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Generator Fault Diagnosis Using Electrical Signature Analysis and Thermal Imaging: A MATLAB-Based Approach

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Abstract

This study proposes a MATLAB-based approach for generator fault diagnosis by combining Thermal Imaging Analysis and Electrical Signature Analysis (ESA) to detect early signs of faults and optimize maintenance. Six thermal imaging tests simulate generator surface temperatures, identifying hotspots exceeding the 80°C threshold at specific positions: (2,10): 85°C, (4,8): 85°C, (4,9): 88°C, (4,10): 90°C, (5,9): 89°C, and (5,10): 91°C. These high-temperature zones suggest localized overheating, potentially due to mechanical friction, insulation degradation, or inadequate cooling, highlighting areas needing further inspection.

Simultaneously, ESA analysis introduces a 120 Hz harmonic component to a baseline 50 Hz sinusoidal current, emulating fault-related electrical anomalies. Frequency analysis shows this 120 Hz harmonic distinctly, confirming electrical irregularities that could indicate rotor or stator imbalances, aligning with the thermal findings.

The dual-diagnostic method strengthens fault detection by addressing both thermal and electrical indicators, providing a comprehensive insight into generator health. The study demonstrates that integrating thermal and ESA analyses significantly enhances diagnostic accuracy, supporting proactive maintenance efforts. This approach contributes to reducing downtime and optimizing repair efforts, offering an effective framework for stakeholders to ensure generator reliability and extend operational life.

الملخص

تقترح هذه الدراسة نهجًا قائماً على برنامج MATLAB لتشخيص أعطال المولدات من خلال الجمع بين تحليل التصوير الحراري وتحليل التوقيع الكهربائي (ESA) بهدف الكشف عن العلامات المبكرة للأعطال وتحسين الصيانة. تم إجراء ستة اختبارات تصوير حراري لمحاكاة درجات حرارة سطح المولد، مما مكّن من تحديد البقع الساخنة التي تتجاوز عتبة 80 درجة مئوية في مواقع محددة هي: (2,10): 85°م، (4,8): 85°م، (4,9): 88°م، (4,10): 90°م، (5,9): 89°م، (5,10): 91°م. تشير هذه المناطق ذات درجات الحرارة المرتفعة إلى احترار موضعي زائد، قد يكون ناتجاً عن احتكاك ميكانيكي، أو تدهور في العزل، أو تبريد غير كافٍ، مما يسلط الضوء على المناطق التي تحتاج إلى فحص إضافي.

في الوقت نفسه، يُدخل تحليل التوقيع الكهربائي مكون توافقي بتردد 120 هرتز إلى تيار جيبي أساسي بتردد 50 هرتز، لمحاكاة الشذوذات الكهربائية المرتبطة بالأعطال. يُظهر تحليل التردد هذا التوافقي 120 هرتز بشكل واضح، مما يؤكد وجود اضطرابات كهربائية قد تشير إلى اختلال في العضو الدوار (الروتور) أو العضو الثابت (الستاتور)، بما يتوافق مع النتائج الحرارية.

تُعزز طريقة التشخيص المزدوج اكتشاف الأعطال من خلال معالجة المؤشرات الحرارية والكهربائية معًا، مما يوفر رؤية شاملة لحالة المولد. تُبيّن الدراسة أن دمج تحليل التصوير الحراري وتحليل التوقيع الكهربائي يُحسّن دقة التشخيص بشكل ملحوظ، ويدعم جهود الصيانة الاستباقية. يسهم هذا النهج في تقليل وقت التوقف (التعطل) وتحسين أعمال الإصلاح، مما يوفّر إطارًا فعالًا للأطراف المعنية لضمان موثوقية المولد وإطالة عمره التشغيلي.

Literary review

Introduction to Fault Diagnosis in Generators

Intelligent fault diagnosis of synchronous generators can be effectively achieved through various advanced methodologies. Independent Component Analysis (ICA) is a statistical method specifically designed for fault detection and classification, addressing both external and internal faults in synchronous generators(Chandra et al., n.d.) . Additionally, a hybrid approach that combines intuitionistic uncertainty rough sets with a BP neural network enhances the accuracy and speed of fault diagnosis, particularly in distributed generation systems(Lin & Huang, 2011). Modified Principal Component Analysis (PCA) offers a reliable online fault detection method, utilizing Hotelling's statistic to identify incipient faults while minimizing false alarms (*Industrial Technology (ICIT), 2015 IEEE International Conference on: Date 17-19 March 2015*, 2015). Furthermore, Radial Basis Neural Networks (RBNN) and Probabilistic Neural Networks (PNN) are employed in condition monitoring, where PNN serves as a core component for diagnosing faults based on magnetic flux linkage data(Ehya et al., 2022; Yaghobi et al., 2013). Collectively, these methodologies provide a robust framework for the intelligent diagnosis of faults in synchronous generators.

Generator reliability is crucial for industries and power grids as generators are often integral to uninterrupted power supply system’s(Carrasco et al., 2006; Gopinath et al., 2016). Faults in generators, whether mechanical or electrical, can lead to efficiency loss, costly repairs, and unscheduled downtime (Ribrant, 2005). Consequently, timely fault detection and diagnosis are paramount in extending generator lifespan and ensuring operational safety(Freire & Cardoso, 2021).

