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Thesis Title

**Fault Diagnosis of Power Transformers Based on
Dissolved Gas Analysis (DGA) Using Artificial
Intelligence Techniques**

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Abstract



Abstract:

Fault diagnosis in oil-immersed power transformers is essential for ensuring the reliability and continuity of electrical power systems. While dissolved gas analysis (DGA) represents one of the most effective condition monitoring techniques, traditional interpretation methods often suffer from limited diagnostic accuracy due to overlapping fault regions and insufficient feature representation. This thesis proposes a systematic comparative framework that evaluates two distinct feature extraction strategies derived from DGA data, namely ratio-based features and graphical features, in combination with state-of-the-art artificial intelligence classifiers to address these limitations.

The research investigates four machine learning algorithms — K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest (RF), and RUSBoost — applied to a dataset of 407 samples distributed across six fault categories: partial discharge (PD), low-energy discharge (D1), high-energy discharge (D2), and thermal faults (T1, T2, T3). Ratio-based features are derived from established gas ratio methods, while graphical features are constructed from visual diagnostic representations including the Duval Triangle and related geometric techniques. Both feature sets are systematically evaluated using a comprehensive set of performance metrics, including accuracy, precision, recall, F1-score, Matthews Correlation Coefficient (MCC), and Cohen's Kappa.

The experimental results demonstrate that graphical feature representation consistently outperforms ratio-based features across all tested classifiers, raising the average diagnostic accuracy from 77.25% to 93.85%, corresponding to an overall improvement of 16.60%. The most substantial gains are observed for KNN and SVM, with accuracy improvements of 31.15% and 28.69% respectively, confirming that graphical features produce a more geometrically separable feature space. These findings establish that feature engineering plays a decisive role in transformer fault diagnosis performance, often surpassing the influence of classifier selection itself, and provide a robust foundation for intelligent predictive maintenance systems in power transformers.

Keywords: Dissolved Gas Analysis (DGA), Power Transformer Diagnostics, Fault Classification, Graphical Feature Representation, Ratio-Based Features, Machine Learning, Ensemble Learning, Predictive Maintenance, IEC

Résumé:

Le diagnostic des défauts des transformateurs de puissance immergés dans l'huile est essentiel pour garantir la fiabilité et la continuité des systèmes d'alimentation électrique. Bien que l'analyse des gaz dissous (Dissolved Gas Analysis – DGA) constitue l'une des techniques les plus efficaces de surveillance de l'état des transformateurs, les méthodes traditionnelles d'interprétation présentent souvent une précision diagnostique limitée en raison du chevauchement des zones de défaut et d'une représentation insuffisante des caractéristiques. Cette thèse propose un cadre comparatif systématique évaluant deux stratégies distinctes d'extraction de caractéristiques issues des données DGA, à savoir les caractéristiques basées sur les rapports de gaz (ratio-based features) et les caractéristiques graphiques (graphical features), combinées à des classificateurs d'intelligence artificielle de pointe afin de surmonter ces limitations.

Cette recherche étudie quatre algorithmes d'apprentissage automatique — K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest (RF) et RUSBoost — appliqués à un ensemble de données comprenant 407 échantillons répartis en six catégories de défauts : décharge partielle (PD), décharge de faible énergie (D1), décharge de haute énergie (D2) et défauts thermiques (T1, T2, T3). Les caractéristiques basées sur les rapports sont dérivées des méthodes classiques des rapports de gaz, tandis que les caractéristiques graphiques sont construites à partir de représentations diagnostiques visuelles, notamment le Triangle de Duval et d'autres techniques géométriques associées. Les deux ensembles de caractéristiques sont évalués de manière systématique à l'aide d'un ensemble complet d'indicateurs de performance, notamment l'exactitude (accuracy), la précision (precision), le rappel (recall), le score F1 (F1-score), le coefficient de corrélation de Matthews (MCC) et le coefficient Kappa de Cohen.

Les résultats expérimentaux montrent que la représentation graphique des caractéristiques surpasse systématiquement les caractéristiques basées sur les rapports pour l'ensemble des classificateurs évalués, faisant passer la précision diagnostique moyenne de 77,25 % à 93,85 %, soit une amélioration globale de 16,60 %. Les gains les plus importants sont observés avec les algorithmes KNN et SVM, dont la précision augmente respectivement de 31,15 % et 28,69 %, confirmant que les caractéristiques graphiques génèrent un espace de représentation plus facilement séparable sur le plan géométrique. Ces résultats démontrent que l'ingénierie des caractéristiques joue un rôle déterminant dans les performances du diagnostic des défauts des transformateurs, dépassant souvent l'influence du choix du classificateur lui-même, et constituent une base solide pour le développement de systèmes intelligents de maintenance prédictive des transformateurs de puissance.

Mots-clés: Analyse des gaz dissous (DGA), diagnostic des transformateurs de puissance, classification des défauts, représentation graphique des caractéristiques, caractéristiques basées sur les rapports de gaz, apprentissage automatique, apprentissage par ensembles, maintenance prédictive, IEC.

خلاصة

يُعدّ تشخيص أعطال المحولات الكهربائية المغمورة في الزيت أمراً بالغ الأهمية لضمان موثوقية منظومات الطاقة الكهربائية واستمراريتها. وعلى الرغم من أن تحليل الغازات الذائبة (DGA) يمثل أحد أكثر أساليب مراقبة الحالة فعالية، إلا أن طرق التفسير التقليدية كثيراً ما تعاني من محدودية في الدقة التشخيصية، نتيجة تداخل مناطق الأعطال وضعف تمثيل الخصائص. لذلك، تقترح هذه الأطروحة إطاراً مقارناً منهجياً يُقيّم استراتيجيتين مختلفتين لاستخراج الخصائص من بيانات DGA، هما الخصائص النسبية والخصائص البيانية، وذلك بالتكامل مع خوارزميات الذكاء الاصطناعي الحديثة للتغلب على هذه القيود.

تبحث الدراسة في أربع خوارزميات تعلم آلي، هي: K-Nearest Neighbors و Support Vector Machine و Random Forest و RUSBoost، وقد طُبقت على مجموعة بيانات تضم 407 عينة موزعة على ستة أصناف من الأعطال: التفريغ الجزئي (PD)، والتفريغ الكهربائي منخفض الطاقة (D1)، والتفريغ الكهربائي عالي الطاقة (D2)، والأعطال الحرارية بثلاث مستويات (T1 و T2 و T3). وتُستخرج الخصائص النسبية من طرق النسب الغازية المعتمدة، في حين تُبنى الخصائص البيانية انطلاقاً من التمثيلات التشخيصية البصرية كمثلث دوفال والتقنيات الهندسية المرتبطة به. ويخضع كلا النوعين من الخصائص للتقييم الشامل باستخدام مجموعة متكاملة من مقاييس الأداء، تشمل: الدقة الكلية والدقة التنبؤية والاستدعاء ودرجة F1 ومعامل ماثيوس الارتباطي (MCC) ومعامل كاپا لكوهين.

تُظهر النتائج التجريبية أن التمثيل البياني للخصائص يتفوق باستمرار على الخصائص النسبية عبر جميع النماذج المختبرة، إذ ترتفع متوسط الدقة التشخيصية من 77.25% إلى 93.85%، بما يعادل تحسناً إجمالياً قدره 16.60%. وتبرز أكبر المكاسب في نموذجي KNN و SVM، بتحسينات في الدقة بلغت 31.15% و 28.69% على التوالي، مما يؤكد أن الخصائص البيانية تُنتج فضاءً أكثر قابلية للفصل الهندسي. وتُرسخ هذه النتائج أن هندسة الخصائص تؤدي دوراً محورياً في أداء تشخيص أعطال المحولات، وكثيراً ما يتجاوز تأثيرها تأثير اختيار الخوارزمية ذاتها، مما يوفر أساساً متيناً لأنظمة الصيانة التنبؤية الذكية في محولات القدرة.

الكلمات المفتاحية: تحليل الغازات الذائبة (DGA)، تشخيص محولات القدرة، تصنيف الأعطال، التمثيل البياني للخصائص، الخصائص النسبية، التعلم الآلي، التعلم التجميعي، الصيانة التنبؤية، IEC

Summary



Summary

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Notations et symbols

V_s : [v] : Représentent respectivement les vecteurs tensions Statoriques.

V_r : [v] : représentent respectivement les vecteurs tensions Rotoriques.

φ_s, φ_r : [Wb] : Les vecteurs flux statoriques et rotoriques.

L_s : Matrice des inductances statoriques.

L_r : Matrice des inductances rotoriques.

M_{sr} : Matrice des mutuelles stator-rotor.

M_{rs} : Matrice des mutuelles rotor- stator.

M_0 [H] : Inductance mutuelle entre une phase statorique et Une phase rotorique.

L_s [H] : Inductance propre d'une phase statorique.

