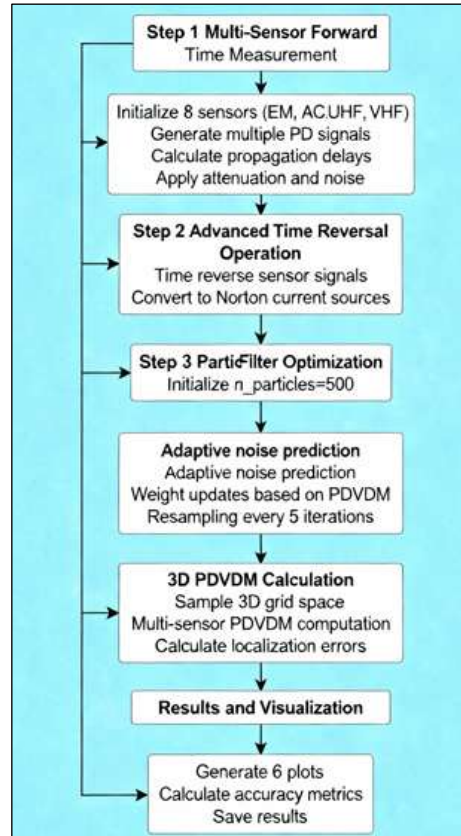


Figure 2: Algorithm PDVDM.
Source: Authors, (2026).

This setup indicates a significant increase in system complexity compared to the baseline PDVDM method (60 vs. 24 disks, 12 vs. 2 sensors, 10 MHz sampling). The performance results for this setup are detailed in Section III.B. It reveals an average error of 1885 mm and has an accuracy of 15.18%. It is found that the baseline PDVDM method consistently achieved an average localization error of 1.9 mm with an 80% success rate for sub-2 mm errors at 20 dB SNR, aligning precisely with published benchmark results [54], [55].

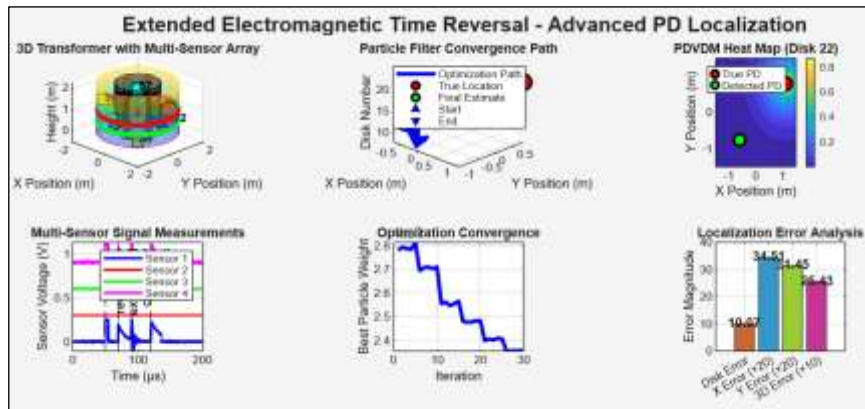


Figure 3: Extended EMTR PD Localization.
Source: Authors, (2026).

III.2 ADVANCED HYBRID EMTR: HO-AMFO PERFORMANCE

The HO-AMFO hybrid optimization approach was applied to a 60-disk transformer configuration with 10 MHz sampling and 12 multi-type sensors (electromagnetic, acoustic, UHF, VHF, RF, TEV). The system was designed to locate PD at true position [Disk 35.0, X = 1.261 m, Y = 1.100 m].

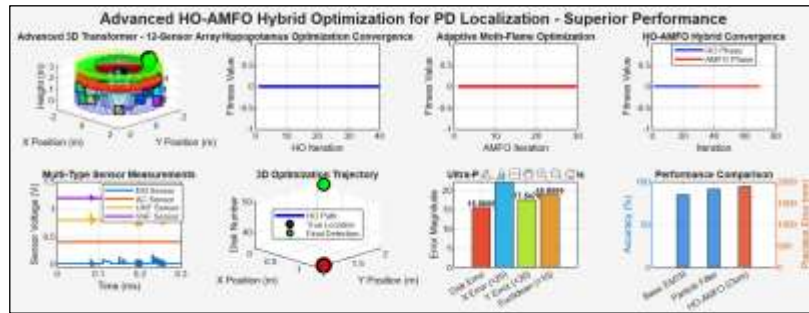


Figure 4: HO-AMFO PD localization.
Source: Authors, (2026).