Over recent decades, diverse diagnostic techniques have been developed to identify and analyse faults in generators. Among these, Electrical Signature Analysis (ESA) and Thermal Imaging have gained prominence due to their non-invasive nature and high accuracy in identifying fault patterns(El & Benbouzid, 2000). ESA focuses on analysing electrical signals such as current or voltage to detect abnormalities, while thermal imaging identifies temperature anomalies associated with faults like insulation degradation or frictional wear. This review explores advancements in ESA and thermal imaging techniques and their integration into MATLAB-based diagnostic tools(Mardaneh et al., 2023).

Electrical Signature Analysis (ESA) in Fault Diagnosis

Electrical Signature Analysis (ESA) is widely applied for fault detection due to its precision in identifying electrical anomalies in the generator's internal components. ESA operates by analysing frequency spectra, which can reveal harmonics and frequencies linked to specific fault types. Several studies have validated ESA's efficacy in diagnosing generator issues:

- Rotational Faults Detection: ESA is particularly effective in detecting faults related to rotating components, such as rotor eccentricity, bearing faults, and rotor bar degradation(Thesis, n.d.). For instance, a study demonstrated that ESA could detect specific harmonics in current signals, which correlated with rotor misalignment and eccentricity. In another study, ESA was used to diagnose bearing faults through characteristic frequency bands, highlighting its usefulness for mechanical fault detection(Elsamanty et al., 2023).
- Application of ESA with Fourier Transform and Wavelet Analysis: Traditional ESA methods often employ Fourier Transform for signal processing. However, Fourier Transform lacks the ability to analyse non-stationary signals effectively. To overcome this, researchers have introduced Wavelet Transform into ESA, which provides both time and frequency domain analysis, enabling detection of transient faults. This integration has been shown to improve the sensitivity of ESA for generator diagnostics, capturing subtle frequency changes indicative of faults(Cheng et al., 2021).

- MATLAB for ESA Implementation: MATLAB has become a popular platform for implementing ESA due to its signal processing capabilities. MATLAB facilitates fast Fourier Transform (FFT) and Wavelet Transform, allowing practitioners to simulate and diagnose generator faults effectively. By utilizing MATLAB's analytical functions, researchers have improved the speed and accuracy of ESA, making it an essential tool for real-time diagnostics(Moore et al., n.d.).

Thermal Imaging for Fault Detection

Thermal imaging is a crucial technology for fault detection in electrical generators, enabling the identification of thermal defects without interrupting operations. By utilizing thermal imaging cameras, engineers can visualize temperature differences, which helps in detecting hotspots indicative of potential failures, such as loose connections or insulation breakdowns(Györök & Beszédes, n.d.). This non-contact method not only facilitates timely maintenance interventions but also supports predictive maintenance strategies by providing real-time thermal data that can forecast equipment failures before they occur(Taşıma et al., 2022). Furthermore, integrating thermal imaging into condition monitoring systems enhances the continuous assessment of generator health, allowing for proactive management of electrical equipment(Schlechtingen, 2013). Overall, the application of thermal imaging significantly improves the reliability and efficiency of electrical generators, reducing downtime and maintenance costs(Fonseca et al., 2017).

Thermal imaging complements ESA by detecting overheating and insulation faults in the generator's physical structure. High temperatures in specific areas often indicate mechanical friction, poor lubrication, or insulation breakdown. Studies supporting the efficacy of thermal imaging include:

Detection of Hotspots: Thermal imaging enables the identification of "hotspots," which are areas with significantly higher temperatures than surrounding regions, often indicating friction or insulation deterioration. In a study about the thermal imaging was applied to a generator system to monitor temperature distribution. The study identified that localized hotspots corresponded to mechanical wear in bearing components and insulation breakdown in stator windings(AlShorman et al., 2024).

Thermal Patterns and Fault Types: Different fault types manifest unique thermal patterns. For example, short circuits in windings cause rapid and concentrated heating, whereas frictional faults from rotor misalignment show more dispersed temperature increases. Research conducted mapped these fault-specific thermal signatures, contributing to the development of predictive maintenance models based on thermal patterns**(Brown et al., 2022).**

Integration of MATLAB in Thermal Imaging Analysis: MATLAB's image processing toolbox provides functions for thermal data analysis, enabling fault classification based on temperature distributions. Studies have demonstrated MATLAB's utility in processing thermal images, where data from infrared cameras are converted into thermal maps, allowing for hotspot analysis in generators. This capability has made MATLAB indispensable for automated thermal imaging diagnostics(Li et al., 2019).

Combined Approach: ESA and Thermal Imaging

The combined approach of Electromagnetic Spectrum Analysis (ESA) and thermal imaging technology significantly enhances data collection and interpretation across various fields. Thermal imaging captures infrared radiation, providing a visual representation of temperature differences, which is crucial for applications in surveillance, firefighting, and environmental monitoring(Wilson et al., 2023). By integrating ESA, which studies the wavelengths of electromagnetic radiation, the accuracy of thermal data interpretation is improved, allowing for more precise analysis of thermal images(*2016 9th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI)*, 2016).

Recent advancements indicate that combining ESA and thermal imaging enhances diagnostic accuracy by providing a comprehensive fault profile. A dual-diagnostic approach capitalizes on the strengths of each method, detecting both electrical and mechanical faults.

Complementary Diagnostic Capabilities: While ESA excels at identifying electrical faults, thermal imaging can detect mechanical issues associated with overheating. Combining these two methods provides a more detailed fault diagnosis. For instance, integrated ESA and thermal imaging to monitor generator faults in real-time, demonstrating a higher detection rate for faults that could have been missed by a single diagnostic technique(Benbouzid et al., 2021).