L_r [H] : Inductance propre d'une phase rotorique.

l_{ss} [H] : Inductance mutuelle entre deux phases statorique.

l_{rr} [H] : Inductance mutuelle entre deux phases rotoriques.

θ [rad] : L'angle de rotation du rotor par rapport au stator.

θ_s [rad] : L'angle de rotation de stator.

θ_r [rad] : L'angle de rotation du rotor.

d : Indice de l'axe direct.

T_s, T_r : Constant de temps rotorique (statorique).

σ : Coefficient de dispersion.

ω_s, ω_r : Pulsation de fréquence statorique (rotorique).

Ω_r : Vitesse rotorique nominal.

i_s [A] : Les vecteurs courants statoriques.

i_r [A] : Les vecteurs courants rotoriques.

$\sigma = 1 - \frac{lm^2}{L_s L_r}$: Facteur de dispersion.

j : Inertie des masses tournantes.

$T_r = \frac{L_r}{R_r}$: Constante de temps rotorique.

R, L, L_s : Résistance, Inductance, Inductance mutuelle.

C_r [N. m] : Couple résistant imposé par la charge mécanique.

C_{em} [N. m] : Couple électromagnétique.

Ω [rad/s] : Vitesse mécanique de rotation.

g : glissement.

Transformations :

S : Opérateur de Laplace,

P : Transformation de Park,

General Introduction



General Introduction

1. General overview:

The electrical power industry is commonly divided into three main sectors: generation, transmission, and distribution. Within transmission and distribution systems, essential equipment such as power transformers, tap changers, circuit breakers, instrument transformers, substation batteries, and interconnection devices ensure the efficient transfer of electrical energy from power plants to end users.

These components are considered critical assets, as their failure can result in power outages, safety risks to both people and the environment, and significant repair costs. For this reason, continuous monitoring and accurate assessment of their operating conditions are necessary to maintain high reliability and availability.

Among these assets, large oil-filled power transformers are particularly important due to their high cost and key role in the network. In fact, they can represent up to 60% of the total investment in a substation. Therefore, their proper operation is essential for ensuring the stability and efficiency of power systems.

In response to economic constraints and the need for improved asset management, electric utilities have shifted from traditional time-based maintenance strategies to more advanced approaches such as Reliability-Centered Maintenance (RCM) and Condition-Based Maintenance (CBM). These strategies aim to extend the operational lifespan of transformers while minimizing unnecessary maintenance and planning effectively for their eventual replacement.

Condition-based maintenance focuses on the early detection of faults and the monitoring of aging processes. In this approach, faults are identified through observable symptoms using off-line diagnostic techniques. In contrast, on-line monitoring systems provide continuous evaluation of transformer performance, enabling operators to detect faults, assess their severity, and determine whether the transformer can safely remain in service.

One of the most effective diagnostic methods is oil analysis, particularly the study of dissolved gases, which provides valuable insights into the internal condition of transformers. This technique can be applied either off-line through detailed laboratory analysis or on-line

through real-time monitoring systems that trigger alarms when gas levels exceed acceptable limits.

With recent advances in computing technologies and artificial intelligence, it has become possible to perform more sophisticated analyses of the phenomena affecting transformer performance. As a result, intelligent and hybrid models can be developed to improve condition assessment and support preventive maintenance strategies, ultimately enhancing the reliability and efficiency of electrical power systems.

2. Thesis objective:

This study presents a comparative analysis between two feature extraction approaches derived from Dissolved Gas Analysis (DGA) data for power transformer fault diagnosis. The first approach relies on ratio-based features, which are derived by calculating specific ratios between dissolved gases in transformer oil. The second approach employs graphical features, which represent gas concentrations through visual diagnostic methods such as the Duval Triangle and related graphical techniques. Both approaches were evaluated using four artificial intelligence classifiers — KNN, SVM, Random Forest, and RUSBoost — applied to a dataset of 407 samples distributed across six distinct fault types, enabling a comprehensive and systematic comparison of diagnostic performance between the two feature representations.

3. Thesis contribution:

The research presented in this thesis contributes to the field of power transformer fault diagnosis through the application of artificial intelligence techniques combined with Dissolved Gas Analysis (DGA) data. Several key contributions have been made

A comparative study was conducted between two feature extraction • approaches derived from DGA data, namely ratio-based features and graphical features, evaluating their effectiveness in diagnosing six distinct fault types: PD, D1, D2, T1, T2, and T3.

Four artificial intelligence classifiers — KNN, SVM, Random Forest, • and RUSBoost — were systematically applied and evaluated using multiple performance metrics, including accuracy, precision, recall, F1-score, Matthews Correlation Coefficient (MCC), and Cohen's Kappa, providing a comprehensive benchmarking framework.

The study demonstrated that graphical feature representation, • derived from methods such as the Duval Triangle and related graphical techniques, significantly outperforms ratio-

based features across all tested classifiers, raising the average diagnostic accuracy from 77.25% to 93.85%.

The findings confirm that feature engineering plays a decisive role in transformer fault diagnosis performance, often exceeding the impact of classifier selection itself, offering valuable guidance for researchers and engineers working on DGA-based diagnostic systems.

4. Thesis outline:

- **Chapter One: Power Transformers**

This chapter introduces power transformers, their operating principle based on electromagnetic induction, and their classification types. It also covers the main fault types including electrical, thermal, and partial discharge faults, highlighting the importance of early detection and proper insulation for transformer reliability.

- **Chapter Two: Literature Review**

This chapter reviews traditional DGA interpretation methods, including ratio-based approaches such as IEC and Rogers ratios, and graphical methods like the Duval Triangle and Pentagon. It identifies their key limitations in handling complex faults and large datasets.

- **Chapter Three: Artificial Intelligence**

This chapter presents the machine learning algorithms used in the study, including KNN, SVM, Decision Tree, Random Forest, RUSBoost, and XGBoost, explaining the working principle of each and the evaluation metrics used to measure their diagnostic performance

- **Chapter Four: Application and Evaluation**

This chapter compares ratio-based and graphical features extracted from DGA data using four AI classifiers on 407 samples. Graphical features achieved an average accuracy of 93.85% versus 77.25% for ratio-based features, confirming that feature engineering is crucial for accurate transformer fault diagnosis.

Chapter I:

Literature Review on Internal Fault Diagnosis in Power Transformers



I.1. Introduction:

Power transformers are among the most critical elements of electrical power systems. Implementing regular maintenance strategies based on condition monitoring significantly extends their operational lifespan and ensures the continuity of power supply. Any failure or instability in transformer operation may lead to severe financial losses as well as negative environmental impacts. Consequently, gaining a clear understanding of fault origins is highly recommended.

Such failures can be effectively mitigated through condition evaluation techniques, including monitoring and diagnostic approaches. This chapter presents fundamental concepts related to power transformers, various fault categories, and their underlying causes. Furthermore, it reviews the most widely adopted techniques for monitoring and diagnosing faults in oil-immersed transformers, with particular emphasis on dissolved gas analysis (DGA).

I.2 Power Transformers:

The electrical power network is generally divided into two main subsystems: transmission and distribution, each serving a specific function in the delivery of electricity. The transmission system is responsible for transporting electrical energy over long distances, ensuring that power generated at plants reaches substations efficiently. It operates at high voltage levels to minimize energy losses and maintain stable, reliable power flow across the network.

In contrast, the distribution system delivers electricity from substations to end users, including residential, commercial, and industrial consumers. Voltages are stepped down to levels suitable for safe and practical use. Distribution networks include primary feeders, transformers, and secondary circuits that ensure power is supplied efficiently and reliably to various types of consumers.

Power transformers are essential components in both transmission and distribution systems. The International Electrotechnical Commission (IEC) defines a power transformer as a static electrical device with two or more windings. Through electromagnetic induction, a transformer converts alternating voltage and current from one level to another, typically with different magnitudes, while maintaining a constant frequency. This process enables efficient power transmission and ensures electricity can be delivered safely over long distances and at voltages appropriate for end-user requirements.

I.2.1 The History of the Emergence of Power Transformers:

The discovery of electromagnetic induction in 1831 by the British scientist Michael Faraday laid the scientific foundation for the operation of electrical transformers; without this discovery, transformers could not have been developed. In 1885, Hungarian engineers known as the ZBD group—Károly Zipernowsky, Ottó Bláthy, and Miksa Déri—designed the first practical closed-core transformer, which is very similar in principle to modern transformers. In 1886, William Stanley, in cooperation with Westinghouse, further developed a practical transformer based on the ZBD concepts, while during the same period Nikola Tesla strongly promoted the alternating current system, accelerating the widespread adoption of transformers in electrical power networks.

I.2.2 Transformer Types:

Based on apparent power ratings, the IEC categorizes oil-immersed power transformers into three main groups [10]:

- **Distribution transformers:** rated up to 2,500 kVA for three-phase units and up to 833 kVA for single-phase units.
- **Medium power transformers:** with power ratings ranging from 2.5 MVA to 100 MVA for three-phase transformers, and up to 33.3 MVA for single-phase transformers.
- **Large power transformers:** exceeding 100 MVA for three-phase transformers and above 33.3 MVA for single-phase transformers.

