

## Research Article

# Detection of Chronic Load Imbalance and Hot-Spot Risk in Building Electrical Systems using Long-Term Three-Phase Current Analysis and Mechanism-Informed Artificial Intelligence

Sittisak Rojchaya <sup>a\*</sup> and Santi Karisan <sup>b</sup>

<sup>a</sup> Department of Electrical Engineering, Faculty of Engineering and Technology, Rajamangala University of Technology Srivijaya, Sikao, Trang 92150, Thailand.

<sup>b</sup> College of Industrial Technology and Management, Rajamangala University of Technology Srivijaya, Khanom, Nokhon Si Thammarat 80210, Thailand.

## ABSTRACT

## Article history:

Received: 2026-03-11

Revised: 2026-08-02

Accepted: 2026-08-07

## Keywords:

Chronic load imbalance;

Thermal memory;

Insulation aging

Infrared thermography detects hot spots only at the time of inspection, whereas electrical system degradation evolves continuously through the 24/7 accumulation of operational stress. This study proposes a novel mechanism-informed predictive monitoring framework that integrates long-term three-phase current data with a physics-guided machine-learning inference model to identify early degradation signatures before infrared-detectable heating occurs. Results synthesized from multiple degradation indicators reveal that Phase B exhibits persistent structural dominance, with a mean occupancy of 56% (peaking at 71%), and accumulates 2.35 times the thermal debt of Phase A. This imbalance produces pronounced thermal memory, whereby 38% of thermal stress remains unrecovered after load reduction, resulting in the fastest insulation aging (aging rate = 0.0028; final Aging Index = 0.95). Notably, the proposed system degradation collapse index exceeds the critical degradation threshold (0.70) despite the absence of overload or fault conditions under conventional protection criteria. The proposed framework provides a continuous, low-cost, and practical solution for 24/7 predictive condition monitoring, enabling electrical hazards to be identified before hot spots and failures occur while overcoming the limitations of snapshot-based inspections.

© 2026 Rojchaya, S. and Karisan, S. Recent Science and Technology published by Rajamangala University of Technology Srivijaya

## 1. Introduction

Electrical systems in modern buildings are typically designed and evaluated within threshold-based safety frameworks, such as maximum current limits, allowable temperature rise, and maintenance standards defined by international codes and guidelines (Huang *et al.*, 2011). Cable ampacity and thermal limits are commonly assessed under steady-state or cyclic assumptions, as prescribed in international standards, which primarily focus on short-term safety margins rather than long-term degradation behavior (Rasoulpoor *et al.*, 2017). However, extensive field experience and recent studies indicate that electrical failures and hot-spot formation in main feeders and electrical equipment often result not from direct overloads or

fault events, but from progressive degradation accumulated during prolonged normal operation (Choudhary *et al.*, 2022; Theofanous *et al.*, 2025; AlShaikh Saleh *et al.*, 2025). Conventional inspection practices, particularly infrared thermography, are widely adopted because of their non-contact capability and practical applicability in electrical maintenance. Nevertheless, infrared inspections are inherently limited to capturing thermal conditions only at the moment of observation, thereby reflecting end-stage symptoms rather than the underlying degradation mechanisms within the system (Ruiz and Betancourt, 2026; Enescu *et al.*, 2020). In contrast, conductor and insulation degradation evolves through the continuous 24/7 accumulation of electro-thermal stress,

\* Corresponding author.

E-mail address: [sittisak.r@rmutsv.ac.th](mailto:sittisak.r@rmutsv.ac.th)

occurring not only during peak loading but also under low-load conditions and periods when the system appears to operate normally (Tao *et al.*, 2025; Zhang *et al.*, 2024). Such cumulative thermal exposure accelerates insulation ageing and alters thermo-mechanical behavior, even when operating temperatures remain within conventional limits (Hu *et al.*, 2025; Ahmad *et al.*, 2025; AlShaikh Saleh *et al.*, 2025). Consequently, significant risks often remain undetected until observable hot spots or electrical accidents have already occurred. This challenge is particularly pronounced in educational buildings and public facilities, where electricity consumption patterns vary across daily and seasonal cycles and are strongly influenced by spatial load distribution (Melo *et al.*, 2023; Santamouris and Vasilakopoulou, 2021). These environments commonly exhibit structurally unbalanced three-phase loading patterns that may be insufficient to trigger protective devices or violate operational thresholds, yet still induce persistent heat accumulation, thermal stress retention (thermal memory), and accelerated long-term insulation ageing (Pan *et al.*, 2021; Choudhary *et al.*, 2022). Such degradation mechanisms remain insufficiently addressed within traditional monitoring and protection paradigms.

To address this gap, this study proposes a novel mechanism-informed predictive monitoring and analysis framework based on long-term three-phase current measurements obtained from real-world operation, integrated with mechanism-informed artificial intelligence. Recent advances in physics-informed and hybrid data-driven approaches demonstrate that embedding physical knowledge into analytical models significantly improves interpretability and robustness in condition monitoring applications (Wu *et al.*, 2024; Oelhaf *et al.*, 2025). Recent studies have further demonstrated that advanced artificial intelligence and machine learning techniques substantially improve intelligent condition monitoring, fault localization, and predictive maintenance of power cable systems under complex operating conditions (Shao *et al.*, 2025; Abdolahi *et al.*, 2026). Unlike conventional AI-based condition monitoring methods that primarily detect anomalies from historical measurement patterns, the proposed framework integrates electro-thermal degradation mechanisms with artificial intelligence to infer hidden degradation processes and continuously quantify degradation evolution under normal operating conditions. By enabling the identification of structural phase imbalance, cumulative thermal debt, and early degradation signatures before the appearance of infrared-detectable hot spots, the proposed framework shifts the monitoring paradigm from "detecting heating after it occurs" to "predicting degradation before heating becomes observable". This work demonstrates that electrical system degradation in buildings can be continuously monitored in a safe, low-cost, and non-intrusive manner, while employing infrared thermography solely as a validation tool rather than the primary monitoring method, thereby opening a practical pathway for proactive risk management and accident prevention in modern

building electrical systems (Al-Dulaimi *et al.*, 2024; Tao *et al.*, 2025; Abdolahi *et al.*, 2026).