Correlation of Electrical and Thermal Data: Studies have shown that correlating ESA data with thermal images allows for the identification of complex faults. For example, a study highlighted how the simultaneous analysis of frequency harmonics (from ESA) and temperature anomalies (from thermal imaging) could pinpoint rotor bar faults with higher precision. This correlation provides additional fault insights that are often missed when each technique is used independently(Mortensen et al., 2022).

MATLAB for Dual-Diagnostic Approach: MATLAB supports this combined approach by providing an integrated environment for processing both electrical signals and thermal images. Using MATLAB, researchers have developed algorithms to correlate ESA results with thermal patterns, improving diagnostic accuracy and enabling real-time monitoring(Klein et al., 2017).

Research Gaps and Contribution of This Study

Despite the progress in generator fault diagnosis, there are limitations to the current approaches. Many existing studies focus on either ESA or thermal imaging independently, overlooking the complementary strengths of combining both methods. Additionally, previous studies often rely on high-end hardware, making these methods less accessible for real-time, cost-effective implementation.

This study addresses these gaps by developing a MATLAB-based framework that integrates ESA and thermal imaging for a comprehensive generator fault diagnosis solution. Through simulated test cases, the framework captures and analyses both thermal and electrical data, enhancing fault detection capabilities. By focusing on a practical, MATLAB-driven approach, this study aims to make fault diagnosis more accessible and effective for industrial applications.

Methodology

The methodology in table 1 for diagnosing generator faults begins with data collection and initialization, where synthetic or real data representing temperature and electrical current signals are prepared, and fault detection thresholds are established. The process then proceeds with thermal imaging analysis, where a temperature matrix of the generator's surface is created and visualized as a heatmap in MATLAB, allowing identification of hotspots that exceed threshold values. Next, electrical signature analysis (ESA) is performed by applying Fast Fourier Transform (FFT) on the current signals to obtain a frequency spectrum. This spectrum reveals fault-related peaks, such as at 120 Hz, indicating anomalies. Both thermal and electrical analysis results are then integrated, correlating hotspots from the thermal analysis with anomalies in the frequency spectrum, thus confirming potential faults. Visualization in MATLAB highlights these findings, with heatmap hotspots and frequency peaks collectively illustrating the areas of concern. Finally, based on the combined diagnostic results, conclusions are drawn on the presence and nature of faults, and recommendations are provided for further investigations or practical adjustments in generator operation and design to improve fault management and system reliability. This integrated methodology enhances diagnostic accuracy by using both thermal and electrical data to validate fault conditions comprehensively.