I.2.3 Structure:

Regardless of their rated capacity, power transformers are mainly composed of several essential elements [11], which can be summarized as follows

- **Active part :** This component includes the magnetic core, which guides the magnetic flux, along with the low- and medium-voltage windings. Its primary function is to generate a varying magnetic flux in the primary winding and induce a corresponding voltage in the secondary winding. The active part is generally housed within a metallic tank.
- **Bushings :** These components provide insulated pathways that allow the transformer windings to be connected to external power networks through the tank wall.
- **Tap changer :** This device is used to regulate the output voltage by modifying the number of effective turns in the windings, thereby adapting the voltage level according to load variations on the network.
- **Cooling system:** The cooling system ensures heat dissipation and maintains the transformer temperature within acceptable limits. Cooling techniques differ depending on transformer rating, operating conditions, and system requirements.
- **Insulation system:** Typically composed of insulating oil and solid materials such as paper, this system provides electrical insulation between components and enhances heat removal.
- **Auxiliary equipment:** These include monitoring and protection devices such as thermometers, Buchholz relays, silica gel breathers, expansion tanks, and other accessories.

Figure II.1 illustrates the main structural components of a power transformer, including: (1) bushings and porcelain terminals, (2) tap changer, (3) magnetic core, (4) cooling and protection system, (5) insulation between windings and ground, (6) tank and grounding system, (7) winding connections, (8) winding arrangement, (9) winding geometry, (10) inter-turn insulation, and expansion tank

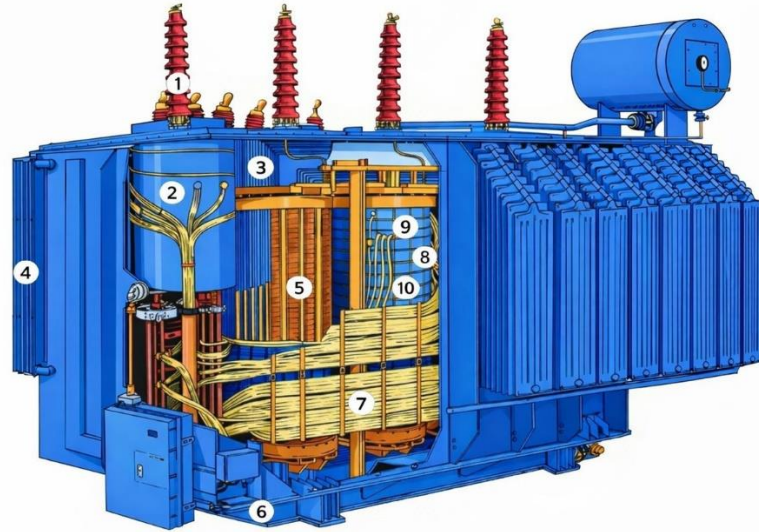


Figure I.1: Structural Overview of a Power Transformer [10]

I.2.4 Types of Faults in Power Transformers:

Power transformers may experience failures due to electrical, thermal, or mechanical stresses encountered during normal operating conditions. While the occurrence of stress-induced faults generally remains low and relatively constant over the majority of a transformer's service life, such faults should not be neglected. This is because their root causes can often be detected at an early stage, allowing preventive measures to be taken before a complete failure occurs. The following subsections present the principal fault causes examined in this study.

- **Electrical Faults:**

Electrical faults arise when electric current unintentionally flows between points that are normally separated by adequate electrical insulation. In power transformers, this type of fault typically develops as a consequence of insulation degradation, excessive electrical stress, aging, manufacturing defects, or inadequate maintenance practices. Over time, the combined effects of thermal stress, moisture ingress, mechanical vibrations, and transient overvoltages can

weaken the dielectric strength of both solid and liquid insulation systems, thereby increasing the likelihood of electrical breakdown.

One of the most common forms of electrical fault is the inter-turn short circuit, which occurs when insulation between adjacent turns of a winding fails. Although initially localized, such faults can rapidly escalate due to the high circulating currents generated within the affected turns, leading to significant localized heating and further insulation damage. Similarly, insulation deterioration between different windings—such as between the high-voltage and low-voltage windings—can result in more severe internal faults, often accompanied by substantial energy release. Weak, loose, or poorly secured electrical connections also contribute to fault initiation, as they create points of high resistance that generate excessive heat and may trigger partial discharges or arcing.

Electrical faults in transformers are commonly classified according to their energy level into low-energy discharges (D1) and high-energy discharges (D2). Low-energy discharges (D1), often associated with partial discharge phenomena, involve localized dielectric breakdowns that do not completely bridge the insulation gap. While the energy involved is relatively limited, repeated occurrences can progressively degrade insulation materials and weaken the transformer's dielectric integrity. In contrast, high-energy discharges (D2), also known as arc faults, involve a complete electrical breakdown of the insulation, resulting in intense localized temperatures and substantial energy release within a very short duration. These arc faults are particularly destructive and may cause rapid deterioration of winding conductors, structural components, and insulation materials.

Both D1 and D2 faults have significant implications for the transformer's insulation system. The intense thermal and electrical stresses associated with these faults can damage solid insulation, such as cellulose-based paper, and decompose the insulating oil. This decomposition often leads to the formation of carbon particles and combustible gases within the liquid insulation. The accumulation of such by-products not only reduces dielectric strength but also increases the risk of catastrophic failures, including internal explosions or fire. Therefore, early detection and accurate classification of electrical faults are essential for preventing hazardous outcomes and ensuring the reliable operation of power transformers.. As depicted in the figure

II.2 Electrical Faults.

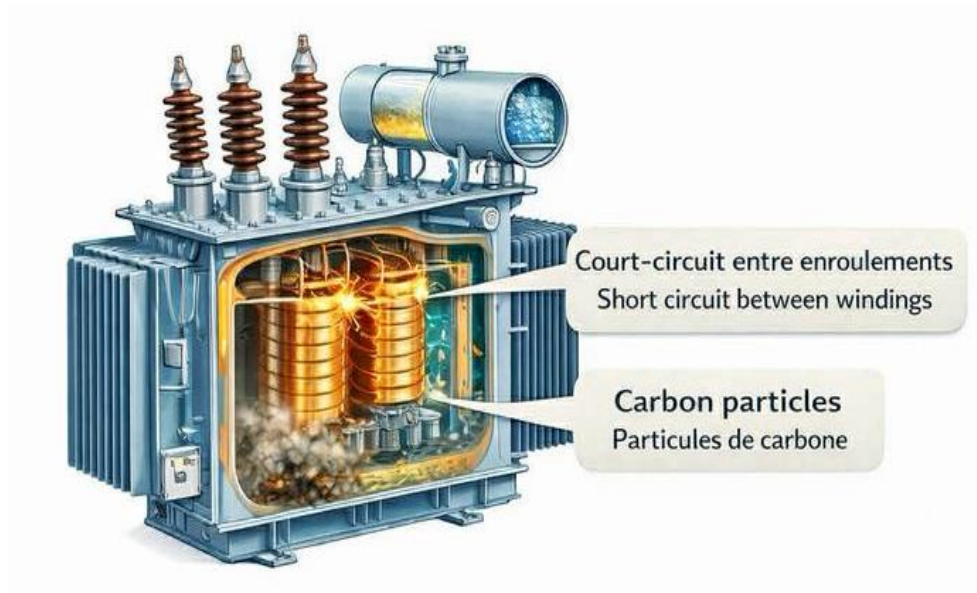


Figure I.2: Electrical Faults

- **Partial Discharge Faults:**

Partial discharge (PD) faults occur when localized dielectric breakdown takes place within a small portion of the insulation system, without forming a complete conductive path between energized components. In other words, the insulation does not fail entirely, but its dielectric strength is weakened in specific regions where the electric field exceeds the local withstand capability. These discharges are typically repetitive, low-energy events that progressively deteriorate the insulation structure over time.

Partial discharge commonly develops in areas where the electric field is non-uniform or highly concentrated. Such conditions may arise due to manufacturing imperfections, sharp edges on conductors, voids within solid insulation, cracks in paper insulation, contamination, moisture ingress, or gas bubbles in the insulating oil. One of the most frequent forms of PD is corona discharge, which usually appears in gaseous regions surrounding high-voltage conductors. Corona occurs when the electric field intensity in the surrounding gas exceeds its ionization threshold, causing localized ionization without full electrical breakdown. This phenomenon is often accompanied by faint light emission, audible noise, and the generation of ozone or other chemical by-products.

