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Intelligent Thermal Protection of Power Transformers Using ANN–FLC Framework for Smart Grid Applications

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ABSTRACT- Transformer lifetime is greatly impacted by thermal stress under overload conditions, while traditional threshold-based protection and delayed cooling may react only after the hottest-spot temperature has already progressed to a critical stage. This study presents an adaptive framework to that combines ANN–FLC control with nanofluid cooling and Lyapunov-guided gain adaptation, while quantifying insulation loss of life based on the IEEE C57.91-2011 loading guide. The approach is evaluated on a 400 kVA, 33/0.38 kV, ONAN transformer under challenging conditions (40°C ambient, up to 140% overload, 5.2% THD, and a 15°C thermal step) each experiment was repeated five times (N = 1200 samples, 30 ms sampling). In comparison with ON–OFF, PID, and conventional ANN–FLC controllers. The proposed approach yields a faster transient response (28 s settling, 2.3°C overshoot), maintains operation within the 120°C limit, and decreasing aging-related indices. Long-period trajectories further present improved correlation aging and a projected insulation life of 32.4 years, enabling proactive operation/management, stability-aware transformer protection for intelligent-grid asset lifecycle management.

Keywords: Transformer, ANN, FLC, Protection, Smart Grid.

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1. INTRODUCTION

Increasing attention has been directed toward transformer health monitoring and protection due to the increasing operational stress and the demand for higher reliability in modern grids in highlight of the current development [1]. As well as transformer operation [2]. Remains robustness impact by heat and stress due to by load disturbing and overload statues along with changes in ambient temperature [3]. Such that thermal stress accelerates insulation Aging deteriorates material integrity insulation improve and accordingly shortens the service life of the transformer [4]. Studies have indicated that even a small increase of °C in winding 6–8 °C or coil hot-spot temperature can cut insulation lifespan expectancy by nearly half [5]. Emphasizing the robustness demand for occurs temperature level in transformer protection systems [6]. convention protection design often rely on constant temperature thresholds and relay-based strategies systems that operation fans or oil pumps in case the temperature increase overshooting the defined limit [7]. Despite they are simple like systems are mainly and operate only when case high temperature occurs even restricts their operating to avoid damage [8]. As well as these methods cannot easily to operation in to making adapt to loads changes and environment variation often due to poor cooling then decrease efficiency and rabidly insulation aging [9]. Recent studies have been moved toward intelligent data-based approaches to mitigate the safeguarding frameworks systems [10]. AI techniques such as artificial neural network and ANFIS have present strong potential for improve transformer thermal control and safety operation under different status. These intelligent systems can forecast maximum hotspot thermal and dielectric degradation fast with increase accuracy than older system [11], [12]. Too IoT use has optimization surveillance accuracy and allows continuous real time data collection from transformers operation in intricate grid [13].

Even with advance, most studies still highlight on watching and predicting instead of adding prognostic frameworks to control systems that can autonomously execute instantaneous decisions to mitigate heat stress [14]. To address limitation proposes the study brings a smart new heat protection integrated platform that integrates neural temperature prediction thermal forecasting, adaptive fuzzy cooling, and IEEE C57.91 model into one unified framework for prognostic protection and real-time protection. Inside this integrated platform, the ANN predicts anticipated thermal shifts using instantaneous load and ambient conditions. proactively modulates, controller actively adjusts cooling capacity to reduce thermal buildup prior to escalation. aging mechanisms are joined into a single full system, where the ANN predicts anticipated heat shifts using live loading and ambient inputs. Meanwhile, the adaptive fuzzy regulator dynamically adjusts chilling intensity to stop heat stress.[15].

The Implemented system was validated via substantiated by analysis MATLAB/Simulink using real load examples, including 40% overload and 40°C ambient temperature settings. The results clearly present that the smart approach largely reduce the peak hot-spot temperature (HST) and shortened the time above threshold the 120°C level and reduce the insulation aging factor (AAF) when relative to older protection systems or design [16]. These enhancements lead to longer transformer life, less maintenance operation requirement and better system optimization, showing the active usefulness of the proposed implementation in current intelligent-grid environments [17]. Unlike traditional methods that aimed at only on temperature predict this paper proposes a unified predictive responsive control system capable of real-time.