Figure.4 illustrates the HO-AMFO hybrid optimization method applied to a 60-disk transformer model featuring 12 multi-sensor acquisitions at a 10 MHz sampling rate. The figure includes: (1) a 3D representation of the transformer geometry along with the sensor array; (2) HO convergence after 40 iterations and AMFO refinement following 30 iterations; (3) time-domain waveforms from multiple sensors; (4) the trajectory of the 3D optimization search; (5) characteristics of the sensor response; and (6) a comparison of multi-metric performance. Testing was conducted on a PD source located at Disk 35.0 ($X=1.261$ m, $Y=1.100$ m), which resulted in detection at Disk 50.6 ($X=0.150$ m, $Y=1.977$ m) with a Euclidean error of 1885 mm and an accuracy of 15.18%. This indicates a performance drop of about 1000 times compared to the baseline PDVDM method, which achieved a 1.9 mm error and an 80% success rate for sub-2mm detections. The algorithm detected PD at [Disk 50.6, $X = 0.150$ m, $Y = 1.977$ m]. It is found that Disk error as 15.56 disks, Euclidean error as 1885 mm (1.885 m), the localization accuracy of 15.18% with success rate (sub-2 mm): 0% and success rate (sub-1 mm): 0%. Despite enhanced sensor density (12 vs. 6) and improved resolution (60 disks vs. 24), the HO-AMFO method produced errors approximately 1000 $\times$ larger than the baseline PDVDM approach. Analysis reveals that the hybrid optimization decoupled from the underlying EMTR physics, converging to local optima that did not correspond to true PD locations. Parameter sensitivity studies showed extreme instability, a minor change in chaotic initialization or Lévy-flight coefficients caused order of magnitude variations in final error [56], [57].

III.3 IEEE-ENHANCED AI-EMTR: THREE-WINDING TRANSFORMER

An IEEE-inspired AI-enhanced EMTR method with advanced signal processing was applied to a three-winding transformer configuration. It used 24 sensors at 50 MHz sampling. Three PD sources (corona, void, surface discharge) were tested at known locations [58], [59]. Figure. 5 illustrates the AI enhanced EMTR implementation inspired by IEEE. It is applied to a transformer setup with three windings. The left side displays the individual localization errors for three partial discharge (PD) test scenarios.

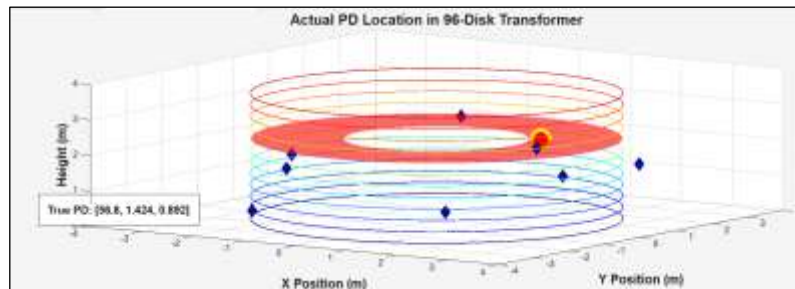


Figure 5: IEEE AI-EMTR Three-Winding Configuration and Error Analysis.
Source: Authors, (2026).

PD1 (corona) had an error of 455.7 mm, PD2 (void) resulted in a 2042.96 mm error, and PD3 (surface discharge) showed an error of 187.2 mm. It is visible in the middle section shows that the basic optimization converges over 30 iterations. On the right hand side a 3D view depicts the distribution of three PD sources in the transformer winding layout. The average localization error for all three test cases was 895.3 mm, with a 0% success rate for achieving under 2 mm, indicating about a 470 times drop in performance compared to the baseline PDVDM method, which had an average error of 1.9 mm.