Unlike high-energy arc faults, partial discharge does not immediately create a low-resistance current path between conductors. However, the cumulative effect of repeated discharges can be highly destructive. Each discharge event releases a small amount of energy

that causes localized heating, chemical decomposition, and mechanical stress within the insulation material. In solid insulation such as cellulose paper, PD can lead to carbonization, erosion, and the formation of microscopic channels. In liquid insulation, it can produce gas bubbles and decomposition by-products that further reduce dielectric strength.

Over time, these localized defects grow in size and severity, intensifying the electric field concentration in the affected region. This creates a self-accelerating deterioration process, where insulation damage promotes stronger discharges, which in turn cause more damage. If left undetected and unmitigated, partial discharge activity may eventually evolve into a full insulation breakdown or a high-energy arc fault, resulting in significant transformer damage or catastrophic failure.

For this reason, early detection of partial discharge—through techniques such as dissolved gas analysis (DGA), acoustic emission monitoring, or electrical PD measurement—is essential for effective condition-based maintenance and for preventing major transformer outages.. As depicted in the figure II. 3 Partial Discharge Faults.

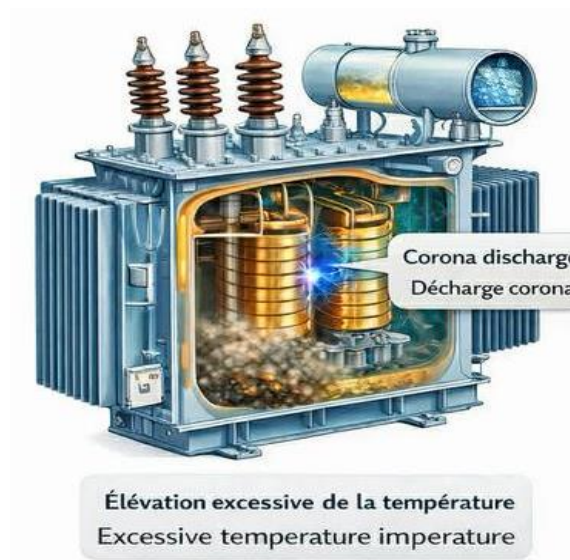


Figure I.3: Partial Discharge Faults

- **Thermal Faults:**

Thermal faults in power transformers occur as a result of excessive temperature rise inside the transformer tank, leading to the formation of localized hot spots within the insulation system. These hot spots typically develop in winding conductors, core regions, or structural metallic parts when heat generated by electrical and magnetic losses is not properly dissipated.

Since transformer insulation—both solid cellulose paper and liquid insulating oil—is highly sensitive to temperature, prolonged thermal stress significantly accelerates insulation aging, reduces dielectric strength, and weakens the mechanical integrity of the winding structure.

The main causes of thermal faults include poor electrical contacts such as loose connections or deteriorated tap changer contacts, which create high-resistance points that generate localized I^2R heating. Circulating currents within parallel windings or metallic structural components can also produce additional losses, while leakage flux may induce eddy currents in tank walls and clamping structures, resulting in localized overheating. Depending on the maximum temperature reached, thermal faults are classified into three categories: T1 (below 300 °C), representing low-temperature overheating mainly affecting the insulating oil and producing light hydrocarbon gases; T2 (between 300 °C and 700 °C), indicating more severe overheating that causes significant oil decomposition and initial carbonization of solid insulation; and T3 (above 700 °C), corresponding to extreme overheating conditions that lead to rapid decomposition of both oil and cellulose insulation, generation of large amounts of combustible gases, and potential structural damage.

A distinguishing feature of thermal faults is the production of characteristic gases as a result of thermal decomposition of insulating materials. The type and concentration of these gases vary with temperature level, forming the basis of dissolved gas analysis (DGA), which is widely used for diagnostic and condition monitoring purposes. Through gas pattern evaluation, engineers can assess fault severity and progression, allowing early intervention before minor overheating develops into a critical transformer failure. As depicted in the figure II.4 Thermal Faults.

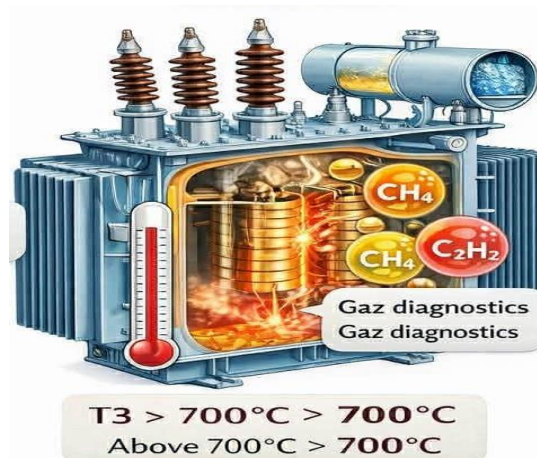


Figure I.4: Thermal Faults

I.2.5. Application Areas:

Condition monitoring and diagnostic techniques for power transformers are applied in several key areas, including.

1. Electric Power Transmission Networks:

These techniques are widely used to monitor high-voltage transformers in transmission substations, where high reliability and continuous operation are critical

2. Power Distribution Systems:

Diagnostic methods are applied to distribution transformers to detect incipient faults early, thereby reducing unexpected outages and improving power quality.

3. Electrical Substations:

Techniques such as frequency response analysis and vibration monitoring are used to assess the mechanical condition of transformers installed in substations.

4. Large Industrial Facilities:

Industries that rely heavily on power transformers employ condition monitoring to ensure uninterrupted operation and avoid financial losses due to unplanned shutdowns.

5. Condition-Based Maintenance Programs:

Diagnostic results support maintenance strategies based on the actual condition of the transformer rather than fixed maintenance schedules.

6. Insulation Monitoring in Oil-Immersed Transformers:

Partial discharge and thermal analysis techniques are used to monitor the degradation of oil and paper insulation systems.

7. Power System Reliability Enhancement:

These techniques contribute to improving overall power system reliability and reducing the risk of large-scale transformer failures.

I.2.6 Insulating oil for power transformers :

is a fundamental component in ensuring safe and efficient transformer operation, as it performs two main functions:

electrical insulation and thermal cooling. The oil provides insulation between live parts, preventing electrical discharges, and helps transfer the heat generated by losses in the windings and the core to the transformer walls and radiators, thereby maintaining acceptable operating temperatures.

In addition, insulating oil protects solid insulation materials (such as insulating paper) from moisture and oxidation. The byproducts of its thermal and electrical degradation, particularly dissolved gases, are widely used as important diagnostic indicators to identify internal transformer faults through Dissolved Gas Analysis (DGA). Therefore, maintaining high oil quality and regularly monitoring its physical and chemical properties are crucial for extending the service life and ensuring the reliability of power transformers.

I.2.7 Factors Affecting the Performance of Power Transformers:

The overall performance of power transformers depends on a combination of interacting electrical, thermal, and mechanical factors. Any degradation in one of these aspects may lead to reduced efficiency or internal faults. Therefore, analyzing the factors that influence transformer performance is essential for assessing its operating condition and ensuring reliable power system operation.

I.2.8 Thermal Behavior of Power Transformers:

Thermal behavior is one of the most important indicators of the operating condition of power transformers. Continuous temperature rise accelerates insulation aging and reduces transformer service life. In addition, non-uniform temperature distribution inside the transformer may result in the formation of hot spots that negatively affect winding and insulation integrity. Consequently, monitoring thermal performance is crucial for early detection of thermal faults and prevention of unexpected failures.

I.2.9 Mechanical Stresses During Transformer Operation:

Power transformers are subjected to mechanical stresses caused by electromagnetic forces, vibrations, and sudden load variations. These stresses may lead to winding deformation,

loosening of mechanical supports, or internal misalignment. Studying mechanical stresses is important for identifying mechanical faults that can compromise transformer stability and long-term performance.

I.2.10. Electrical Stresses and Insulation Degradation:

Electrical stresses play a major role in the degradation of the insulation system in power transformers. Voltage fluctuations, partial discharges, and electrical disturbances can progressively weaken insulation materials. Analyzing the impact of electrical stresses on insulation helps in diagnosing early electrical faults and implementing preventive measures to maintain transformer safety.

I.2.11. Importance of Condition Monitoring in Fault Reduction :

Condition monitoring of power transformers is a key approach for reducing failures and improving system reliability. Monitoring techniques enable early detection of abnormal electrical, thermal, and mechanical behaviors. This approach contributes to minimizing unplanned outages, reducing maintenance costs, and extending transformer operational lifetime.

I.3. Comprehensive review of condition monitoring methods:

Power transformers are among the most important components of electrical power systems, as they are essential for the efficient and safe transmission and distribution of energy. Due to the harsh operating conditions these devices are exposed to—such as varying loads, high electrical stresses, and elevated temperatures—their performance and operational condition may degrade over time. For this reason, monitoring the condition of power transformers has become a critical necessity to ensure the continuity of electrical service and reduce the risk of sudden failures, which can lead to significant technical and economic losses.