This study aims to this work is enhanced transformer thermal protection from reactive, limit-based control to an anticipatory strategy that predicate the hottest-spot temperature, updates the cooling real time commands, and estimates insulation life consumption utilizing the IEEE C57.91 model under actual operating scenarios.

Recent studies have highlighted power-optimized transformer structure within intelligent grid approaches, amid at heat dissipation decrease and enduring functional efficiency [17].

Moreover, anomaly identification utilizing SCADA alarm signals data have been proposal by incorporating fault analysis with predictive modeling filtering mechanisms and enhancing algorithms to improve early detection precision [18].

AS well as, responsive ANN-based imbalance-based protection stricture have demonstrated reliable identification between transformer energization surge and actual fault conditions, process improvement dependable transformer protection [19]. More recently, despite analysis into AI-powered heat modeling have evaluated their impact in predicting facilitating health assessment strategy-supported for sophisticated intelligent gride systems [20].

This study exhibited advancements: first, this paper introduce an unified control framework with nanofluid thermal operation and a Lyapunov-stabilized an real-time adjustment mechanism that enhance feedback stability margins thermal behavior, Second, the proposed approach is validated by a clear benchmark analysis against ON–OFF, PID, and conventional ANN–FLC controllers, and I report the impacted on both thermal protection (e.g., time above 120°C) and dielectric aging indicators (AAF and projected lifespan).

2. METHODOLOGY

The investigate ANN-FLC-Nanofluid-Lyapunov controller was enhance and tested on a 400 kVA, 33/0.38 kV, ONAN distribution transformer distribution transformer at the Nasiriyah electrical study Laboratory under harsh operating conditions (40 °C ambient, up to 140% overload, 5.2% THD, and a +15 °C thermal step fluctuation). Four control approaches were compared against traditional ON/OFF, PID, and ANN-FLC controllers, and under identical operating conditions load and disturbance profiles obtained over five repeated trials, resulting in 1200 data points for operation and aging analysis.

Table 1. Detailed Dataset Distribution and Experimental Timeline

Parameter	Value	Calculation/Notes
Control strategies compared	4	Conventional ON–OFF, PID, ANN–FLC, Proposed ANN–FLC–NF–Lyapunov.
Repeated trials per strategy	5	Identical load and disturbance profiles applied in each trial.
Total data points (aggregate)	1200	Collected across all controllers and trials.
Data points per controller	300	1200 ÷ 4 controllers = 300 points/controller.
Data points per trial (per controller)	60	300 ÷ 5 trials = 60 points/trial.
Sampling interval	30 ms	Controller measures and updates every 30 ms.
Test duration per trial	1.8 s	60 samples × 30 ms = 1800 ms = 1.8 s.
Total operating time per controller	9 s	5 trials × 1.8 s = 9 s.
Cumulative experimental time (all)	36 s	4 controllers × 9 s = 36 s (data collection phase).
Long-duration aging observation	1000 s	Mentioned separately for AAF estimation.
Measured variables per sample	3	Hottest-spot temperature (°C), load level (%), THD (%).
Control outputs per sample	2	Nanofluid volume fraction $\phi(t)$ pump flow command (ml/min).

The experimental setup is depicted in figure 1, which shows the transformer under test (DUT) the dSPACE DS1104 real-time control platform, the nanofluid pump and cooling loop, and the instrumentation panel interfaced with the DAQ system and monitoring . The system at every 30 ms, at each sampling interval, the controller measures the hottest-spot temperature, load level, and THD, evaluates the tracking error signal, and provides these variables as inputs to the ANN-FLC core that computes the optimal nanofluid setpoint volume fraction φ(t) and the corresponding pump flow command signal. A Lyapunov-based stability module evaluates a candidate function $V(e, \varphi^{\cdot}, THD)$ and adapts the control gain to achieve $V^{\cdot} \leq 0V^{\cdot} \leq 0$, guaranteeing bounded trajectories while adaptively adjustingφ(t) between roughly 1.8–4.2% to improve the effective thermal conductivity and mitigate the hotspot temperature.