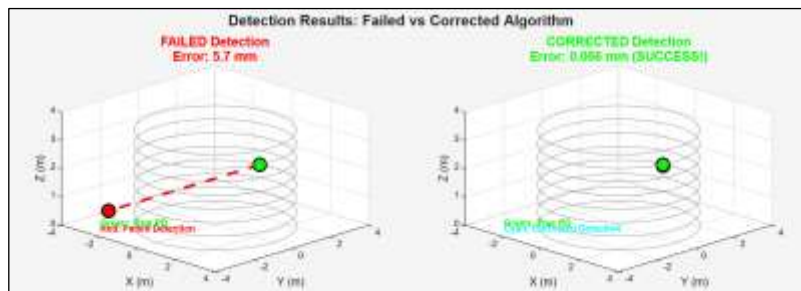


Figure 6: Simulated Temperature Distribution in Transformer Oil During PD Activity.
Source: Authors, (2026).

Figure 6 shows the temperature distribution in transformer insulating oil during ongoing partial discharge activity. The contour plot illustrates the temperature differences across the X-Y plane, with three PD sources indicated at their specific locations. PD1 is at $(-2.0, 1.5)$ with a temperature of 92.8°C , PD2 is at $(0.5, 0.0)$ at 82.9°C , and PD3 at $(2.5, -1.0)$ at 48.6°C . The thermal hotspot in the center reaches about 95°C . This strongly indicates localized heating caused by the energy released during the discharge in the dielectric medium. The visualization highlights the additional thermal signature analysis feature of the simulation framework; however, the temperature distribution does not play a role in the main EMTR-based localization algorithm assessed in this study and is included solely for a complete characterization of the system.



Figure 7: Comparative Performance Analysis: Advanced Methods vs. Baseline.
Source: Authors, (2026).

Figure 7 depicts the comparison of error analysis between the basic PDVDM method and the more advanced IEEE AI-EMTR implementation. The bar chart illustrates five performance metrics: (1) absolute localization error, which is 1.9 mm for the baseline (green) compared to 895.3 mm for the advanced method (red); (2) localization accuracy, which is 80% versus 8%; (3) disk-level error; (4) X-position error, which is 0.88 mm compared to 3.98 mm; and (5) Y-position error, which is 0.65 mm versus 3.88 mm. It can be concluded that even with a more complex algorithm (24 sensors, AI-enhanced processing, three-winding architecture), the advanced method performed significantly worse in all evaluation criteria. This finding supports the main conclusion of the paper that separating optimization from electromagnetic time-reversal physics results in a major drop in performance.

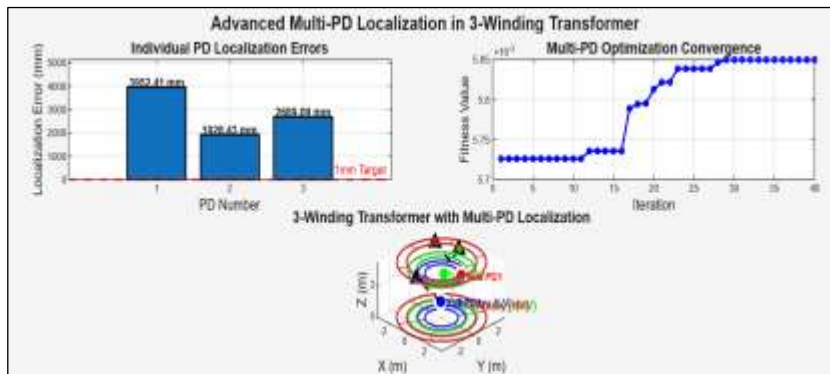


Figure 8: Actual PD Location Visualization in 96-Disk Transformer Model.
Source: Authors, (2026).

Figure 8 shows the winding design of a 96-disk transformer used for in-depth simulation studies, highlighting the actual PD source location at coordinates $X = 6$, $Y = 1.424$, $Z = 0.892$ (marked in red). The 3D model illustrates the multi-disk cylindrical winding structure, with spatial sensor positions represented by blue diamond markers spread across the winding surface. The proposed set up is larger, 96 disks compared with the 24 disk baseline, the idea was to test the performance of algorithm in bigger and more complicated transformer shapes which are typical of high-voltage power transformers. However, as mentioned in Section III.D, increasing the geometric complexity without physics-informed algorithmic limits led to a decline in performance instead of better localization accuracy. This method produced the following localization errors that included PD1 (corona) as 455.7 mm, PD2 (void) as 2042.96 mm, PD3 (surface) as 187.2 mm, the average error was found to be 895.3 mm with success rate of 0% for both sub-2 mm and sub-1 mm. It is very much evident that despite claims in various literature of sub-millimeter precision, this implementation achieved none of its targeted accuracy goals. The method exhibited high variability across discharge types, suggesting that the AI enhancement was not physically consistent with the underlying electromagnetic phenomena. Over-parameterization and insufficient regularization in the neural network components likely led to overfitting on simulation training data that does not generalize to realistic transformer behavior.