The process of assessing the operational condition of power transformers relies on a comprehensive set of monitoring and diagnostic techniques aimed at the early detection of various types of internal faults. These techniques include electrical methods used to evaluate the insulation system's integrity, such as insulation resistance measurement and partial discharge analysis. These methods help identify the initial stages of insulation deterioration, whether in the oil or in the solid insulating materials. Other techniques rely on frequency

response analysis to detect mechanical faults related to winding deformation or displacement caused by electromagnetic forces, especially during short circuits or sudden load changes.

In addition, mechanical methods play an important role in diagnosing faults associated with vibrations and imbalance within the transformer. Abnormal vibrations may indicate mechanical issues such as loose fastenings or misalignment, which can worsen over time. Thermal analysis techniques, particularly infrared thermography, are also employed to monitor the transformer's thermal distribution and detect hot spots, which are critical indicators of thermal faults and insulation degradation.

Chemical testing is another essential part of condition monitoring, where insulating oil is analyzed to assess its quality and the extent of oxidation or aging. Certain chemical indicators, such as interfacial tension and breakdown voltage, are important signs of the deterioration of the insulating oil and its ability to perform efficiently. The condition of solid insulation, like paper, can also be evaluated through indicators such as the degree of polymerization, which helps estimate the remaining life of the transformer's solid insulation.

Dissolved Gas Analysis (DGA) is considered one of the most advanced and reliable techniques for diagnosing the condition of power transformers, due to its high capability to detect thermal and electrical faults at early stages. Dissolved gases are generated as a result of various stresses the transformer experiences during operation, and by analyzing the type and concentration of these gases, the nature and severity of a fault can be determined. For example, the presence of hydrogen (H_2) usually indicates partial discharge or low-level electrical stress, while methane (CH_4) and ethane (C_2H_6) indicate thermal decomposition of oil at low to moderate temperatures. Ethylene (C_2H_4) signals moderate thermal decomposition of oil at approximately 150–200 °C, whereas acetylene (C_2H_2) indicates severe electrical arcing or high-energy discharge, pointing to serious electrical faults. The presence of carbon monoxide (CO) and carbon dioxide (CO_2) is associated with the degradation of solid insulation, such as paper, due to heat. Ammonia (NH_3) may result from the decomposition of other insulating materials or oil and indicates potential insulation quality issues or the presence of moisture. Figure II.5 presents methods for evaluating power transformer and methods for interpreting DGA in particular.

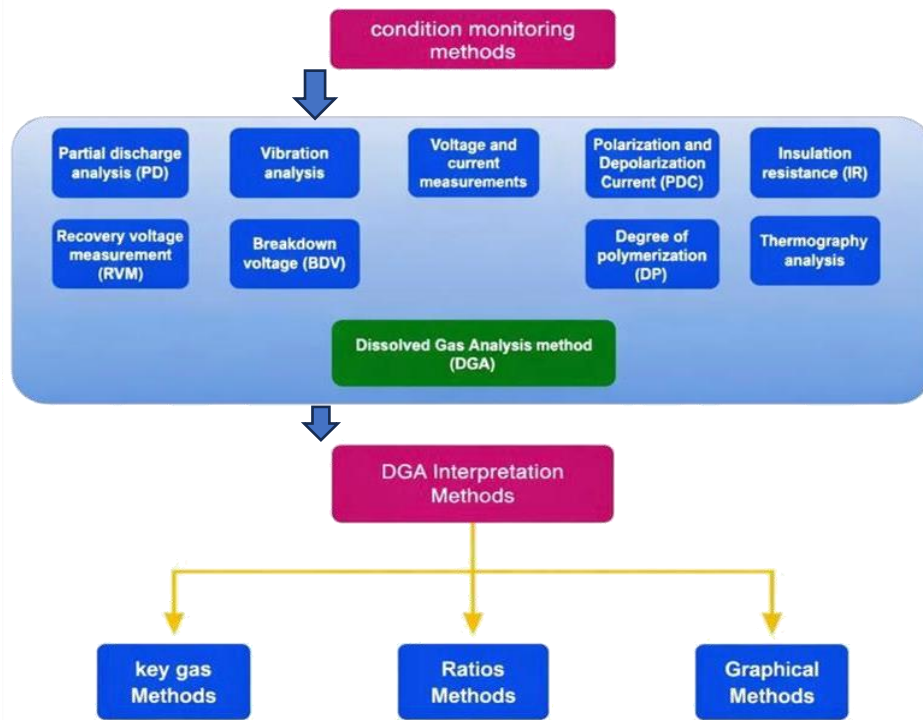


Figure I.5: Power transformer condition assessment and DGA interpretation methods

I.4. Dissolved Gas Analysis Techniques:

Dissolved Gas Analysis (DGA) is an essential diagnostic technique for identifying early-stage faults in oil-filled power transformers [44]. It is widely used to examine the gases dissolved in insulating oil, which form as a result of thermal and electrical stresses impacting transformer operation [45, 46]. The main gases monitored in DGA include hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), and acetylene (C_2H_2), while carbon monoxide (CO) and carbon dioxide (CO_2) serve as important indicators in cases of cellulose degradation . [48 ,47]

An early protective device, the Buchholz relay, was introduced in 1928 [49] to safeguard transformers by detecting gas accumulation caused by faults. As illustrated in Figure II.6, the relay operates by sensing gas build-up in a pipeline connected to an expansion tank, triggering an alarm or disconnecting the transformer to prevent damage.

By the late 1950s, improvements in analytical techniques enabled the collection and examination of gas and liquid samples, culminating in H.H. Wagner's development of a field chromatography analyzer in 1959 [50]. Today, gas chromatography (GC) is widely employed to identify and quantify dissolved gases in transformer oil, particularly those generated by electrical faults[51] .

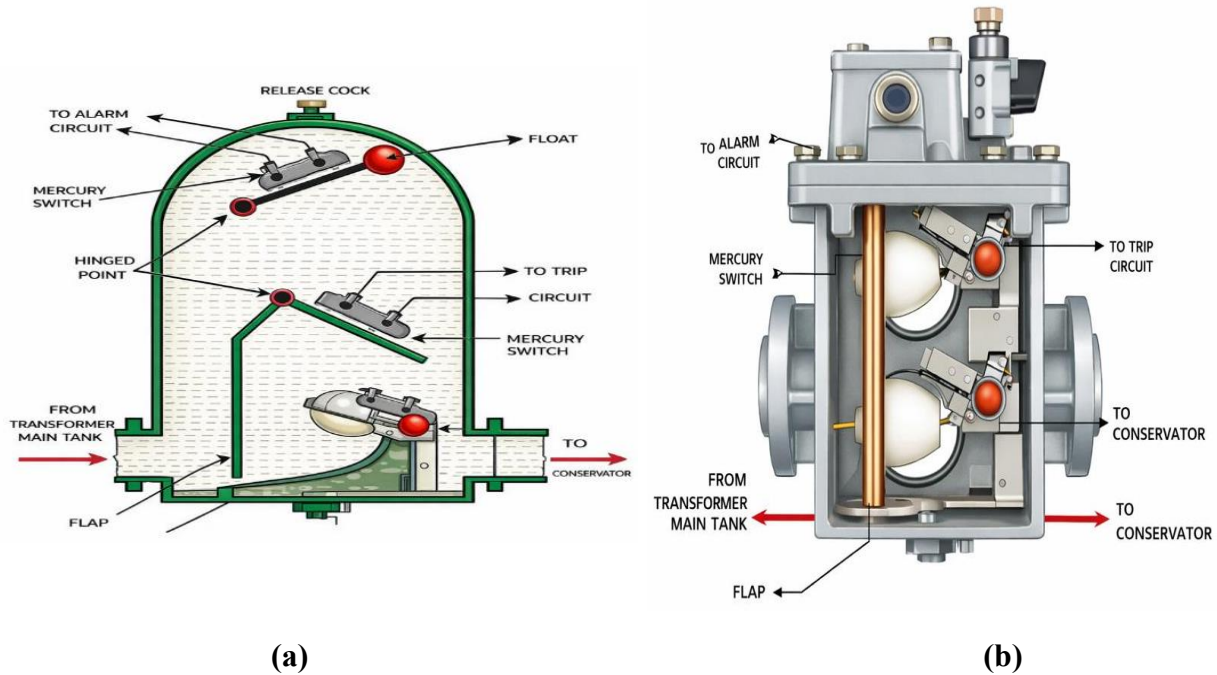


Figure I.6: Buchholz relay, (a) electrical schematic; (b) an example of a Buchholz relay

The chromatographic analysis of dissolved gases in transformer oil involves several systematic steps. The process begins with sampling, which can be performed using flexible aluminum bottles or syringes. In some cases, gases extracted from the oil sample may be temporarily collected in the Buchholz relay [52]. Once the sample is collected, the gases are extracted and introduced into a gas chromatograph, which separates the different gas components for accurate identification and quantification [53]. As illustrated in Figure II.7, the procedure encompasses sample collection, gas extraction, and the analytical separation and detection of dissolved gases. This structured methodology ensures precise fault diagnostics, allowing for timely maintenance and minimizing the risk of transformer failures.