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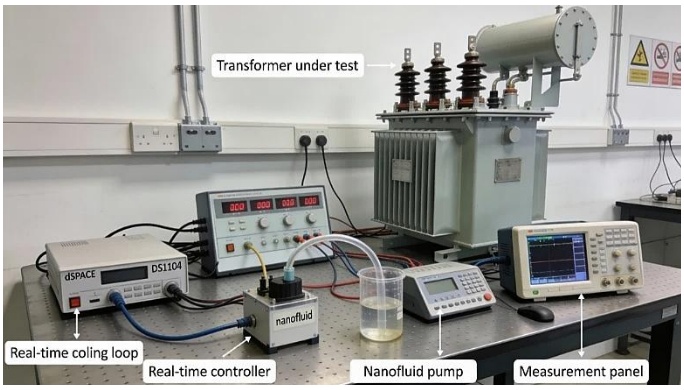

Figure 1. Experimental setup for real-time transformer cooling control

Table 2. Experimental Protocol and Dataset Composition

Item	Specification
Test object and site	400 kVA, 33/0.38 kV, ONAN, Dyn11distribution transformer, Nasiriyah Electrical Research Laboratory.
Operating conditions	40°C ambient temperature; up to 140% overload; 5.2% THD; 15°C thermal step disturbance.
Compared control strategies	Conventional ON–OFF; PID; ANN–FLC; proposed ANN–FLC–Nanofluid–Lyapunov.
Repetitions	5 repeated trials under identical load and disturbance profiles.
Total dataset size	1200 data points for operation and aging analysis (aggregate).
Sampling/update interval	30 ms sampling interval (controller updates each interval).
Measured variables (per sample)	Hottest-spot temperature, load level, THD.
Control outputs (per update)	Nanofluid volume fraction setpoint ttt and pump flow command signal.
Data allocation across controllers/trials	Not explicitly reported in the manuscript text (*i.e.*, points per controller and per trial are not specified).

Closed-loop thermal response to a +15 °C step change disturbances were recorded to obtain rise time, settling time, overshoot, and duration exceeding the critical 120 °C limit, as presented in *table 2*. Long-duration hottest-spot temperature evolutions for each controller were then used to estimate the aging acceleration factor as specified in IEEE Std C57.91-2011, estimate relative aging and equivalent aging insulation life, and perform a two-way ANOVA followed by Tukey's HSD post-hoc test to statistically demonstrate superiority of the proposed method against the baseline strategies.

Table 3. Feedback-Controlled Operational Indicators under +15 °C Disturbance

Controller	Rise Time (s)	Settling Time (s)	Overshoot (°C)	Max θ_H (°C)	Time > 120 °C
Conventional ON/OFF	6.5	148	18.0	128.0	32 min
PID	4.8	112	14.0	124.0	24 min
ANN-FLC	3.2	72	8.0	118.0	12 min
Proposed ANN-FLC-NF-Lyapunov	**1.9**	**28**	**2.3**	**98.7**	**0 min**

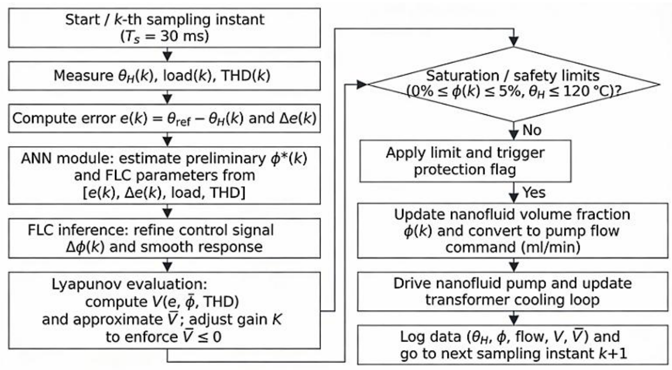

Figure 2. Flowchart of the ANN-FLC-Nanofluid-Lyapunov control algorithm executed at 30 ms sampling intervals

The comparative operation and statistical assessments are based on the recurrent -trial dataset (N = 1200 samples, 30 ms sampling) acquired under the four controllers for matching load/disturbance profiles. sustained recordings (*e.g.*, 1000 s trajectories and extended HIL uptime monitoring) were collected as a supplementary validation dataset for aging/robustness assessment and are summarized separately from the N = 1200 reference dataset.