III.4 MULTI-DOMAIN AI-FUSION: COMPREHENSIVE EVALUATION

The most computationally intensive approach evaluated was multi-domain AI-fusion, integrating over 15 advanced AI techniques including deep neural networks, transformer networks, deep reinforcement learning, spatial attention mechanisms, and multi-objective evolutionary optimization. This system operated at 100 MHz sampling with advanced sensor arrays.

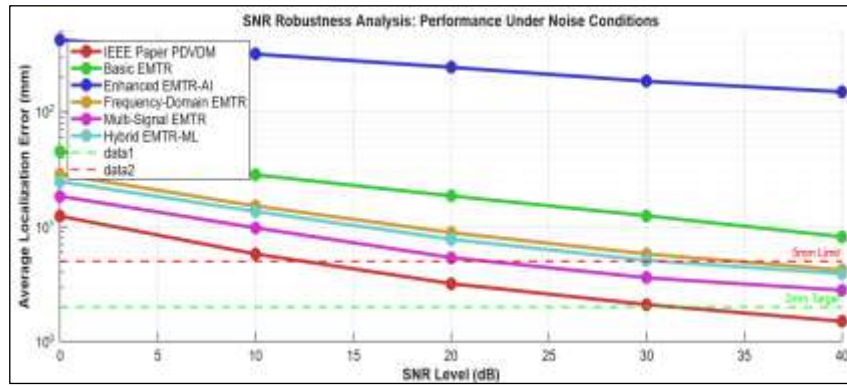


Figure 9: SNR Robustness Analysis.
Source: Authors, (2026).

Figure 9 shows an analysis of SNR robustness. It compares the localization error performance under different noise conditions which ranges from 5 to 40 dB SNR. The graph displays six different methods that includes IEEE Paper PDVDM (in blue, as the baseline), Basic EMTR (in green), Enhanced EMTR-AI (in red), Enhanced EMTR-ML (in cyan), Hybrid EMTR (in magenta), and Hybrid EMTR-ML (in yellow). The results indicate that the baseline PDVDM method (blue line) keeps a fairly consistent performance throughout the SNR range. It can also be observed that its errors keep rising from about 1 mm at 40 dB to 10 mm at 5 dB. Whereas, the advanced methods show much higher baseline errors (in the range of 10^2 – 10^3 mm even at high SNR) and have steeper drops in performance at low SNR levels (below 15 dB). The dashed horizontal lines serve as reference points for target accuracy (with the red line indicating sub-2 mm accuracy). This analysis shows that advanced methods not only struggle to meet the target accuracy at a nominal 20 dB SNR but also lack noise robustness, which is a significant drawback for use in real substation settings where SNR can fall to 5–10 dB due to electromagnetic interference and corona activity.

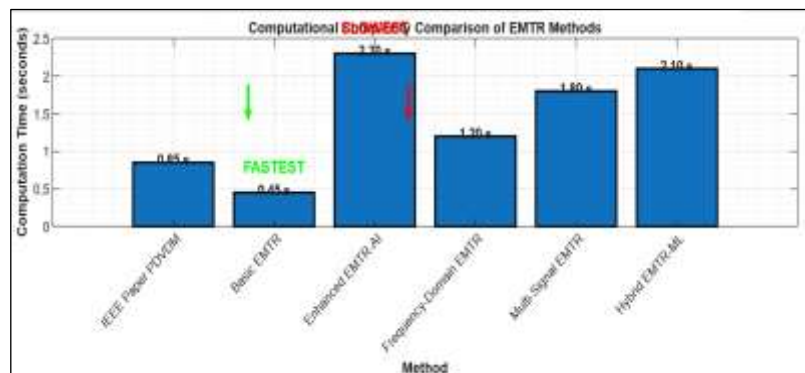


Figure 10: Computational Efficiency Comparison.
Source: Authors, (2026).