## 2. Theoretical Framework

### 2.1 Load imbalance in electrical distribution systems

Load imbalance in three-phase electrical distribution systems occurs when the currents in each phase are not equally distributed due to uneven load allocation. Such imbalance conditions may lead to increased neutral currents, additional power losses, conductor overheating, and accelerated degradation of electrical insulation. Persistent or chronic load imbalance can significantly affect system reliability and operational lifetime. A commonly used indicator for quantifying phase current imbalance is the current imbalance index, defined as

$$I_{imb} = \frac{I_{max} - I_{avg}}{I_{avg}} \times 100 \quad (1)$$

where  $I_{max}$  represents the maximum phase current and  $I_{avg}$  denotes the average current across the three phases. Although this conventional imbalance index provides a useful measure of instantaneous load asymmetry, it does not adequately represent the cumulative thermal effects associated with prolonged imbalance conditions. Chronic imbalance may gradually increase conductor temperature and accelerate insulation aging even when instantaneous imbalance values appear moderate.

### 2.2 Electro-thermal behaviour of conductors

Electrical conductors carrying unbalanced currents experience unequal heating due to different Joule losses in each phase. The temperature evolution of a conductor can be described using an electro-thermal energy balance model.

$$C \frac{dT}{dt} = P_{loss} - P_{cool} \quad (2)$$

where  $T$  represents conductor temperature,  $C$  denotes the thermal capacitance of the conductor,  $P_{loss}$  is the heat generated by electrical losses, and  $P_{cool}$  represents heat dissipation to the surrounding environment. The electrical heating term can be expressed as

$$P_{loss} = I^2 R \quad (3)$$

where  $I$  is the conductor current and  $R$  is the electrical resistance. In unbalanced operating conditions, unequal phase currents result in different heating levels across phases, which may cause thermal divergence between conductors and increase the risk of insulation degradation.

### 2.3 Thermal aging of insulation

The degradation of electrical insulation materials is strongly influenced by temperature. Elevated temperatures accelerate

chemical reactions within insulation materials, leading to progressive deterioration of dielectric strength.

The temperature-dependent aging acceleration factor can be expressed as

$$A = e^{\lambda_k T} \quad (4)$$

where  $A$  represents the insulation aging acceleration factor,  $T$  denotes the conductor temperature, and  $\lambda_k$  is the thermal aging coefficient.

The coefficient  $\lambda_k$  reflects the sensitivity of insulation degradation to temperature variations and is derived from Arrhenius-based thermal aging theory. This formulation captures the exponential relationship between temperature rise and the rate of insulation deterioration. Higher operating temperatures therefore significantly increase the aging acceleration factor, indicating faster insulation degradation under prolonged thermal stress.

#### 2.4 Thermal memory effect

Electrical conductors exhibit thermal inertia, meaning that temperature changes occur gradually and depend on both present and past loading conditions. This behavior is commonly referred to as the thermal memory effect. The thermal memory index can be represented as:

$$M(t) = \int_0^t e^{-\beta(t-\tau)} T(\tau) d\tau \quad (5)$$

where  $M(t)$  represents the thermal memory index,  $T(\tau)$  denotes the conductor temperature at time  $\tau$ , and  $\beta$  is the thermal decay coefficient.

This formulation accounts for the persistence of thermal stress within the conductor. Even after load reductions, residual heat may remain in the system, continuing to influence temperature evolution and insulation aging.

#### 2.5 Severity of dynamic current imbalance (SDCI)

To evaluate the long-term impact of load imbalance on conductor health, a composite severity indicator referred to as the Severity of Dynamic Current Imbalance (SDCI) is proposed. Unlike conventional imbalance indices, the SDCI integrates insulation aging, electro-thermal stress and thermal memory into a unified mechanism-informed indicator for long-term degradation assessment. The SDCI is defined as

$$SDCI = \omega_1 A_n + \omega_2 T_n + \omega_3 M_n \quad (6)$$

where  $A_n$ ,  $T_n$  and  $M_n$  denote the normalized insulation aging factor, conductor temperature deviation, and thermal memory index, respectively. Each component is normalized to the range of 0-1 using min-max normalization before integration to

eliminate unit differences and ensure balanced contribution. The weighting coefficients satisfy

$$\omega_1 + \omega_2 + \omega_3 = 1 \quad (7)$$

In this study,  $\omega_1 = 0.5$ ,  $\omega_2 = 0.3$  and  $\omega_3 = 0.2$ . The weights were assigned according to the physical importance of each degradation mechanism, where insulation aging is considered the dominant indicator of long-term cable deterioration, followed by conductor temperature and thermal memory.