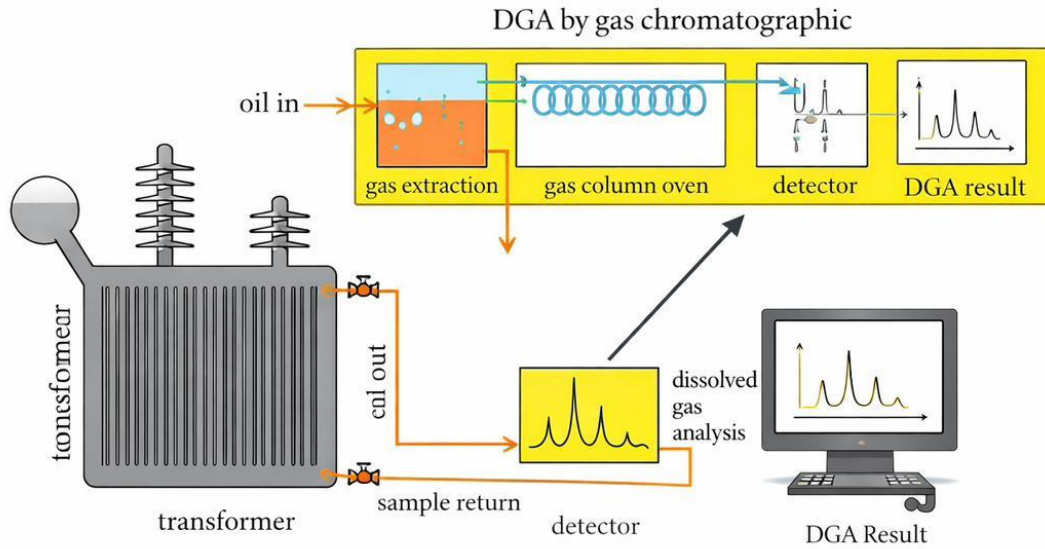


Figure I.7: Steps for gas chromatography analysis [54]

I.5. The Most Commonly Used DGA Methods:

This section presents a comprehensive review of the principal Dissolved Gas Analysis (DGA) techniques, with particular emphasis on those that have become widely recognized in recent years for their effectiveness, precision, and extensive industrial application. By examining the most commonly implemented approaches, this section seeks to illustrate prevailing developments and established best practices in the field of transformer condition monitoring and fault diagnosis.

I.5.1. Key gas Methods:

I.5.1.1. IEEE key gas:

The IEEE Key Gas method, first developed in 1973 by Doble Engineering Company, is a widely recognized approach for evaluating the condition of power transformers based on the analysis of gases produced under thermal and electrical stresses. The technique was formally presented by David Pugh in 1974 [55], and a revised version was subsequently adopted in the IEEE C57.104 standard.

This method relies on measuring the concentrations of selected key gases—such as hydrogen, various hydrocarbons, and carbon monoxide—formed due to the degradation of insulating oil and cellulose paper. Table II.1 identifies the main gases used in the analysis and the types of faults associated with each, whereas Table II.2 presents the gas ratio criteria

corresponding to the four principal fault categories defined by this technique. The percentage values provided in both tables are derived from extensive empirical data and expert experience in transformer diagnostics[56]

Despite its broad acceptance, the IEEE Key Gas method has certain drawbacks. It may occasionally lead to unclear or inaccurate fault identification. In some situations, the predominant gas detected does not belong to the set of key gases considered by the method. Furthermore, the presence of carbon monoxide may be incorrectly interpreted as definitive evidence of paper insulation involvement in the fault process[57].

Table I.1: Key gas generated according to a fault type [56]

Key gas	Fault type	Typical proportions
C ₂ H ₄	Overheating, oil	Mainly C ₂ H ₄ ; Smaller proportions of C ₂ H ₆ , CH ₄ , and H ₂ ; Traces of C ₂ H ₂ at very high fault temperature
CO	Overheating, paper and oil	Mainly CO; Much smaller quantities of hydrocarbon gases (Predominantly C ₂ H ₄ with smaller proportions of C ₂ H ₆ , CH ₄ , and H ₂)
H ₂	Partial discharge	Mainly H ₂ ; Small quantities of CH ₄ ; Traces of C ₂ H ₄ and C ₂ H ₆
H ₂ & C ₂ H ₂	Arcing	Mainly H ₂ and C ₂ H ₂ ; Minor traces of CH ₄ , C ₂ H ₄ , and C ₂ H ₆ ; Also, CO if cellulose is involved

Table I.2: Key gas proportions of fault types of IEEE key gas method [56]

Key gas percentages (%)						
Fault type	H ₂	CH ₄	C ₂ H ₆	C ₂ H ₄	C ₂ H ₂	CO
Partial discharges	85	13	1	1	-	-
Arcing	60	5	2	3	30	-
Overheating, oil	2	16	19	63	-	-
Overheating, paper	-	-	-	-	-	92

I.5.1.2. CSUS Key gas:

The CSUS Key Gas method, commonly known as the Key Gas Quantity approach, was established through joint research conducted by California State University, Sacramento, in partnership with Pacific Gas and Electric Company [58]. This diagnostic methodology is based on the separate and direct evaluation of hydrocarbon and carbon-related gas concentrations by

comparing them to predefined threshold limits. As indicated in Table II.3, both standard and alternative (non-standard) limit values are specified for each individual gas to support fault assessment.

Table I.3 Determination of the type of fault according to the CSUS method [58]

Limit concentrations			
	Normal	Anormal	Fault type
H ₂	150	1000	Corona discharges, arcing
CH ₄	25	80	Corona discharges
C ₂ H ₆	10	35	Local overheating
C ₂ H ₄	20	150	Severe overheating
C ₂ H ₂	15	70	arcing
CO	500	1000	Overload, paper decomposition
CO ₂	10 000	15 000	Overload, paper decomposition

When the measured gas concentrations remain below the established normal threshold values, the transformer is considered to be operating under acceptable conditions. The identification of fault types is carried out by individually comparing each gas concentration with its corresponding limit.

Nevertheless, although the CSUS Key Gas method is simple and easy to implement, it is characterized by relatively low diagnostic precision. One of its main shortcomings is the tendency to indicate the presence of multiple fault types at the same time, which can reduce the reliability of the final diagnosis.

I.5.1.3. CIGRE Key gas:

The direct comparison approach, derived from the CIGRE Key Gas method, relies on evaluating the measured concentrations of key gases against their allowable limits. Proposed by CIGRE Task Force 15.01.01 [59], this method not only addresses the three conventional fault categories but also facilitates the identification of faults associated with cellulose insulation deterioration. Table II.4 summarizes the typical threshold values assigned to each key gas and the corresponding faults indicated when these limits are exceeded.

Despite offering meaningful diagnostic guidance, this technique is seldom applied as a standalone tool for transformer condition evaluation. The CIGRE TF 15.01.01 recommendations emphasize the inclusion of gas ratio analysis to enhance interpretation accuracy. Similar to the CSUS Key Gas approach, a major drawback of the CIGRE method is its propensity to indicate more than one fault type simultaneously, thereby complicating precise fault determination.

I.5.1.4. Fallou Key gas:

In 1975, CIGRE published a significant gas detection methodology founded on experimental investigations into the behavior of gases dissolved in mineral insulating oils under electrical and thermal fault conditions [60]. This technique, established through the experimental work of Fallou, is based on evaluating the relative percentage concentration of each gas generated during such fault events.

Particular emphasis is placed on carbon dioxide and hydrocarbons containing three carbon atoms, which are regarded as principal diagnostic indicators, as presented in Table II.5.

Table I.4 Determination of the type of fault according to the CIGRE method [59]

Key gas	Limit	Fault
C_2H_2	> 20	Arcing
H_2	> 100	Partial discharges
$\sum C_xH_y$	> 1 000	Thermal fault
$\sum CO_x$	> 10 000	Cellulosic degradation

Table I.5: Key gas method proposed by Fallou [60]

Fault type	Key gas percentage (%)							
	H ₂	CH ₄	C ₂ H ₆	C ₂ H ₄	C ₂ H ₂	C ₃ H _x	CO	CO ₂
Low-energy discharge (PD1)	88	7	2	-	-	1	1	1
High-energy discharge (PD2)	55	7	5	6	15	6	1	6
Arcing	39	10	-	6	35	3	4	2
Overheating, oil 300°C	-	37	13	19	-	31	-	-
Overheating, oil 500°C	17	25	8	25	-	23	-	-
Overheating, oil 800°C	16	16	6	41	-	21	-	-
Overheating, paper 300°C	26	1	-	-	-	-	-	73
Overheating, paper 500°C	6	1	-	-	-	-	33	59
Overheating, paper 800°C	9	8	1	4	-	1	50	25

I.5.1.5. Characteristic gas ensemble:

The latest advancement in key gas analysis was presented in 2018 [61] by researchers Davidenko and Ovchinnikov. This advancement is the Characteristic Gas Ensemble (CGE) method, which evaluates the relative concentrations of the main gases through the following equation:

$$c_r^i = C^i / C_{lim}^i \quad (\text{II.1})$$

Where c_r^i , C^i and C_{lim}^i denote relative, observed, and permissible concentration of the i th key gas.