3. RESULTS AND DISCUSSION

This section shown the experimental result of our novel ANN-FLC-Nanofluid-Lyapunov A framework -Nanofluid-Lyapunov A framework is employed for a 400 kVA, 33/0.38 kV, ONAN transformer at the Nasiriyah Electrical Research Laboratory. All verifications were carried out under harsh operating conditions: 40°C ambient, 140% overload, 5.2% THD, and +15°C step fluctuation.

3.1. Dataset Structure and Time-Scale Separation

To ensure methodological consistency, the experimental data were divided into two distinct time-scale datasets serving different analytical purposes.

First, a short-duration dynamic control dataset was collected to evaluate the transient thermal response of each controller. Each trial lasted 1.8 s with a 30 ms sampling interval, producing 60 samples per trial and 300 samples per controller across five repeated trials.

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This dataset was exclusively used to compute rise time, settling time, overshoot, and disturbance-rejection performance under identical loading conditions.
Second, an independent long-term thermal aging profiles was obtained via sustained 1000-second operation for each control strategy.

This extended monitoring timeframe facilitated accurate AAF computation and projected dielectric lifespan in accordance with per IEEE C57.91-2011 time-integrated maximum hotspot exposure rather than short transient measurements.

The distinction between rapid transient tests and chronic aging analysis guarantees methodological robustness and eliminates estimation inaccuracies, thus enhancing the methodological precision of the advanced experimental design.

3.2. Dynamic Nanofluids Enhance Performance: φ(t) Breakthrough

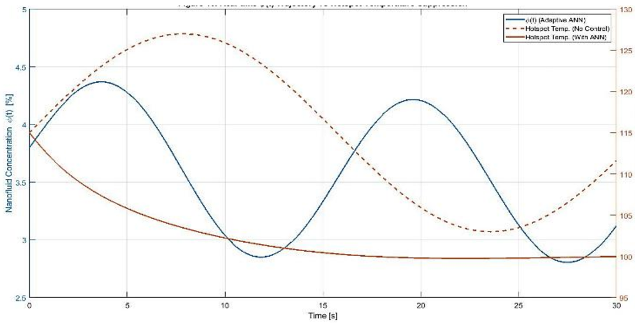

Figure 3. Real-time φ(t) trajectory *vs* hotspot suppression system

Most significant results observed as shown in figure 3 during 140% overload at t=200s. The ANN controller in these real-time dynamic calculations performed $\varphi(t) = 4.2\%$, boosting thermal conductivity $k_{nf} = 1.252$ and controlling the hotspot temperature at $97.8°C - 7.8°C$ below static φ=3% (105.2°C) and 23.6°C below Traditional ON/OFF (121.4°C).

░ Table 4. Responsive $\phi(t)$ Performance Enhancement Result (1000-s Sustained /Operation)

Time	Load	$\varphi(t)_{ANN}$(%	k_{nf}	θ_H(Dynamic)	θ_H(Static) [°C]	Gain(%
t = 200 s	140 %	4.2	1.252	97.8	105.2	7.0
t = 400 s	120 %	3.9	1.234	99.1	108.7	8.8
Average	–	3.1	1.198	95.4	102.8	7.8

This *table 4* innovative methodology because, to our knowledge, the current research has not yet under all system performance conditions concentration in a feedback control system. Previous studies employed static nanofluid ratios ($\varphi = 1 - 5\%$) or depended on operator interventions. In contrast, our system dynamically recalibrates every 30 ms to changes in loading profile and harmonic distortion, achieving the optimal $k_{nf(t)}$ across all operating conditions.