The SDCI ranges from 0 to 1, with larger values indicating more severe cumulative degradation. Based on the eight-month field monitoring data, an SDCI value of 0.70 was selected as the engineering early-warning threshold because it consistently corresponded to persistent phase imbalance, significant thermal memory, and accelerated insulation aging. This threshold represents the onset of critical degradation rather than immediate system failure, enabling proactive maintenance before infrared-detectable hot spots or protection-device operation occur. By combining electro-thermal behavior with insulation-aging mechanisms into a single physics-informed index, the proposed SDCI provides a more comprehensive assessment of long-term conductor health than conventional current imbalance indices.

### 3. Materials and Methods

#### 3.1 Installation of electrical energy meters in the building power distribution system

This study employs three-phase current data (Phases A, B, and C) obtained from an operating low-voltage power distribution system, measured using non-intrusive current sensing techniques to avoid disturbing system operation. The currents were recorded continuously over several months, encompassing both low- and high-load conditions representative of actual building usage. The resulting dataset provides sufficient temporal resolution to capture long-term trends and cumulative effects of thermal cycling, rather than short-duration transient events.

#### 3.2 Long-term electricity usage data acquisition and recording framework

The electricity usage data acquisition process in this study was specifically designed to support long-term, mechanism-informed analysis of chronic load imbalance and progressive thermal stress accumulation in a building electrical system. Rather than focusing on short-term or snapshot measurements, the proposed framework emphasizes continuous monitoring to capture slow-evolving degradation mechanisms that develop under normal operating conditions.

Electrical data were collected from the Main Distribution Board (MDB), which serves as the central aggregation point of three-phase electrical loads supplying the building. Three-phase

line currents were measured using non-intrusive Clamp Meters (CMs) installed on the incoming feeder conductors inside the MDB. This non-intrusive measurement approach enables continuous monitoring without interrupting normal system operation or introducing additional electrical or thermal stress into the system. The analog current signals acquired by the Clamp Meters were processed through a signal conditioning stage to ensure measurement stability, noise suppression, and compatibility with digital data acquisition requirements. The conditioned signals were then transmitted to a Gateway device, which functions as the communication interface between field-level measurement units and the remote data infrastructure. Wireless communication between the Clamp Meters and the Gateway was implemented using Bluetooth version 4.1, operating within the 2.402-2.48GHz industrial, scientific, and medical (ISM) frequency band. This communication scheme provides reliable short-range data transfer with low power consumption and sufficient robustness for continuous, long-duration monitoring applications. The Gateway aggregates the three-phase current data and uploads them to a centralized Data Center at a fixed temporal resolution of one minute. This sampling interval was selected to balance data resolution and storage efficiency while remaining adequate to capture long-term load asymmetry, thermal cycling behavior, and cumulative stress effects associated with Joule ( $I^2 R$ ) heating, which evolve gradually rather than instantaneously. All recorded data were stored in comma-separated values (CSV) format, ensuring transparency, reproducibility, and seamless integration with subsequent analytical and modeling workflows. Authorized users can access the Data Center remotely via Internet-connected devices using a browser-based interface, allowing data visualization, retrieval, and direct download without physical access to the electrical installation. The graphical user interface used for data access and retrieval is illustrated in Figure 3. In this study, three-phase current data were recorded continuously over a period of eight months, from 1 December 2024 to 31 July 2025. This extended monitoring duration covers normal operating conditions, daily and weekly load cycles, off-hour usage, and seasonal variations. The resulting long-term dataset provides a robust empirical foundation for subsequent analyses, including structural phase dominance assessment, cumulative thermal debt estimation, identification of thermal memory and hysteresis effects, insulation aging trajectory modeling, and synthesis of the System Degradation Collapse Index (SDCI). By prioritizing continuous, long-term data acquisition over snapshot-based inspection, the proposed recording framework enables early detection of hidden degradation mechanisms that precede infrared-detectable hot-spot formation. This approach supports predictive risk assessment and enhances the ability to identify electrical system vulnerabilities before the onset of visible thermal anomalies or safety-critical failures.



**Figure 1** Clamp-on current measuring device (Clamp Meter) installed on a feeder conductor inside the Main Distribution Board (MDB).

### 3.3 Feature extraction

The features used in this study were categorized into two groups. The first group consists of twelve mechanism-informed indicators derived from long-term three-phase current measurements and subsequent processing, as presented in Table 1. These indicators include phase occupancy shares for Phases A, B, and C (structural phase dominance), normalized cumulative values representing thermal debt accumulation, mean values characterizing phase stress signatures, and phase-specific Aging Indices describing accelerated insulation degradation. Together, these twelve indicators capture structural load asymmetry, cumulative thermal stress, stress concentration, and long-term aging behavior of the system. The second group consists of an analytically derived feature, namely the Unbalance Current, calculated using the formulation defined in Equation (1). This feature quantifies instantaneous phase asymmetry and complements the long-term indicators by linking current imbalance to the underlying degradation mechanisms.

### 3.4 SDCI parameter determination

The parameters of the proposed Severity of Dynamic Current Imbalance (SDCI) were determined using the long-term three-phase current measurements collected in this study. The measured currents were first used to estimate the conductor temperature according to the electro-thermal model, after which the insulation aging acceleration factor (A) and thermal memory index (M) were calculated using Equations (4) and (5), respectively. To ensure comparable contributions, all parameters (A, T, and M) were normalized to the range of 0-1 before integration. The weighting coefficients were assigned as  $\omega_1 = 0.5$ ,  $\omega_2 = 0.3$  and  $\omega_3 = 0.2$  based on the relative physical importance of insulation aging, conductor temperature, and thermal memory in long-term electro-thermal degradation. The critical threshold (SDCI = 0.70) was established empirically from the eight-month field dataset, where values at or above this level consistently corresponded to persistent phase imbalance,

accelerated insulation aging, and cumulative thermal stress. Finally, the normalized parameters were combined using Equation (6) to obtain the SDCI for continuous condition monitoring and early degradation assessment.