CGE method is implemented through a three-step process. Initially, the relative concentrations of various key gases are determined. Next, these relative concentrations are used to develop a letter-code system for the key gases, which is based on the significance of each gas within the ensemble. The meanings of the letters in this coding system are clarified in Table II.6. Finally, in this step, identify the faults using the letter codes specified in Table II.7.

Table I.6: Alphanumeric coding of major gases

Letter	Fault type
A	Primary gas with the highest relative concentration
B	Gas with the second-highest relative concentration $c_r^i \geq 1$
C	Gas at the second or third level with $c_r^i < 1$
D	Corresponds to all other gases not categorized under the previous letters

Table I.7: Determine the fault of the method of gas ensembles characteristic

Fault type	Key gas				
	H ₂	CH ₄	C ₂ H ₆	C ₂ H ₄	C ₂ H ₂
Overheating, $T < 300^\circ\text{C}$	C, D	B	A	C, D	D
Overheating, $300^\circ\text{C} < T < 700^\circ\text{C}$	D	A	C	B	D
Overheating, $T > 700^\circ\text{C}$	D	B	C	A	D
Partial discharges	A	C	D	D	D
Discharges of low energy	A	C	D	D	B
Discharges of high energy	B	C	D	D	A
A set of faults with electrical fault propagation	D	B	D	C	A
A set of faults with thermal fault propagation	C, D	A	B	D	C, D

I.5.2. Ratios Methods DGA:

I.5.2.1. Dornenburg ratios method:

First proposed in 1974, the Dornenburg Ratio method is considered one of the earliest techniques developed for dissolved gas analysis (DGA) [56]. This approach is designed to diagnose three principal types of faults: thermal decomposition, corona discharges, and arcing faults, as illustrated in Table II.8.

For the method to be applicable, the concentration of at least one of the key gases—hydrogen (H₂), methane (CH₄), ethylene (C₂H₄), or acetylene (C₂H₂)—must reach or exceed twice its specified threshold value, as indicated in Table II.9.

However, certain limitations have been identified. The method may yield diagnostic situations in which the concentrations of ethane (C₂H₆) or carbon monoxide (CO) surpass the defined permissible limits, potentially leading to ambiguity in fault interpretation [57].

Table I.8 Fault classification by Dornenburg Ratio Method

Fault	$R_1 = \frac{CH_4}{H_2}$	$R_2 = \frac{C_2H_2}{C_2H_4}$	$R_3 = \frac{C_2H_4}{C_2H_6}$	$R_4 = \frac{C_2H_2}{CH_4}$
Thermal decomposition	>1.0	<0.75	<0.3	>0.4
Corona	<0.1	/	<0.3	>0.4
Arcing	0.1–1.0	> 0.75	>0.3	<0.4

Table I.9 Permitted limit for Dornenburg Ratio Method

Gas	H ₂	CH ₄	C ₂ H ₆	C ₂ H ₂	C ₂ H ₄	CO
Limit (ppm)	100	120	65	50	1	350

I.5.2.2. The four ratios method of Rogers:

The Rogers Four Ratio Method (RFRM) [58] is a diagnostic technique used to identify transformer faults through the evaluation of four characteristic gas ratios. These ratios are methane to hydrogen (CH₄/H₂), ethane to methane (C₂H₆/CH₄), ethylene to ethane (C₂H₄/C₂H₆), and acetylene to ethylene (C₂H₂/C₂H₄).

The method classifies fault conditions by assigning coded values—ranging from 0 to 5—to each ratio, depending on the interval in which the calculated value falls, as presented in Table II.10. Based on the combination of these coded ratios, the technique is capable of distinguishing among 12 different fault types, summarized in Table II.11 [59].

Table I.10 Rogers Ratio Code

Gas Ratio	Ranges	Code
$R_1 = \frac{CH_4}{H_2}$	< 0.1	5
	0.1- 1	0
	1--3	1
	> 3	2
$R_2 = \frac{C_2H_2}{C_2H_4}$	< 1	0
	> 1	1
$R_3 = \frac{C_2H_4}{C_2H_6}$	< 1	0
	1-3	1
	> 3	2
$R_4 = \frac{C_2H_6}{CH_4}$	< 0.5	0
	0.5-3	1
	> 3	2

Table I.11: Fault Types as stated in Rogers Ratio Method

No	CH ₄ /H ₂	C ₂ H ₆ /CH ₄	C ₂ H ₄ /C ₂ H ₆	C ₂ H ₂ /C ₂ H ₄	Fault type
1	0	0	0	0	No fault
2	1-2	0	0	0	<150 °C thermal fault
3	1-2	1	0	0	150–200 °C thermal fault
4	0	1	0	0	200–300 °C thermal fault
5	0	0	1	0	General conductor overheating
6	1	0	1	0	Winding circulating currents
7	1	0	2	0	Core and tank circulating currents overheated joints
8	5	0	0	0	Partial discharge
9	5	0	0	1-2	Partial discharge with tracking
10	0	0	0	1	Flashover without power follow through
11	0	0	1-2	1-2	Arc with power follow- through
12	0	0	2	2	Continuous sparking to floating potential

I.5.2.3. IEC Ratio Method:

The IEC Ratio Method is a widely applied approach for interpreting dissolved gas analysis (DGA) results [60]. Although it shares similarities with the Rogers Four Ratio Method, it excludes the ethane-to-methane ratio from its analysis.

Instead, fault identification is based on three principal gas ratios, each associated with standardized concentration limits and corresponding diagnostic codes. These ratios include acetylene to ethylene (C_2H_2/C_2H_4), methane to hydrogen (CH_4/H_2), and ethylene to ethane (C_2H_4/C_2H_6). The classification criteria and coding scheme for these ratios are presented in Table II.12, while Table II.13 provides a comprehensive interpretation of the various fault types derived from the combination of these coded ratios.

Table I.12: IEC code

Ratio Codes	Range	Code
$R1 = CH_4/H_2$	$R1 < 0.1$	1
	$0.1 \leq R1 \leq 1$	0
	$R1 > 1$	2
$R2 = C_2H_2/C_2H_4$	$R2 < 0.1$	0
	$0.1 \leq R2 \leq 3$	1
	$R2 > 3$	2
$R3 = C_2H_4/C_2H_6$	$R3 < 1$	0
	$1 \leq R3 \leq 3$	1
	$R3 > 3$	2

Table I.13 Fault diagnosis using IEC code

N	Fault type	code		
1	No Fault	0	0	0
2	Partial discharge with low energy density	0	1	0
3	Partial discharge with high energy density	1	1	0
4	discharge of low energy	1.2	0	1.2
5	discharge of high energy	1	0	2
6	Overheating $T < 150^\circ C$	0	1	0

7	Overheating $150 < T < 300$ °C	2	1	0
8	Overheating $300 \leq T \leq 700$ °C	2	1	0
9	Overheating ≥ 700 °C	2	2	2

I.5.2.4. CIGRE Ratio Method:

The CIGRE Ratio Method [53], developed by CIGRE Working Group 15.01.01, is based on the evaluation of five characteristic gas ratios to diagnose transformer faults. These ratios include acetylene to ethane (C_2H_2/C_2H_6), hydrogen to methane (H_2/CH_4), ethylene to ethane (C_2H_4/C_2H_6), acetylene to hydrogen (C_2H_2/H_2), and carbon dioxide to carbon monoxide (CO_2/CO).

By analyzing these parameters, the method enables the detection of various fault categories, such as electrical discharges, thermal abnormalities, and issues related to solid insulation degradation. The detailed ratio criteria and their corresponding diagnostic interpretations are presented in Table II.14.

Table I.14 Determination of the type of fault according to the CIGRE ratio method

Ratio	limit	Fault type
C_2H_2/C_2H_6	≥ 1.0	Arcing
H_2/CH_4	≥ 10.0	Partial discharges
C_2H_4/C_2H_6	≥ 1.0	Thermal fault
C_2H_2/H_2	≥ 2.0	Discharges in OLTC
CO_2/CO	≥ 10.0	Overheating, paper
	< 3.0	Cellulose decomposition due to electrical fault

When all the gas ratios fall within the specified limits provided in Table II.14 [61], the transformer is deemed to be in normal condition. CIGRE ratio method is often used in conjunction with the CIGRE Key Gas Method, with their combined identification framework described in Table II.15 [61]. The CIGRE methods employ a letter-coding system to classify gas concentrations and ratios. "K1" indicates that all key gases are below the concentration limits in Table II.4, while "K2" shows that at least one gas exceeds these limits. For gas ratios, "R1" means all values are within the limits in Table II.14, and "R2" signals that at least one ratio surpasses these limits.