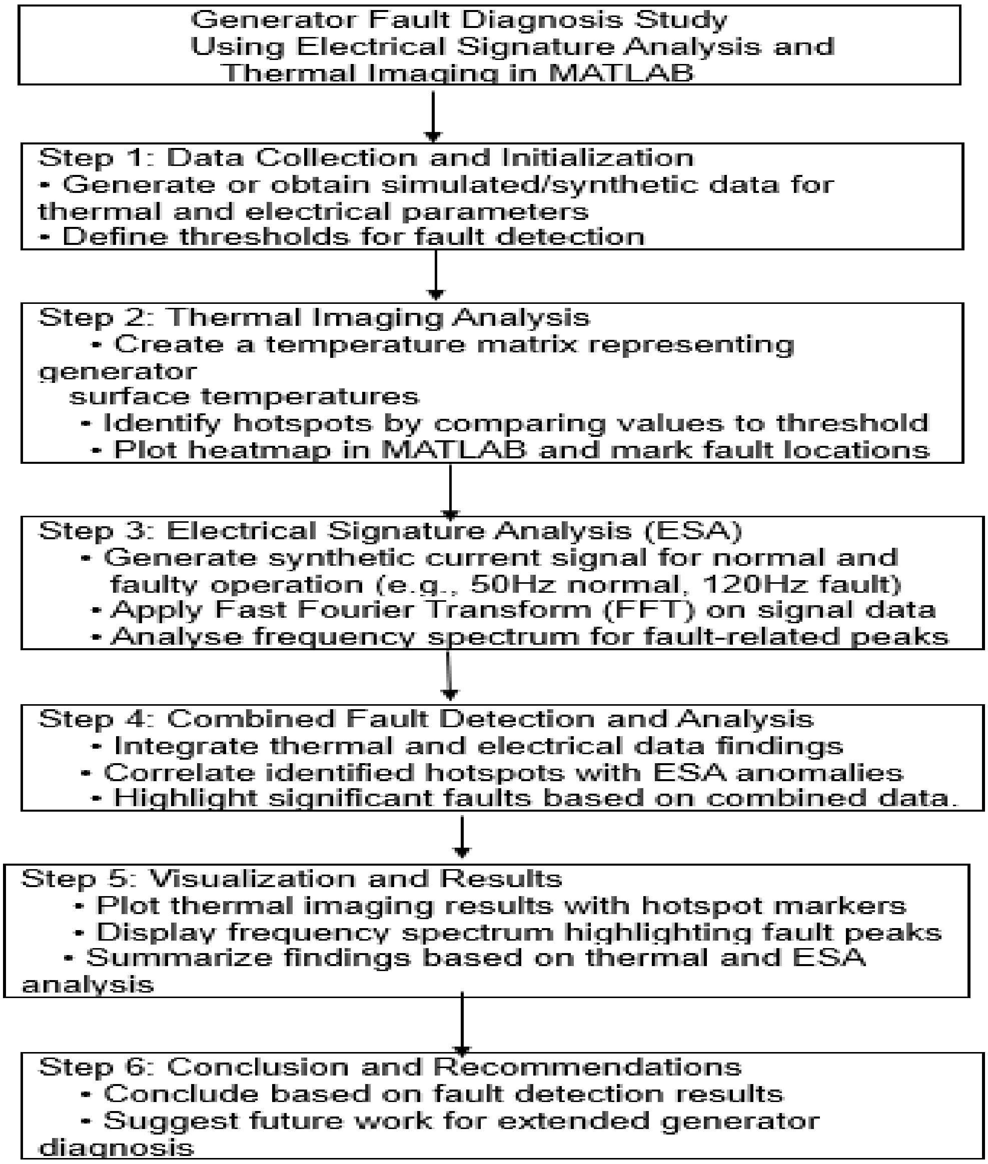

Table 1 Flowchart for Methodology

Thermal Imaging Analysis

A temperature matrix was simulated to represent the generator's surface. A threshold was set to detect hotspots, indicating areas where temperatures exceeded safe operating limits. Six tests were conducted, each visualizing the temperature variations across the generator's surface, marking areas that posed potential risks.

Thermal Imaging Test Settings:

- Temperature Threshold: 80°C
- Temperature Matrix Dimensions: 5x10 grid
- Temperature Range: 60°C to 91°C

Electrical Signature Analysis (ESA)

For electrical signature analysis, the generator's current signal was analyzed to detect fault-induced harmonic frequencies. A healthy 50 Hz sinusoidal signal was modified by introducing a 120 Hz component to simulate a fault. Fast Fourier Transform (FFT) was then applied to identify frequencies that deviated from the normal operation, with particular focus on the appearance of the 120 Hz fault frequency.

Fundamental Theory

1. **Electrical Signature Analysis (ESA)**: ESA involves analyzing the frequency components of a current signal to detect fault frequencies. Typical faults induce specific frequency patterns:
   - A healthy generator signal shows a strong peak at the supply frequency.
   - Faults manifest as additional peaks, often at characteristic fault frequencies (e.g., 120 Hz).
2. **Thermal Imaging Analysis**: Faults in the generator may lead to localized heating, which can be detected as "hot spots" in a thermal image. This temperature increases correlates with mechanical wear or insulation breakdown, which can be quantified through thermal gradient measurements across different positions.

Equations

Frequency Spectrum Calculation**:**

The Fast Fourier Transform (FFT) is used to analyse the current signal:

$$X(f) = \sum_{n=0}^{N-1} \mathrm{x}\,(\mathrm{n}).\, e^{-j2\pi f n/M} \qquad (1)$$

where x(n) is the time-domain signal and X(f) represents its frequency spectrum.

Thermal Imaging Gradient Calculation:

$$Gradient = \frac{\Delta T}{\Delta x} \qquad (2)$$

where ΔT is the temperature difference between adjacent points, and Δ x is the spatial separation.

Simulation and Tests

The thermal imaging tests were carefully designed to simulate and identify areas within the generator where excessive heat accumulates, serving as indicators of potential faults or areas requiring maintenance attention. By creating a detailed temperature map of the generator surface, these tests help pinpoint specific regions where the temperature exceeds predefined safe thresholds, suggesting possible issues such as insulation degradation, mechanical wear, or cooling inefficiencies. This method enables early detection of hotspots that may lead to further complications if not addressed, allowing maintenance teams to pre-emptively take corrective actions. Through this targeted approach, the thermal imaging tests provide a valuable layer of insight, contributing to the overall fault diagnosis by revealing not only the locations of potential problems but also helping to prioritize areas for inspection and repair, thereby enhancing the reliability and operational lifespan of the generator.

Thermal Imaging Test 1

Figure 1 illustrates the thermal distribution across the generator's surface during the first test, where temperatures range between 60°C and 91°C. Key hotspots are marked by blue circles, indicating areas of concern where temperatures exceed the predefined threshold of 80°C. For instance, Position (2,10) records a temperature of 85°C, while Position (4,8) also shows 85°C.