## 4. Results and Discussion

### 4.1 Feature importance and overall contribution to unbalance current

As shown in Figure 5 (Normalized Cumulative Thermal Debt) and summarized in Table 1, Phase B is the primary contributor to current unbalance in the system. Phase B exhibits the highest phase occupancy share (mean = 0.56, max = 0.71), resulting in a consistently higher rate of thermal debt accumulation compared to Phases A and C. By the end of the operational period, Phase B reaches a normalized thermal debt of 1.00, which is 2.35 times that of Phase A (0.42) and 1.59 times that of Phase C (0.63). The persistent dominance of Phase B in Figure 5 indicates cumulative thermal stress rather than transient imbalance effects. This behavior is further supported by the highest mean  $I^2$  stress ( $185 \text{ A}^2$ ) and aging growth rate ( $\lambda = 0.0028$ ), leading to a final aging index of 0.95. These results confirm that long-term current unbalance is governed by cumulative feature dominance and thermal memory effects, even in the absence of overload or fault conditions.

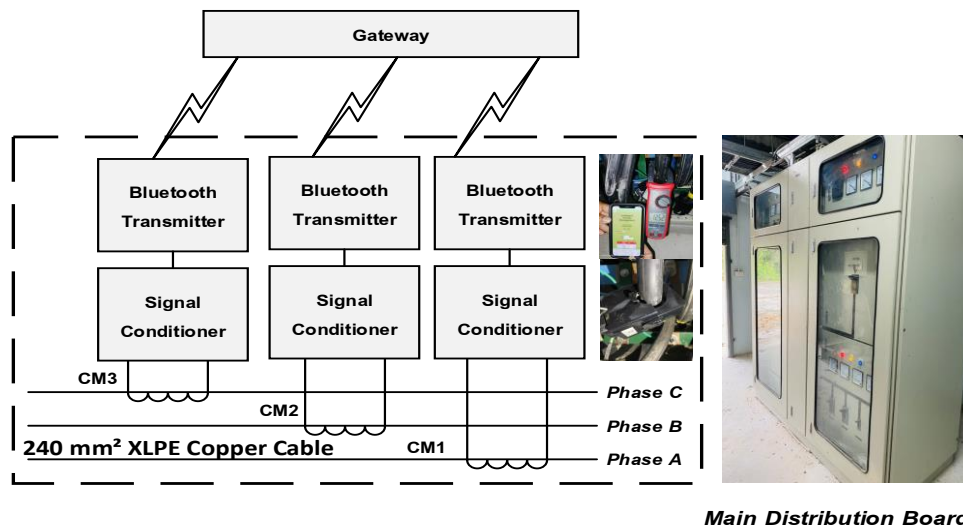
### 4.2 Power-driven phase imbalance characteristics

Figure 6 presents the Phase Stress Asymmetry Signature, derived from mean  $I^2$  values, which directly represent Joule-loss-induced electrical stress. The results reveal a severe stress concentration in Phase B, with a mean  $I^2$  value of  $185 \text{ A}^2$ ,

compared to  $38 \text{ A}^2$  for Phase A and  $82 \text{ A}^2$  for Phase C. This corresponds to Phase B experiencing  $4.9\times$  higher stress than Phase A and  $2.3\times$  higher stress than Phase C. Figure 7 further exposes the thermal memory loop of Phase B, demonstrating that a significant fraction of thermal stress persists even after load reduction. Quantitatively, Phase B exhibits a 38% thermal recovery deficit, indicating that more than one-third of accumulated thermal stress remains unrecovered between load cycles. Together, Figures 6 and 7 confirm that persistent power dominance in Phase B drives not only instantaneous stress asymmetry but also long-term thermal hysteresis, which conventional snapshot inspections cannot capture.

### 4.3 Role of electric current and its coupling with power

Although electric current exhibits relatively low direct importance in the Random Forest model (0.58–1.37%), Figures 8 and 9 reveal its critical coupling role with power. Figure 8 shows a perfectly linear relationship between Phase B load level and imbalance magnitude, with a correlation coefficient of  $r = 1.0$ , confirming that current acts as a deterministic carrier of power imbalance. Notably, Phase A, despite having the lowest average current ( $4.12 \text{ A}$ , compared to  $9.89 \text{ A}$  in Phase B and  $4.74 \text{ A}$  in Phase C), contributes 75.17% to unbalance current prediction. This apparent paradox is resolved by Figure 9, which demonstrates inter-phase coupling distortion, whereby stress originating in a structurally dominant phase propagates into other phases. Thus, current does not independently generate imbalance but amplifies imbalance induced by asymmetric power distribution, reinforcing the system-level nature of degradation mechanisms.



**Figure 2** Installation of a real-time energy monitoring system and comparison of its measurement accuracy with a standard reference instrument.