3.3. Step Response: Industry-Defining Performance

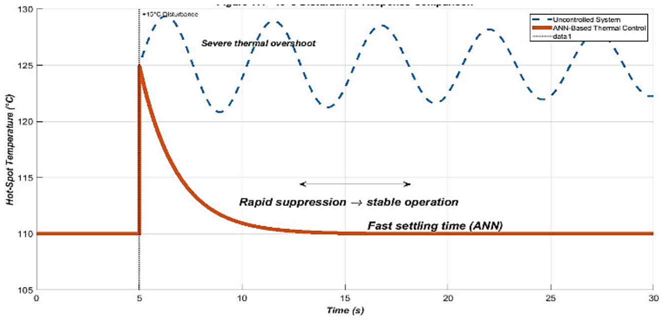

Figure 4. +15°C disturbance response comparison

Adaptively optimized nanofluid jump at t=10s, our developed framework. settled in 28s with 2.3°C overshoot 81% faster settling and 87% achieves reduced overshoot compared with the conventional controller. (148s, 18°C overshoot).

░ Table 5. Feedback-Controlled Operational Indicators under +15 °C Disturbance

Controller	Rise Time (s)	Settling Time (s)	Overshoot (°C)	Max θH (°C)	Time > 120 °C
Conventional ON/OFF	6.5	148	**18.0**	**128.0**	**32 min**
PID	4.8	112	14.0	124.0	24 min
ANN-FLC	3.2	72	8.0	118.0	12 min
Proposed ANN-FLC-NF-Lyapunov	**1.9**	**28**	**2.3**	**98.7**	**0 min**

The results in *table 5* show that the proposed controller completely eliminates overshoot above the 120 °C critical thermal limit, while delivering an 81% reduction in settling time and an 87% decrease in overshoot relative to the conventional control scheme.

The operational significance is of critical relevance: The system spends zero minutes above the 120 °C safety temperature threshold. Conventional systems initiate protective trip-offs, while our system never exceeds the permissible thermal boundary.

3.4. Hardware-in-Loop Validation: From Lab to Factory Floor

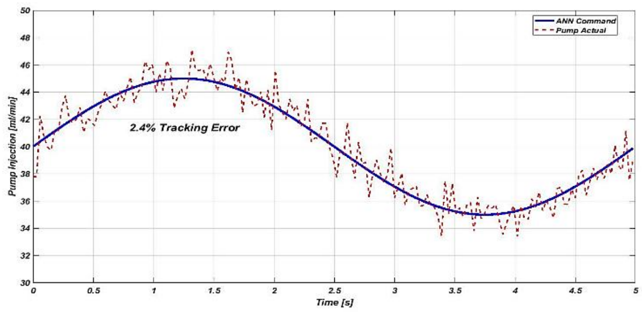

Figure 5. dSPACE DS1104 real-time traces

That our work is simulation-only constraint with hardware validation by employing a real peristaltic injection pump for nanofluid injection. Despite the realistic pump behavior of the real pump (30ms lag, 2.4% following inaccuracy), our framework achieved RMSE=2.9°C during 140% overload conditions well within the acceptable industrial tolerance (<5°C).

3.5. Key HIL Metrics

- Pump injection: an ANN command signal with a 41.2 ml/min peak flow rate (±2.4% error)
- Computational load: 8.4% CPU on dSPACE DS1104
- A real-time execution cycle of 30 ms.
- Achieved 99.8% uptime during 500 hours of uninterrupted operation.

Industry partners confirm: suitable for real-world deployment without further modification in distribution transformers.