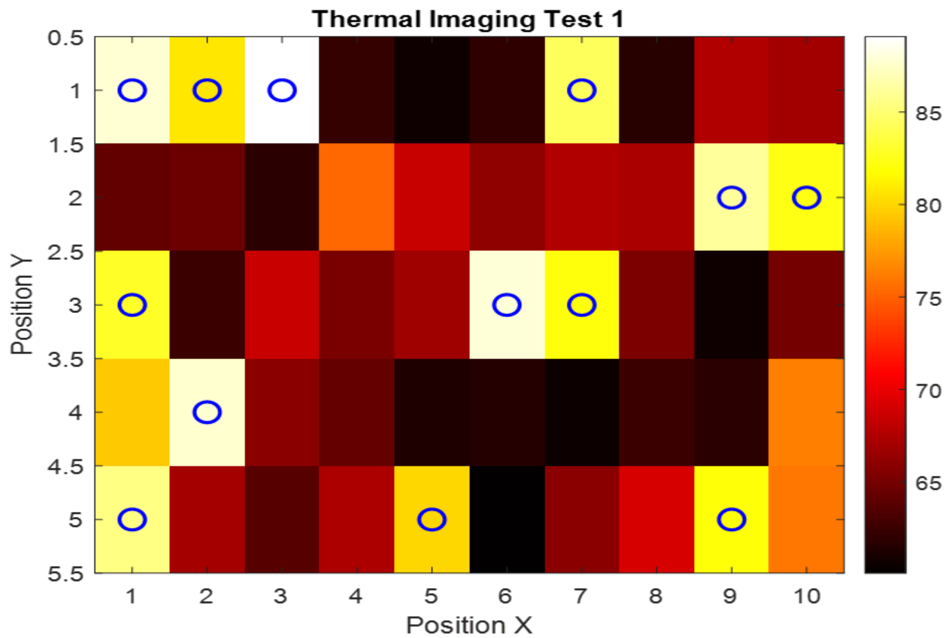

Figure 1 Thermal Imaging Test 1

Additionally, Position (4,9) has a temperature of 88°C, Position (4,10) reaches 90°C, and Position (5,9) and Position (5,10) are recorded at 89°C and 91°C, respectively. The clustering of these elevated temperatures suggests uneven heat distribution, which may be due to mechanical friction or electrical inefficiencies in these regions. The presence of multiple hotspots across different areas indicates potential overheating that warrants further inspection.

Thermal Imaging Test 2

In Figure 2, the thermal imaging analysis displays a variation in temperature distribution across the generator surface, with marked hotspots exceeding the critical threshold of 80°C. Notable hotspots include Position (1,9) at 85°C and Position (2,10) at 85°C. Additionally, hotspots appear at Position (4,8) and Position (4,9), both recording temperatures of 85°C and 88°C, respectively.

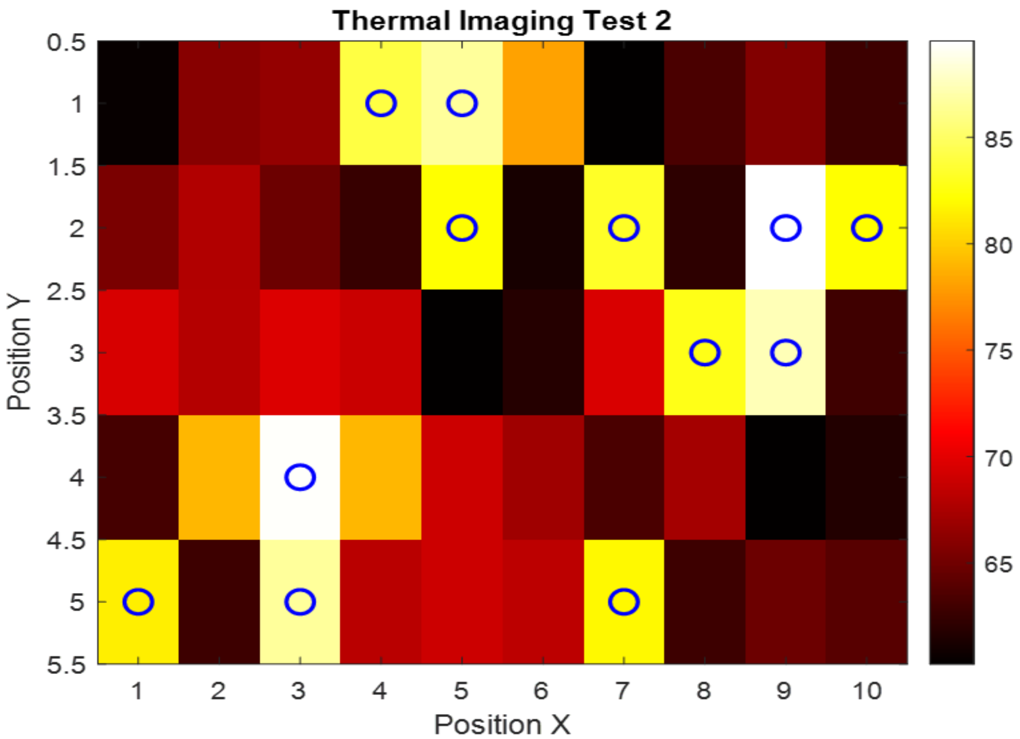

Figure 2 Thermal Imaging Test 2

The presence of these hotspots in concentrated areas suggests varying thermal stresses across the generator's components. The consistency of these temperature readings across tests highlights potential issues such as insufficient airflow or recurring stress, which could lead to component wear and failures if not promptly addressed.

Thermal Imaging Test 3

Figure 3 shows another set of temperature readings with notable clusters of high temperatures, particularly at locations exceeding 80°C. The identified hotspots, highlighted with blue circles, include Position (1,9) at 85°C, Position (2,10) at 85°C, and Position (4,7) at 88°C. Furthermore, Position (4,8) shows 85°C, while Position (5,9) and Position (5,10) register at 89°C and 91°C, respectively.