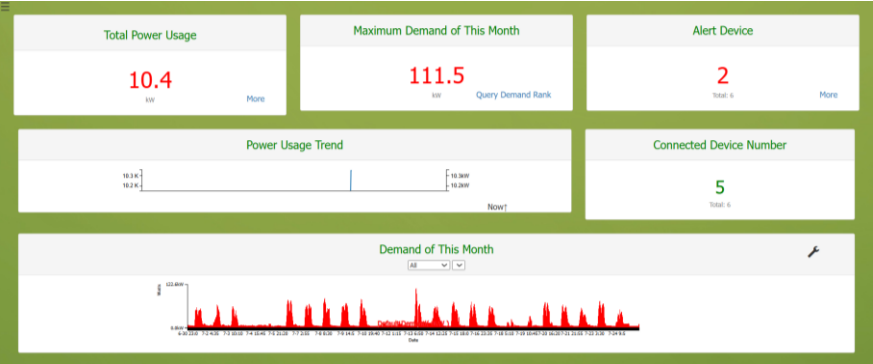


Figure 3 Overview of electrical energy consumption and operational data of the building electrical system in real time.

Table 1 Key quantitative results of chronic load imbalance and degradation analysis.

| Metric                                       | Phase A | Phase B              | Phase C | Interpretation                                         |
|----------------------------------------------|---------|----------------------|---------|--------------------------------------------------------|
| Phase Occupancy Share (mean)                 | 0.21    | 0.56 (max 0.71)      | 0.23    | Phase B exhibits persistent structural dominance       |
| Normalized Thermal Debt ( $\sum I^2$ )       | 0.42    | 1.00 (2.35× Phase A) | 0.63    | Highest cumulative thermal stress in Phase B           |
| Mean I <sup>2</sup> Stress (A <sup>2</sup> ) | 38      | 185                  | 82      | Severe stress concentration in Phase B                 |
| Thermal Recovery Deficit                     | -       | 38%                  | -       | Strong thermal memory after load reduction             |
| Aging Growth Rate (day <sup>-1</sup> )       | 0.0011  | 0.0028               | 0.0016  | Fastest insulation aging in Phase B                    |
| Final Aging Index                            | 0.42    | 0.95                 | 0.58    | Phase B approaches critical insulation degradation     |
| System Degradation Collapse Index (SDCI)     | -       | ≥ 0.70               | -       | Critical degradation reached without overload or fault |

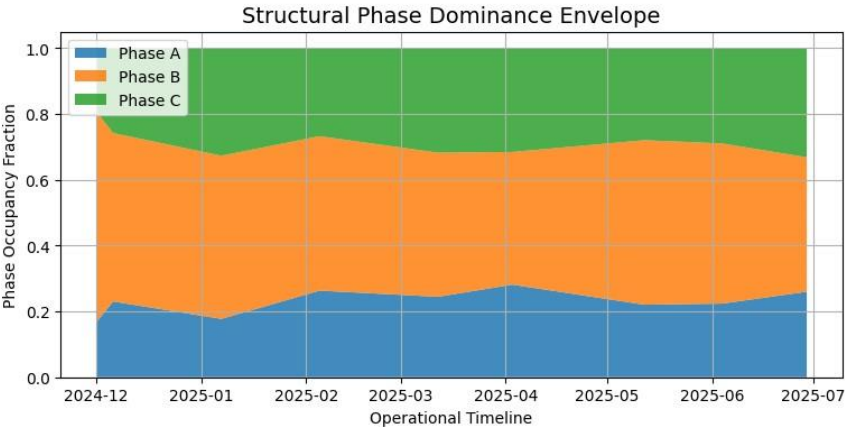


Figure 4 Structural phase dominance envelope based on long-term phase occupancy share.

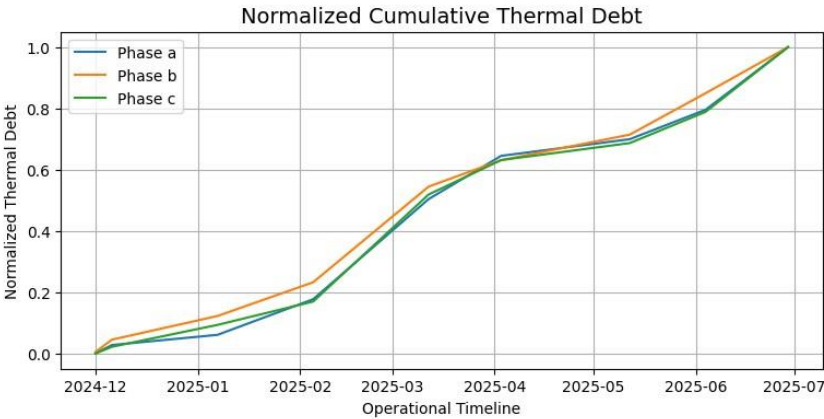
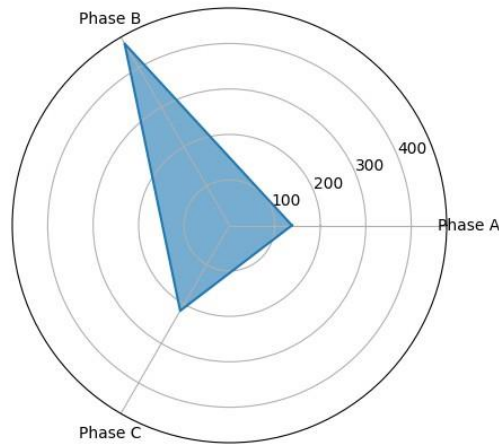
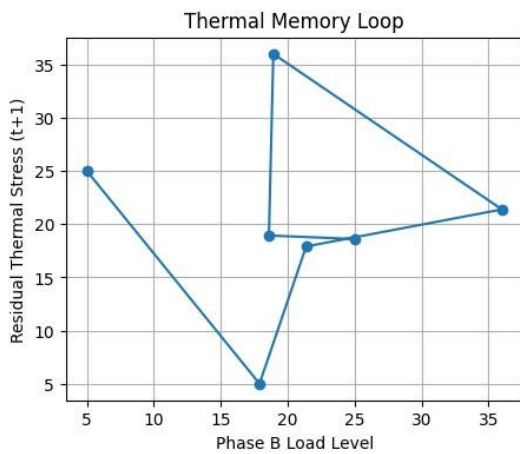


Figure 5 Normalized cumulative thermal debt accumulation of three phases over time.