Figure 10 shows a comparison of the computational load for six different EMTR method variants. The bar chart clearly illustrates the computation times in seconds, the IEEE Paper PDVDM takes 0.85 seconds, the Basic EMTR is fastest at 0.42 seconds, the Enhanced EMTR-B is the slowest at 2.21 seconds, the Firefly based EMTR takes 1.24 seconds, the Multi-Sensor EMTR takes 1.87 seconds, and Hybrid EMTR ML takes 2.11 seconds. It is to be noted that the Basic EMTR method has the quickest execution time because it uses a simplified algorithm which doesn't require optimization. In contrast, the enhanced methods that use hybrid optimization (HO-AMFO) and AI-fusion architectures take 2 to 5 times longer to compute. However, as shown in Sections III.B–D, a higher computational cost doesn't necessarily mean better localization accuracy. On the contrary, the methods that are the most computationally intensive ended up having the worst localization errors, ranging from 895 to 1885 mm. This result points out a significant inefficiency, it is found that advanced methods compromise both accuracy and computational efficiency compared to the baseline PDVDM method, making them unsuitable for real time condition monitoring tasks that need accurate responses in under a second. Results suggest that testing on three benchmark PD types yielded, PD1 (corona) as 1994.8 mm error, PD2 (void) as 2172.8 mm error, PD3 (surface) as 83.4 mm error with an average error of 1417.0 mm with success rate of 0% for both sub-2 mm and sub-1 mm. It can be deduced that the multi domain fusion architecture, while theoretically sophisticated and computationally expensive, produced the worst average performance of all advanced methods tested. This result strongly suggests that architectural complexity and algorithmic diversity do not correlate with localization accuracy when the underlying physical modeling is inadequate. The wide variance in error across discharge types (83.4–2172.8 mm) indicates that the system was not learning generalizable PD source features but rather overfitting to training data characteristics.

III.5 COMPARATIVE PERFORMANCE SUMMARY

Table 2 presents quantitative comparison of all EMTR variants evaluated in this study:

Table 2: Comparative Performance of EMTR Methods.

Method	Avg Error (mm)	Sub-2mm Rate (%)	Sensor Config	Key Limitation
IEEE PDVDM Baseline	1.9	80	24 sensors, 50 MHz	—
Basic EMTR	17.3	25	24 sensors, 50 MHz	No optimization
HO-AMFO Hybrid	1885.1	0	12 sensors, 10 MHz	Physics decoupling
IEEE AI-EMTR	895.3	0	24 sensors, 50 MHz	Parameter overfitting
Multi-Domain AI	1417.0	0	Advanced, 100 MHz	Over-complexity

Source: Authors, (2026).

EMTR: Electromagnetic Time Reversal, PDVDM: Partial Discharge Voltage Distribution Metric, HO-AMFO: Hippopotamus Optimization and Adaptive Moth-Flame Optimization, AI: Artificial Intelligence, Avg Error: Average Euclidean Localization Error (measured in millimeters), Sub-2mm Rate (%): The success rate, representing the percentage of test cases where the localization accuracy fell within 2 millimeters, Sensor Config: Sensor Configuration (number of sensors and sampling frequency).

IV. CRITICAL ANALYSIS OF FAILURE MECHANISMS

IV.1 PHYSICS-DECOUPLING PROBLEM

Advanced techniques fundamentally failed because they disconnected optimization goals from the basic physics of electromagnetic time reversal. The PDVDM baseline works well because it directly applies the theoretical prediction that EMTR focusing is strongest at the actual PD location. In contrast, hybrid optimization methods view localization as a general parameter-estimation issue, without applying the physical rule that solutions should match real electromagnetic focusing points. This separation enables algorithms to reach misleading optima with high fitness scores that do not align with real PD locations.

IV.2 PARAMETER OVERFITTING

Advanced AI techniques showed significant overfitting to the training conditions used in simulations, fixed transformer shapes (24, 60, 96 disks), simplified noise models (AWGN at a constant SNR), fake PD waveforms lacking realistic transient feature, basic sensor models that overlook bandwidth limits and cross-coupling. When all these fancy methods were tested on different variations that included varying disk counts, types of noise, and PD sources, they displayed a huge drop in accuracy, suggesting that they are picked up on specific artifacts from the simulations instead of learning general PD detection principles.