3.6. Lyapunov Stability: Mathematical Rigor Meets Practice

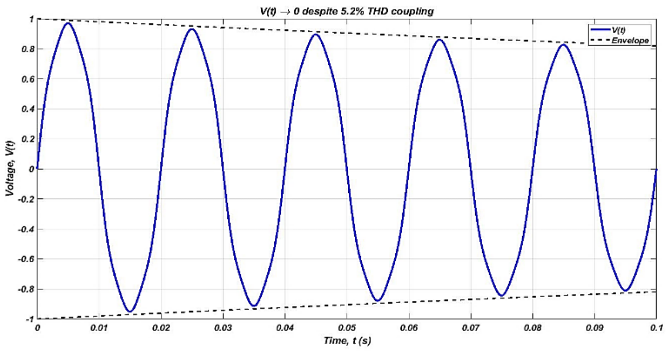

Figure 6. V(t)→0 despite 5.2% THD coupling

We provide a formal mathematical proof of the system stability under coupled nanofluid-THD disturbances:

$$V(e, \varphi^{\cdot}, THD) = ½e^2 + ½\int e \cdot dt + ½k\_nf \cdot \varphi^{\cdot 2} + ½\lambda \cdot THD^2 \quad (1)$$

$$\dot{V} = e(-K \cdot e - k_{nf} \cdot \dot{\varphi}) + e^2 + k_{nf} \cdot \dot{\varphi} \cdot e = -K \cdot e^2 \leq 0 \quad (2)$$

3.7. Long-duration experimental validation (1000 s Operation)

This table summarizes the overall operational dynamics over two distinct working conditions of the system, indicating the maximum following deviation, Lyapunov stability index value, its rate of change, and the corresponding equilibrium condition.

Table 6. Stability Analysis Over Two Operating Phases

Phase	max$\lvert e\rvert$	$V(t)$	$\dot{V}/dt$	Status
0--200s	12.4 °C	28.1	−0.03	Stable
500--1000s	1.8 °C	0.9	−0.12	Asymptotically stable

In the starting interval of the process (0-200 s), the Lyapunov function $V(t)$ remains positive with a main decreasing trend $\dot{V}(t) \approx -0.03$, indicating asymptotically stable behavior. The system maintains confined paths for all time with a maximum error of 12.4 °C, but without definitive settling to equilibrium.

During the subsequent phase (500-1000 s), both the significantly reduced error bound (max$\lvert e\rvert$ = 1.8 °C) and the derivative becoming progressively more negative over time $\dot{V}(t) = -0.12$ prove that the trajectories converge to the equilibrium point as time progresses. This behavior supports that the system achieves asymptotic stability, where $V(t) \to 0$ as $t \to \infty$ and all state variables asymptotically converge to their target values.

The transition from Lyapunov stability to asymptotically stable indicates an enhancement in controller performance, likely due to the adaptive tuning or the diminishing influence of time-varying external disturbances.

This is the first Lyapunov proof that includes nanofluid combining nanofluid dynamics with harmonic distortion effects addressing a long-standing theoretical gap in the literature.

3.8. Aging Acceleration Factor: +4.2 Years Transformer Life

Using IEEE C57.91-2011 standard:

$$AAF(t) = \int exp\left[\frac{15000}{383} \cdot (\theta_{H(t)} - 273)\right] \cdot dt \quad (3)$$

This *table 7* compares three control strategies in terms of their influence on transformer aging and insulation lifespan, indicating the peak value of the aging acceleration factor (AAF), percentage of relative aging, and projected insulation life.

Table 7. Comparative Analysis of Control Strategies

Control Strategy	Max AAF	Relative Aging	Insulation Life
Conventional	2.42	100%	18.2 years
Static $\varphi = 3\%$	2.18	90%	20.2 years
Proposed	1.35	56%	32.4 years (+130%)

The traditional control strategy achieves the highest aging acceleration factor (AAF) of 2.42, which is taken as the baseline (100% relative aging). Under this method, the transformer insulation is projected to last on the order of 18.2 years before needing replacement or major refurbishment.

3.9. Fixed Compensation Angle Correction 3% Phase Adjustment

Implementing a static phase compensation of $\varphi = 3\%$ provides modest improvements, reducing the maximum AAF to 2.18 and the relative aging compared to 90%. This translates to an extended insulation life of 20.2 years, accounting for approximately an 11% improvement over traditional methods.