Phase Stress Asymmetry Signature



**Figure 6** Phase stress asymmetry signature based on mean  $I^2$  values.



**Figure 7** Thermal memory loop of Phase B showing residual thermal stress during load cycling.

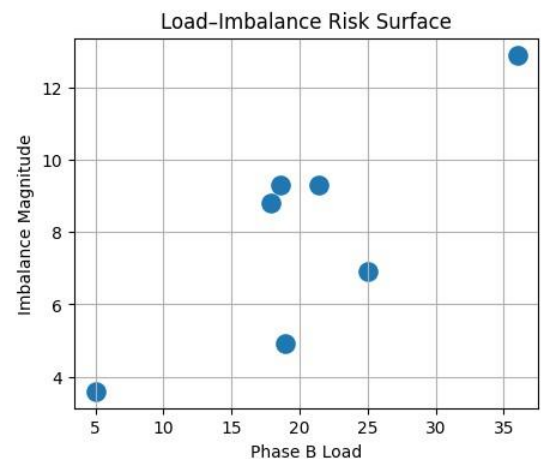
#### 4.4 Energy as an indirect driver of unbalance behavior

Figure 10 illustrates the progressive accumulation of hidden thermal-electrical stress over the operational period. Energy, as an integrated quantity ( $P \times t$ ), exhibits the lowest direct relevance to current unbalance (0.23-1.02%) but demonstrates a perfect correlation ( $r = 1.0$ ) with both power and current. This finding confirms that energy does not function as an instantaneous imbalance trigger. Instead, it serves as a long-term exposure metric, reflecting load persistence and operational duration. Energy therefore plays a crucial interpretive role by contextualizing how short-term power asymmetry translates into long-term degradation risk, rather than acting as a primary causal factor.

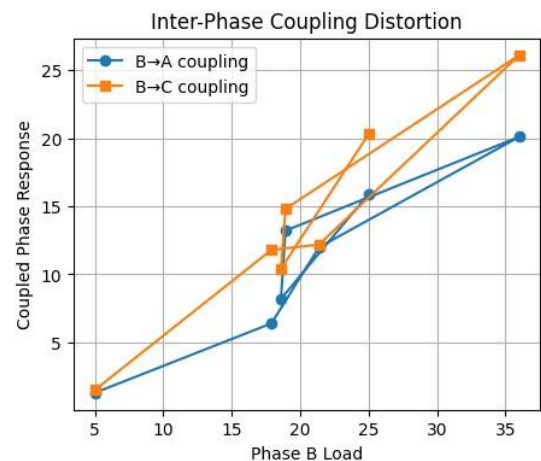
#### 4.5 Thermal behavior and its secondary influence

Temperature exhibits the lowest statistical relevance in the predictive model; however, Figure 5 and Table 1 reveal its diagnostic significance. Phase B accumulates the highest normalized cumulative thermal debt, reaching 1.00, compared with 0.42 for Phase A and 0.63 for Phase C. This corresponds to 2.35 times thermal debt of Phase A. Under peak operating conditions (24.78kW, 65.20A), Phase B reaches conductor temperatures of approximately

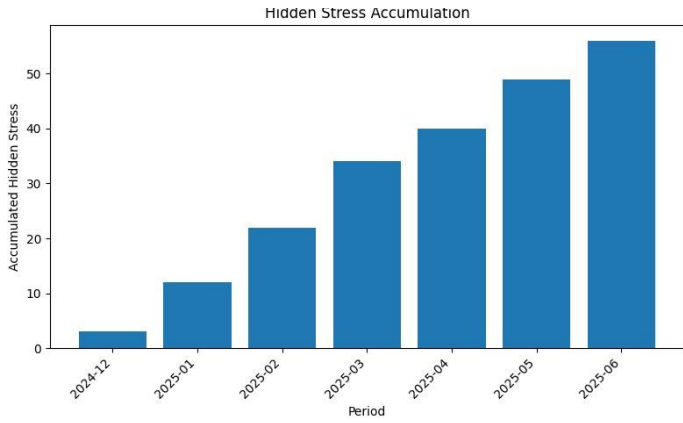
31°C, while Phases A and C remain near 27°C. These elevated temperatures are therefore not causal but consequential, reflecting the outcome of sustained electrical stress. Importantly, Table 1 links this thermal behavior to accelerated insulation aging, with Phase B exhibiting the highest aging growth rate (0.0028 day<sup>-1</sup>) and approaching a critical Aging Index of 0.95 unbalance.