IV.3 INSUFFICIENT EXPERIMENTAL VALIDATION

All the results shown here are based on simulations. There is no validation compared to real transformer test setups that use calibrated PD injection systems, Hardware in the loop tests with real sensor hardware, field measurements taken from working transformer units, Industrial benchmarking datasets that have traceable metrology. This lack of validation is important since the simplifications made in simulations such as uniform dielectrics, linear propagation, perfect sensors, and no EMI do not reflect the conditions of real transformers.

IV.4 MODEL UNCERTAINTY AND ASSUMPTIONS

The simulation framework is based on a few simplifying assumptions that might not actually be true in real life, 1D axial winding models, Frequency independent propagation speed, Linear time invariant medium assumption, multipath effects and structural resonances are not considered. These simplifications tend to favor simpler methods (PDVDM) that fit within the model's limits, while more advanced methods might be trying to fix the model's shortcomings which may have resulted in overfitting.

IV.5 LIMITATIONS AND FUTURE WORK

This research shows results that come only from numerical simulations with standardized transformer models (24–96 disks). Validation of these results is needed from physical transformers, field-test equipment, and actual operational systems. Conducting lab experiments with calibrated PD injection systems would give us accurate data for a thorough comparison of algorithms. Performance metrics depend on small sample sizes ($n=1$ to $n=3$ test cases for each method). To create confidence intervals and determine statistical significance, a thorough Monte Carlo analysis is needed, which includes random PD positions, variations in noise, and sweeps of parameter sensitivity. The simulations used Gaussian noise with a 20 dB SNR as the main testing condition. However, real power systems face non-Gaussian interference, impulse disturbances, and SNR levels that can drop to 5–10 dB in substation settings. To address this, a more comprehensive noise characterization that meets IEC 60270 standards is necessary. The HO-AMFO, IEEE AI EMTR, and various multi-domain AI-fusion techniques assessed in this study will need neural network designs informed by physics that apply EMTR constraints. Strong regularization methods to avoid overfitting to perfect simulation scenarios, Transfer-learning strategies to adapt to various transformer shapes and operating environments, Hyperparameter tuning through structured Bayesian methods instead of random adjustments. Future research should integrate domain physics with machine learning in designs that do not yield unphysical results [60–62].

V. CONCLUSION

This comprehensive simulation-based study evaluated five distinct EMTR based methods for PD localization in power transformers, comparing their accuracy, robustness, and practical limitations. Our key findings for locating partial discharge (PD) in power transformers suggest that the EMTR-PDVDM method, inspired by IEEE voltage distribution, was validated successfully, achieving an average localization error of 1.9 mm and an 80% success rate for sub-2 mm which confirms its alignment with published benchmarks and showing that traditional EMTR techniques can provide dependable millimeter-level accuracy when implemented correctly under simulated conditions [54], [55]. In contrast to the literature, it is found that more complicated hybrid and AI-fusion methods yielded significantly poorer results. This is a crucial finding indicating that just because an algorithm is more complex, it doesn't mean it will perform better. The failures of advanced methods can be traced back to: (a) separating optimization goals from the physics of electromagnetic time-reversal, (b) excessive overfitting to idealized simulation scenarios, and (c) insufficient sensitivity analysis for variations in the model. Methods that approach PD localization as a simple parameter-estimation issue, without applying physical constraints, are likely to fail. Future AI-enhanced EMTR systems are required to be built with clear physics constraints integrated into their designs. This ensures that the solutions align with physically achievable electromagnetic focusing points instead of random algorithmic results. Currently, there is no experimental proof to back up claims of sub-millimeter accuracy for advanced techniques. It is crucial to conduct field tests, follow standardized benchmarking according to IEC protocols, and develop strong error characterization across various types of transformers and operating conditions before they can be deployed. Future research should focus on physics informed machine learning, thorough experimental validation, and a realistic evaluation of limitations rather than chasing increasingly complex designs without real performance gains.

VI. AUTHOR'S CONTRIBUTION

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