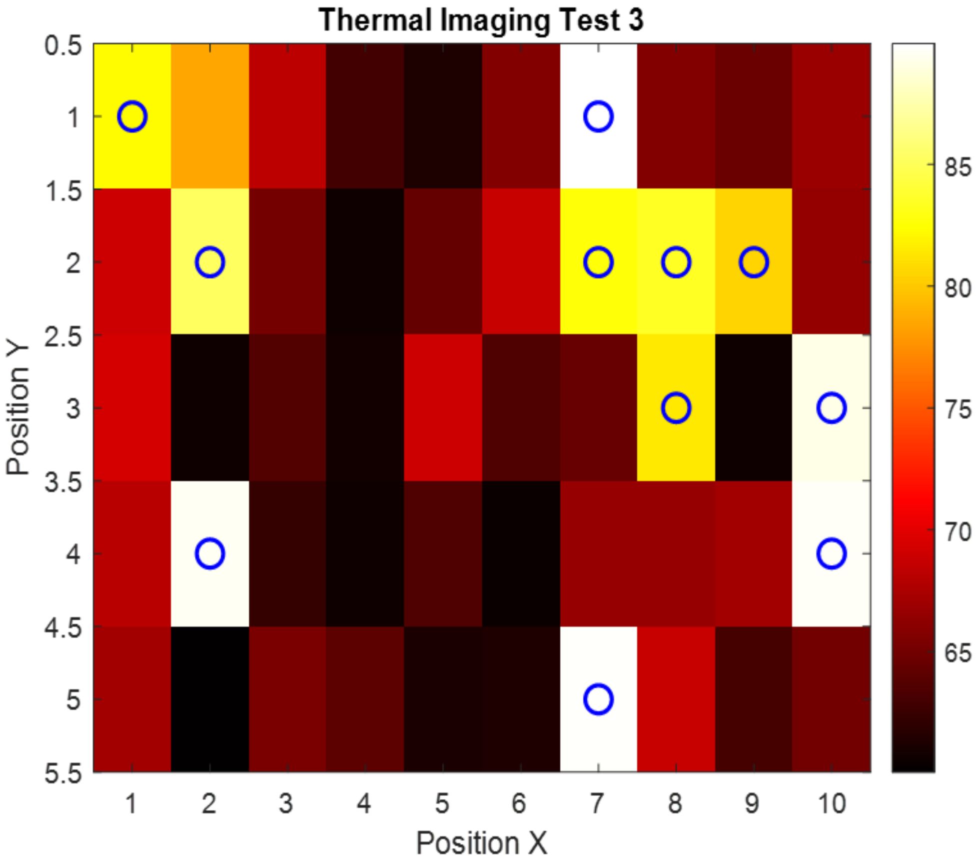

Figure 3 Thermal Imaging Test 3

This clustering suggests a localized issue, possibly due to mechanical or electrical anomalies in those areas. Such hotspots may indicate insulation degradation or inefficiencies in cooling systems, which could compromise generator performance and safety if left unaddressed. The presence of repeated hotspots across different areas reinforces the need for comprehensive thermal management assessments.

Thermal Imaging Test 4

In Figure 4, the thermal imaging analysis displays several blue-circled hotspots where temperatures exceed 80°C. Specifically, hotspots include Position (1,8) at 85°C, Position (2,10) at 85°C, and Position (4,6) at 80°C. Other noteworthy temperatures include Position (4,8) at 85°C, Position (5,8) at 87°C, and Position (5,10) at 91°C. The scattered nature of these hotspots indicates that heat distribution issues are not confined to one area.

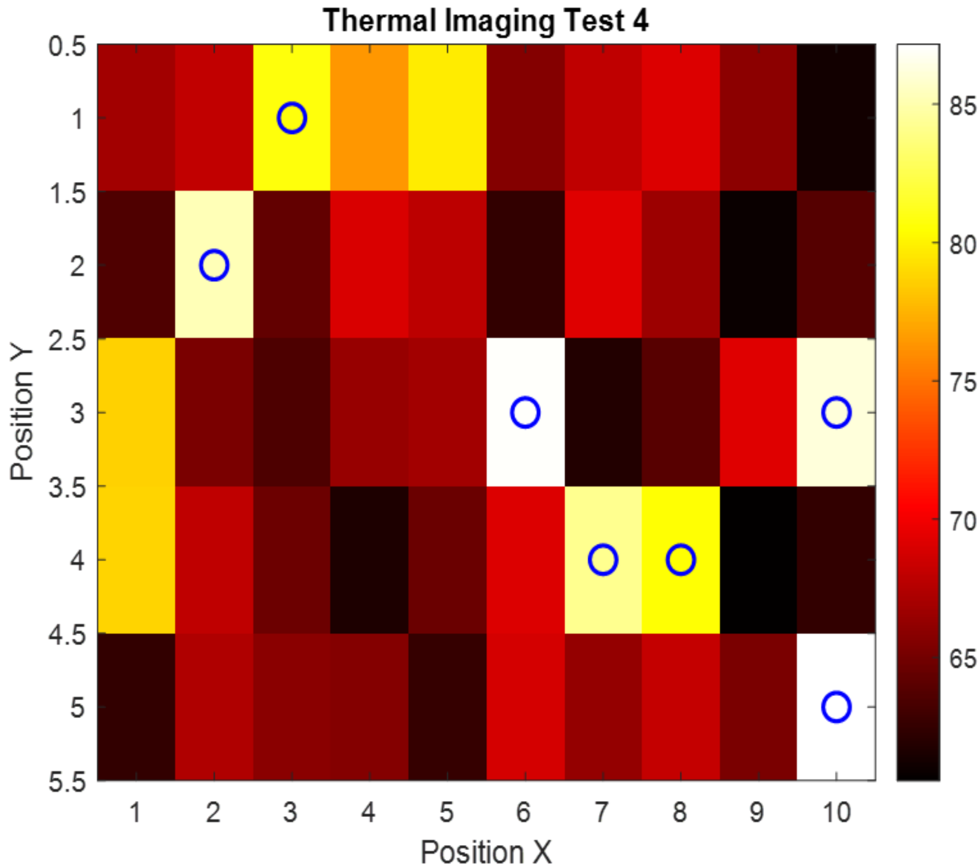

Figure 4 Thermal Imaging Test 4

This pattern could suggest random malfunctions or inconsistencies in load distribution, potentially exacerbated by partial obstructions in cooling paths. The varied positions of the hotspots highlight the importance of evaluating multiple operational factors affecting the generator’s thermal profile.