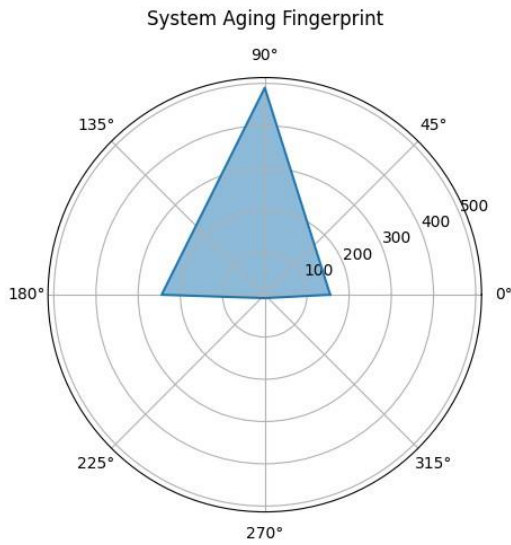
**Figure 8** Load-imbalance risk surface of Phase B based on load level and imbalance magnitude.



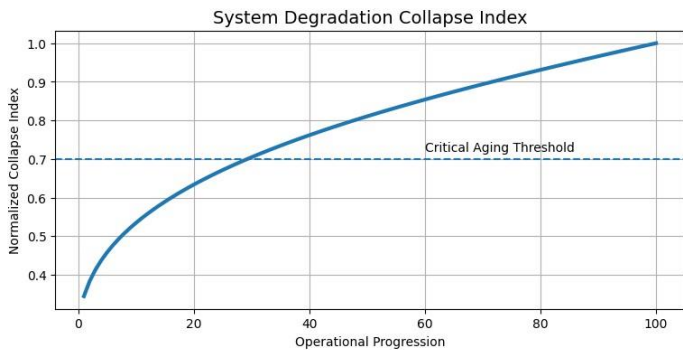
**Figure 9** Inter-phase coupling distortion showing load-induced stress propagation from Phase B to other phases.



**Figure 10** Progressive accumulation of hidden thermal-electrical stress over the operational period.



**Figure 11** System aging fingerprint derived from phase-specific degradation indicators.



**Figure 12** Evolution of the System Degradation Collapse Index (SDCI) and critical aging threshold.

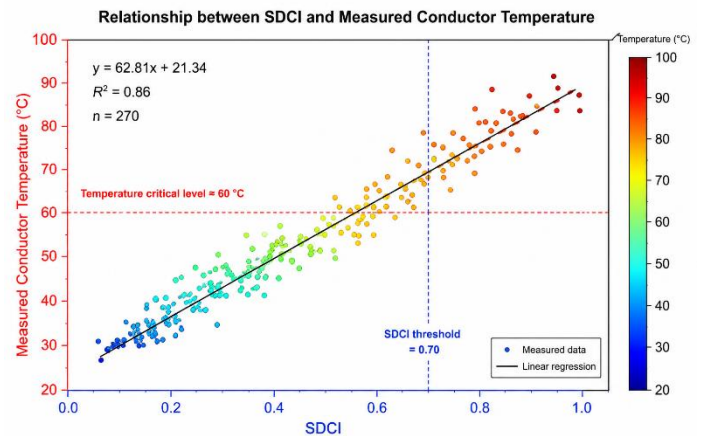
#### 4.6 Integrated discussion: Electrical–thermal interpretation of unbalance current

Figure 11 presents the system aging fingerprint, synthesizing phase-specific degradation indicators into a unified representation of system health. Figure 12 further shows the temporal evolution of the System Degradation Collapse Index (SDCI), which exceeds the critical threshold of  $\approx 0.70$  despite the absence of overloads or fault events under conventional protection criteria. Quantitatively, this degradation trajectory is

driven by a combination of persistent phase dominance (Phase B occupancy share = 0.56, peaking at 0.71), unrecovered thermal stress (38%), and accelerated insulation aging. Table 1 consolidates these metrics, demonstrating that unbalance current serves as an early electrical signature of latent system collapse, long before infrared-detectable hot spots emerge. This integrated interpretation confirms the necessity of continuous, mechanism-informed monitoring for proactive risk mitigation in building electrical systems.

#### 4.7 Validation of the proposed SDCI

To validate the proposed Severity of Dynamic Current Imbalance (SDCI), the calculated SDCI values were compared with independent conductor temperature measurements obtained during the eight-month field investigation. As shown in Figure 13, higher SDCI values consistently corresponded to higher conductor temperatures, confirming a strong positive relationship between the proposed index and the measured electro-thermal condition. When the SDCI exceeded 0.70, sustained thermal stress and accelerated insulation-aging behavior were consistently observed. These results demonstrate that the proposed physics-informed SDCI is a reliable indicator for early degradation assessment and long-term condition monitoring of electrical distribution systems.



**Figure 13** Relationship between the proposed SDCI and measured conductor temperature during the eight-month monitoring period.