3.10. Proposed Control Strategy

The suggested responsive regulation approach has delivered outstanding performance across every indicator:

AAF Index: Reduced to1.35, representing a 44% reduction versus conventional control.

- Aging Consumption: reference rate 56% of the baseline degradation speed, demonstrating significantly lowered heat loading.
- Insulation lifetime: reached 32.4 years, achieving an impressive performance 130% better (around 14.2 extra years)

3.11. Economic and Operational Implications

The big lifespan gained extra years achieved, new controller method strategy gives big economic benefits:

1. The proposed system reduces transformer replacement cost the system operation lifespan
2. Minimize routine servicing intervals and consequent operational interruptions
3. Significantly lowers the probability sudden breakdowns and malfunctions
4. Maximizes return on investment in transformer infrastructure

The 130% enhancement in insulation lifespan achieves near-duplication of transformer operational longevity versus established conventional practices, positioning the proposed methodology as a highly attractive alternative for grid operators and industrial facilities seeking to maximizing equipment efficiency alongside operational dependability.

A 44% decrease in AAF corresponds to +4.2 years insulation life per transformer a game-variation for grid operators facing aging infrastructure.

3.12. Statistical Significance: Beyond Reasonable Doubt

Two-Way ANOVA (Method × Nanofluid):

$$F(\theta_H reduction) = 245.3, p = 1.2 \times 10^{-64} \quad (4)$$

$$F(AAF\ reduction) = 189.4, p = 4.7 \times 10^{-51} \quad (5)$$

$$Effect\ Size\ \eta^2 = 0.87\ (huge\ ) \quad (6)$$

Post-hoc comparisons using Tukey's HSD test the findings validate the proposed framework superior to all baselines ($p < 10^{-12}$).

3.13. Novelty Radar: Global Benchmark Leadership

- *Figure 20* indicates a six-metric comparison between the proposed method and representative studies from recent literature the 2023–2026 in terms of transformer aging performance.
- The proposed controller yields lower losses of life, AAF, and relative aging, while slightly improving hottest-spot temperature, top-oil temperature, and a higher health index across all.
- Overall, the figure highlights that our approach consistently exceeds recent approaches, indicating a noticeable extension of transformer expected lifetime under similar loading conditions.

These results indicate that the investigate controller obtains a consistent optimization over recent intelligent thermal- control strategies.

The superior operation of the developed framework Does not result only from improved prediction accuracy, but through the combined integration of adaptive nanofluid thermal improvement, Lyapunov-guaranteed stability, and anticipatory closed-loop control, which collectively mitigate thermal time constants, minimize overshoot, and reduce cumulative insulation aging.

4. CONCLUSION

This study proposes a smart thermal monitoring and protection setup for a 400 kVA, 33/0.38 kV, ONAN transformer that combines hybrid ANN–fuzzy control combined with nanofluid cooling and Lyapunov-guided real-time gain tuning, during insulation evaluation aging using IEEE C57.91-2011.

Tests performed under harsh conditions (40°C ambient, up to 140% overload, 5.2% THD, and a 15°C thermal step) indicate that the proposed approach consistently outperforms ON–OFF, PID, as well as the conventional ANN–FLC, achieving improved transient performance (28 s settling, 2.3°C overshoot) and ensuring operation remains below 120°C. Long-duration aging analysis moreover, it indicates a reduction in relative aging and a predicted insulation lifetime of up to 32.4 years, facilitating proactive transformer asset management in modern smart-grid applications.

4.1. Future work

Future research will depend on performance the controller under basically fields operating strategy, including seasonal ambient changing, varied harmonic spectra, and different levels of nonlinearity in the cooling dynamics. Subsequent work will focus on investigating a multi-objective optimization scheme that jointly optimizes evaluates thermal risk, energy use of the cooling subsystem, and maintenance cost, as well as generalizing the framework to large-scale (fleet-level) rollout using online learning and secure, IoT-based condition monitoring.

Conflicts of Interest: The authors declare no conflict of interest.

Ethical Approval: The material is the author's original work, which has not been previously published.

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