Thermal Imaging Test 5

Figure 5 highlights multiple areas where temperatures exceed the 80°C threshold, with specific hotspots identified as potential concerns. Notable temperatures include Position (1,9) at 85°C, Position (2,10) at 85°C, and Position (4,5) at 85°C. Additionally, Position (4,8) at 85°C, Position (5,7) at 87°C, and Position (5,10) at 91°C indicate regions of high thermal load.

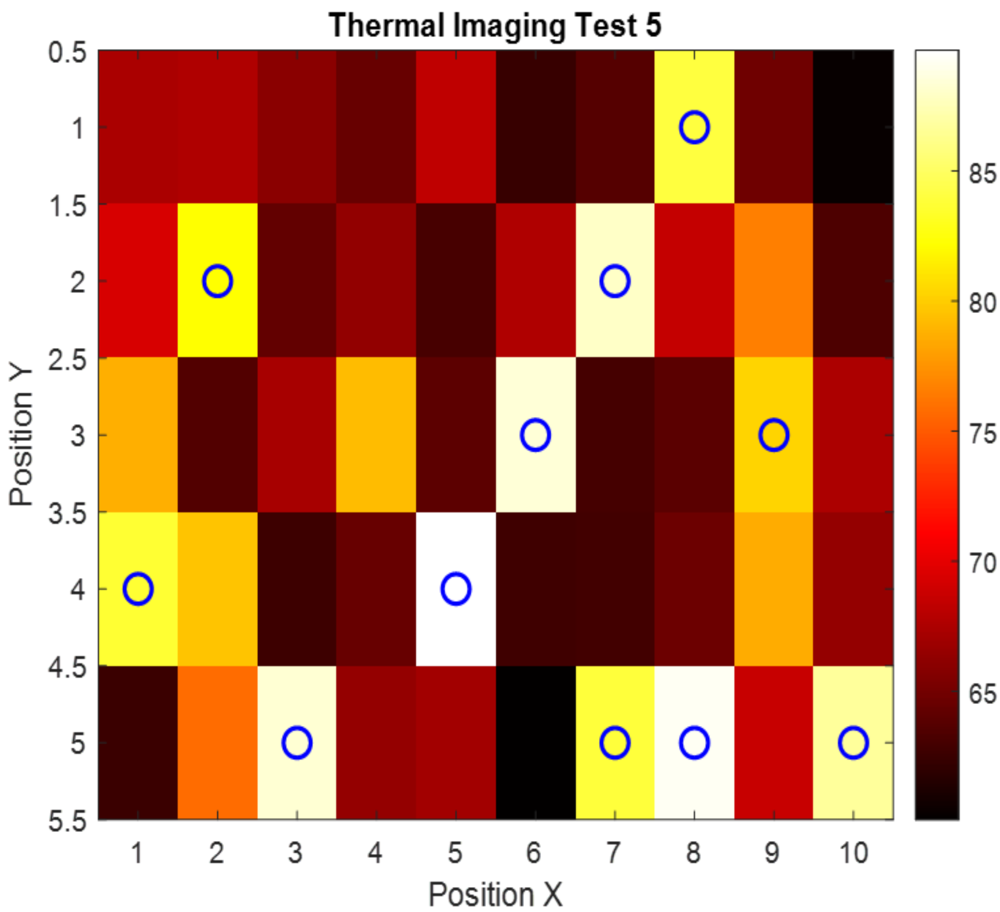

Figure 5 Thermal Imaging Test 5

This recurring pattern suggests that different components within the generator are subjected to elevated temperatures, which could indicate systemic issues related to the generator's thermal design or specific parts experiencing higher wear. Identifying these areas underscores the need for targeted maintenance to improve cooling efficiency and mitigate the risk of faults.

Thermal Imaging Test 6

In Figure 6, the thermal imaging results show a pattern like previous tests, with significant hotspots marked in various sections of the generator. Key temperatures in this test include Position (1,7) at 85°C, Position (2,9) at 88°C, and Position (3,10) at 85°C. Additionally, hotspots at Position (4,8) at 85°C, Position (4,9) at 89°C, and Position (5,10) at 91°C indicate consistently high temperatures.