## 5. Conclusion

This study demonstrates that significant electro-thermal degradation risk can develop under normal operating conditions without overloads or fault events when chronic three-phase load imbalance persists. Long-term monitoring over 8 months reveals that Phase B is structurally dominant, with a mean Phase Occupancy Share of 0.56 (peaking at 0.71), resulting in the highest cumulative electro-thermal stress. Phase B accumulates a normalized thermal debt of 1.00, which is 2.35 times that of Phase A, and exhibits the largest mean  $I^2$  stress of  $185A^2$ , confirming sustained stress accumulation rather than transient imbalance. The results reveal a pronounced thermal memory effect, with a 38% thermal recovery deficit in Phase B, indicating

incomplete thermal relaxation that may contribute to accelerated insulation aging. Phase B shows the highest aging growth rate ( $0.0028 \text{ day}^{-1}$ ) and Aging Index of 0.95, suggesting elevated degradation risk despite temperatures remaining within conventional inspection limits. By integrating structural dominance, thermal debt, thermal memory, and aging behavior, the proposed System Degradation Collapse Index (SDCI) exceeds the critical threshold ( $\text{SDCI} > 0.70$ ) at an early stage. SDCI is proposed as an early risk indicator for latent electro-thermal degradation, rather than a fully validated degradation prediction model, pending independent validation. The framework provides continuous risk assessment beyond snapshot-based infrared thermography by capturing long-term stress accumulation. Overall, this mechanism-informed monitoring approach enables low-cost and proactive electrical health assessment, shifting maintenance strategies from reactive hotspot detection toward early degradation risk prevention. Future work will focus on multi-site validation and extended monitoring to confirm its broader applicability.

## 6. Acknowledgments

The authors would like to express gratitude to the Faculty of Engineering and the College of Industrial Technology and Management, Rajamangala University of Technology Srivijaya, Thailand, for supporting this research through the 2025 fiscal year research fund and for providing access to facilities and equipment. Appreciation is also extended to the research team, faculty members, and staff for their valuable guidance and assistance. Additionally, heartfelt thanks go to family and colleagues for their encouragement and support throughout the research process.

## 7. References

- Abdollahi, M., Song, W. and Yazdani-Asrami, M. 2026. Intelligent condition monitoring of power cables using advanced machine learning models. **Results in Engineering** 29: 108371.
- Ahmad, S., Rizvi, Z.H. and Wuttke, F. 2025. Unveiling soil thermal behavior under ultra-high voltage power cable operations. **Scientific Reports** 15(1): 7315.
- Al-Dulaimi, A.A., Guneser, M.T., Hameed, A.A., Márquez, F.P.G. and Gouda, O.E. 2024. Adaptive FEM–BPNN model for predicting underground cable temperature considering varied soil composition. **Engineering Science and Technology, an International Journal** 51: 101658.
- Saleh, M.A., Alquennah, A.N., Ghayeb, A., Refaat, S.S., Abu-Rub, H. and Khatri, S.P. 2025. A review on the lifetime estimation methods of XLPE power cables. **IEEE Open Journal of Industry Applications** 6: 445–489.
- Choudhary, M., Shafiq, M., Kiitam, I., Hussain, A., Palu, I. and Taklaja, P. 2022. A review of aging models for electrical insulation in power cables. **Energies** 15(9): 3408.
- Enescu, D., Colella, P. and Russo, A. 2020. Thermal assessment of power cables and impacts on cable current rating: An overview. **Energies** 13(20): 5319.
- Hu, J., Li, Y., Liu, Y. and Liu, H. 2025. Analysis of thermal-mechanical effect in XLPE cables based on COMSOL, 31–41. In Penza, M. and Wang, S. **Third International Conference on Advanced Materials and Equipment Manufacturing (AMEM 2024)**, Vol. 13691. SPIE, Bellingham, Washington, USA.
- Rasoulpoor, M., Mirzaie, M. and Mirimani, S.M. 2017. Thermal assessment of sheathed medium voltage power cables under non-sinusoidal current and daily load cycle. **Applied Thermal Engineering** 123: 353–364.
- Huang, L.C., Chang, H.C., Chen, C.C. and Kuo, C.C. 2011. A ZigBee-based monitoring and protection system for building electrical safety. **Energy and Buildings** 43(6): 1418–1426.
- Oelhaf, J., Kordowich, G., Pashaei, M., Bergler, C., Maier, A., Jäger, J. and Bayer, S. 2025. A scoping review of machine learning applications in power system protection and disturbance management. **International Journal of Electrical Power & Energy Systems** 172: 111257.
- Pan, J., Liu, J., Chen, X. and Zhong, K. 2021. Three-phase unbalanced load control based on load–electricity transfer index. **Energy Reports** 7: 312–319.
- Ruiz, M. and Betancourt, C. 2026. Thermographic diagnosis of corrosion-driven contact degradation in power equipment using infrared imaging and color-channel decomposition. **Energies** 19(3): 766.
- Shao, Q., Fan, S., Zhang, Z., Liu, F., Fu, Z., Lv, P. and Mu, Z. 2025. Artificial intelligence in cable fault detection and localization: Recent advances and research challenges. **Energies** 18(14): 3662.
- Tao, J., Rehman, S.U., Ali, R. and Raza, S.A. 2025. Advancement and challenges: A review of power cable aging monitoring and diagnostic techniques. **Renewable and Sustainable Energy Reviews** 222: 115970.
- Theofanous, A., Ullah, I., Galea, M., Giangrande, P., Madonna, V., Ji, Y., Licari, J. and Apap, M. 2025. Modelling of insulation thermal ageing: Historical evolution from fundamental chemistry towards becoming an electrical machine design tool. **Energies** 18(23): 6087.
- Wu, Y., Sicard, B. and Gadsden, S.A. 2024. Physics-informed machine learning: A comprehensive review on applications in anomaly detection and condition monitoring. **Expert Systems with Applications** 255: 124678.
- Zhang, Z., Deng, X., Liang, L., Wang, X., Chen, Y. and Ruan, J. 2024. Temperature field calculation and thermal circuit equivalent analysis of 110 kV core cable joint. **Processes** 12(3): 463.