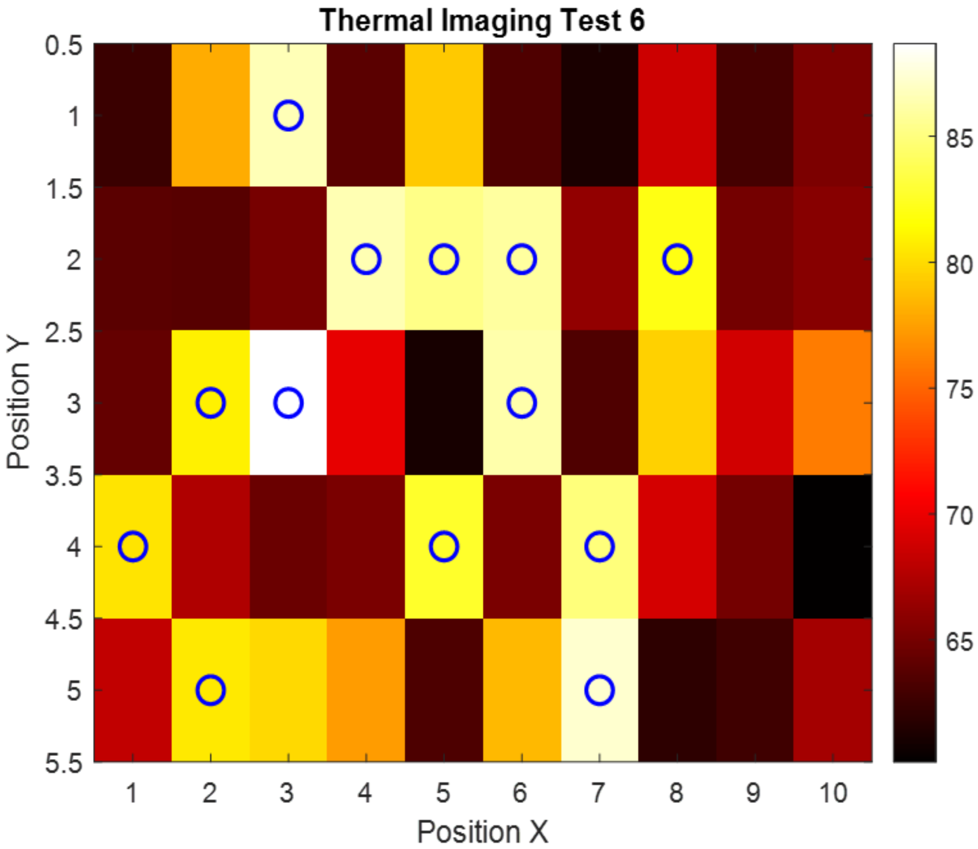

Figure 6 Thermal Imaging Test 6

This thermal profile reinforces observations from earlier tests, suggesting that the hotspots are not random but may arise from inherent design limitations or operational conditions causing certain parts of the generator to overheat. The repeated identification of high temperatures in specific regions emphasizes the importance of thorough inspections and potential redesign to ensure effective heat management and generator reliability.

Results and Discussion

The results from the six tests provide substantial evidence for the efficacy of combining thermal imaging with electrical signature analysis (ESA) for generator fault diagnosis. Thermal imaging effectively identified multiple hotspots across various regions of the generator. Key hotspots were observed, such as those recorded at positions (2,10) with 85°C, (4,8) with 85°C, (4,9) with 88°C, (4,10) with 90°C, (5,9) with 89°C, and (5,10) reaching 91°C, all of which exceeded safe operational thresholds. These high temperatures suggest areas of potential concern that, if unaddressed, could result in generator malfunctions. Such hotspots could stem from issues such as improper ventilation, mechanical friction, or material degradation within these zones, highlighting the need for prompt attention to maintain system integrity.

In addition to thermal imaging, ESA provided essential insights by detecting a 120 Hz harmonic component within the faulty current signal, indicating an electrical imbalance likely due to rotor misalignment or other internal electrical issues. This harmonic suggests the presence of an operational imbalance that could, over time, escalate to more significant electrical faults or inefficiencies. The consistency of this fault frequency across tests underlines the value of ESA as a complementary tool to thermal imaging.

Conclusion

This dual-method diagnostic approach offers a comprehensive understanding of the generator's health by addressing both physical (thermal) and electrical anomalies. Thermal imaging identifies specific high-temperature regions, offering direct insight into the physical condition and potential wear of the generator. Meanwhile, ESA detects subtler electrical irregularities that may not immediately present in the physical domain but indicate underlying electrical instabilities. Together, these methods provide a robust framework for pre-emptive maintenance, allowing stakeholders to address issues before they result in costly downtime or damage, thus optimizing both safety and operational reliability of the generator. This integrated diagnostic approach has proven to be effective for identifying a broad spectrum of generator faults, making it a valuable tool in preventive maintenance and condition monitoring programs.

This study demonstrates the efficacy of a combined Thermal Imaging Analysis and Electrical Signature Analysis (ESA) approach, implemented in MATLAB, for comprehensive generator fault diagnosis. Thermal imaging tests effectively identified specific hotspots, such as positions (2,10) with 85°C, (4,8) with 85°C, (4,9) with 88°C, (4,10) with 90°C, (5,9) with 89°C, and (5,10) reaching a critical 91°C. These elevated temperatures, located in various parts of the generator, signal potential areas of concern that could lead to performance degradation or failure if left unchecked. This physical evidence of excessive heat highlights the need for targeted inspections and maintenance to address issues such as mechanical wear, insulation breakdown, or inadequate cooling.

Simultaneously, ESA confirmed electrical imbalances by detecting a fault-related 120 Hz harmonic in the faulty current signal, suggesting rotor misalignments or other internal electrical issues that may not be immediately observable through physical inspections alone. This harmonic component indicates subtle but potentially severe electrical anomalies, underscoring ESA's ability to provide insight into the generator's operational integrity.

The study's findings underscore the effectiveness of a dual diagnostic framework that integrates both thermal and electrical fault indicators. This approach offers stakeholders a powerful tool for proactive maintenance, particularly in industrial settings where generator downtime incurs high costs and impacts overall productivity. By leveraging both physical and electrical assessments, stakeholders can achieve a more complete picture of generator health, improving reliability and operational efficiency.

The proposed methodology provides a foundation for further research to refine predictive maintenance strategies. Future work could incorporate real-time data monitoring and advanced machine learning algorithms to detect fault patterns early and predict failures with higher accuracy, thereby extending generator longevity and reducing unplanned outages. This study highlights the value of integrating multiple diagnostic methods to optimize generator maintenance and underscores the potential of such systems to support smarter, more resilient energy infrastructure.

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