Table I.15 identification procedures using CIGRE ratios and major gas methods

Ratios	Key gases	Explanation
R1	K1	No action, transformer most probably healthy
R2	K2	Transformer most probably faulty, additional analyses needed
R2	K1	Possible incipient failure, additional analyses needed
R1	K2	Possibility of more than one failure, further investigations needed

I.5.2.5. SOU-N EE 46.501: 2006 method:

The SOU-N EE 46.501:2006 method, formalized as a standard in 2007, provides a structured framework for performing dissolved gas analysis (DGA) in the Ukrainian power industry [62]. This approach enables the detection and classification of different transformer fault conditions by examining specific gas ratio ranges, which are presented in detail in Table II.16 [62].

Table I.16 Identification scheme according to SOU-N EE 46.501:2006

Fault type	C_2H_2/C_2H_4	CH_4/H_2	C_2H_4/C_2H_6
No fault	no significant	0.1 – 1.0	< 0.2
PD	no significant	< 0.1	< 0.2
D1	> 1.0	0.1 – 0.5	> 1.0
D2	> 1.0	0.1 – 1.0	> 2.0
D3	< 1.0	0.3 – 0.5	> 5.0
T12	Not significant	> 1.0	< 1.0
T2	Not significant	> 1.0	1.0 – 4.0
T3	< 0.2	> 1.0	> 4.0

In addition to detecting 6 fundamental faults defined by the IEC, the method also identifies the normal operating condition and creeping discharges (D3), which are discharges occurring on the surface and within the solid insulation. These ratios used in this method are based on those initially proposed in the Russian Standard RD 153-34.0-46.302-00, introduced in 1989 and later revised in the 2001 standard. The diagnostic criteria employed in the SOU-N

EE 46.501:2006 method align with the ratio-based approach of the RRM/IEC methods, offering nine diagnostic outcomes. However, the specific ratio ranges for these diagnoses differ from those used in the RRM/IEC approach.

I.5.2.6. ETRA ratios method:

The ETRA Ratios Method utilizes three specific gas ratios derived from the concentrations of ethane (C_2H_6), ethylene (C_2H_4), and acetylene (C_2H_2) to identify the six primary fault types defined by the IEC. The associated coding scheme and recommended diagnostic interpretations are presented in Table II.17 and Table II.18, as documented in [63]. This method offers a clear and efficient framework for analyzing DGA results and supporting transformer fault diagnosis.

Table I.17. Gas ratio coding using ETRA ratio method

Ratio	Range	Code
$R_1 = C_2H_2/C_2H_4$	$R_1 \leq 0.01$	0
	$0.01 < R_1 < 0.2$	1
	$R_1 \geq 0.2$	2
$R_2 = C_2H_2/C_2H_6$	$R_2 \leq 0.01$	0
	$0.01 < R_2 < 1.0$	1
	$1.0 \leq R_2 < 10.0$	2
	$R_2 \geq 10.0$	3
$R_3 = C_2H_4/C_2H_6$	$R_3 < 1.0$	0
	$1.0 \leq R_3 < 4.0$	1
	$4.0 \leq R_3 < 10.0$	2
	$R_3 \geq 10.0$	3

Table I.18 Reference explanation using ETRA ratio method

Fault type	R_1	R_2	R_3
Thermal fault, $T > 700^\circ\text{C}$	0	0/1	2/3
Thermal fault, $T < 300^\circ\text{C}$	0	0	0
Thermal fault, $300^\circ\text{C} < T < 700^\circ\text{C}$	0	0/1	1

Partial discharge	2	1	0/1/2
Low-energy discharge	2	2	0/1/2
High-energy discharge	2	2	3
High-energy discharge	2	3	/

I.5.2.7. Hyosun cooperation ratio:

The Hyosung Corporation Ratios Method [64], developed in 2013 by a team of Korean researchers from Hyosung Company in collaboration with scientist Duval, marks an important advancement in transformer fault diagnostics. This method utilizes six specific gas ratios, listed in Table II.19, to accurately identify the six primary fault types defined by the IEC.

Table I.19 Gas ratios used in the HYOSUN Corporation gas ratio method

Ratio	R1	R2	R3	R4	R5	R6
Expression	$\frac{CH_4}{H_2}$	$\frac{C_2H_2}{C_2H_4}$	$\frac{C_2H_2}{CH_4}$	$\frac{C_2H_6}{C_2H_2}$	$\frac{C_2H_4}{C_2H_6}$	$\frac{C_2H_4}{CH_4}$

The core concept of this technique involves using these gas ratios to distinguish between various types of transformer faults. The diagnostic process begins with the use of two gas ratios (R1 and R2) to distinguish thermal faults and electrical faults. Once this distinction is made, each fault group can be analyzed independently. For thermal faults, the T1 faults are separated from other thermal faults by gas ratios R5 and R6. When T1 faults are detected, the method uses gas ratio pairs (R2, R5) to differentiate between T2 and T3 faults. In power faults, the same two ratios (R2, R5) are used to differentiate partial discharge (PD), D1, and D2 faults. The overall diagnostic process is visually illustrated in the flow chart shown in Figure II.8 [64].

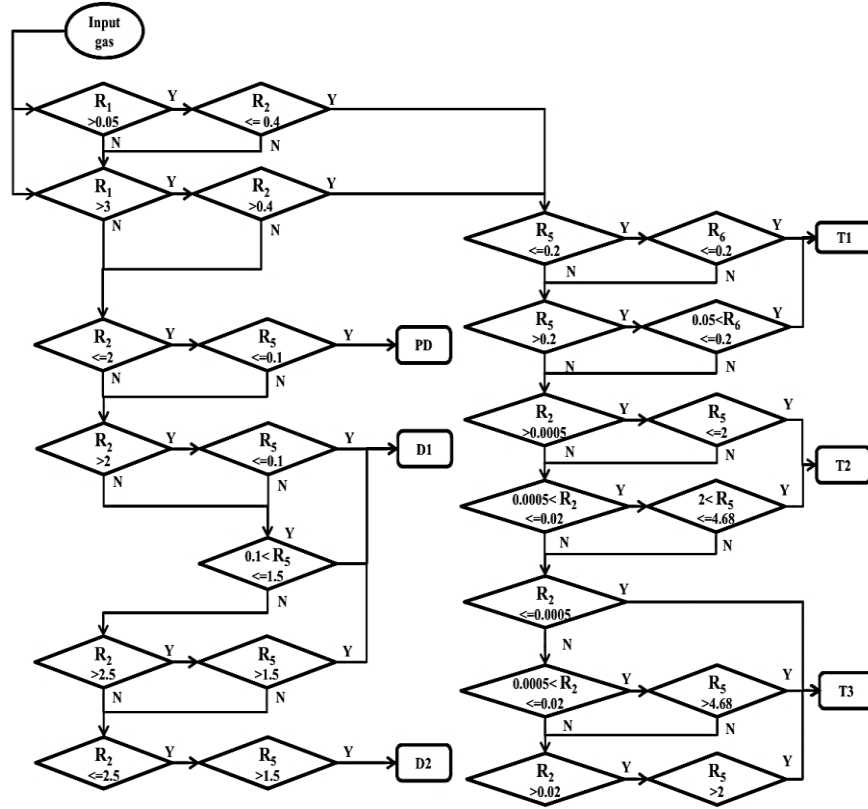


Figure I.8: Flowchart of gas ratio method of HYOSUN Corporation

I.5.2.8. Three Ratios Techniques:

Gouda et al. introduced an improved diagnostic approach known as the Three-Ratio Technique (TRT) [65], building upon earlier methods of gas analysis interpretation. This technique incorporates three novel gas parameters specifically designed to enhance both fault detection and the assessment of fault severity, as outlined in Table II.20 [66].

Table I.20: TRT codes

Ratio Codes	Range	Code
$R_1 = \frac{C_2H_2}{C_2H_4}$	$R_1 < 0.05$	0
	$0.05 \leq R_1 \leq 0.9$	1
	$R_1 > 0.9$	2
$R_2 = \frac{(C_2H_6 + C_2H_4)}{(H_2 + C_2H_2)}$	$R_2 < 1$	0
	$1 \leq R_2 \leq 3.5$	1
	$R_2 > 3.5$	2
	$R_3 < 0.05$	0

$R_3 = \frac{(CH_4 + C_2H_2)}{C_2H_4}$	$0.05 \leq R_3 \leq 0.5$	1
	$R_3 > 0.5$	2

A first-order fault detection method based on different rules is presented in Table II.21 [66]. Indicate the faults and and severity. The TRT method works on the principle that if the concentration of one gas is significantly higher than the other, it still remains within normal limits [66].The normal limits and conditions are shown in Table II.22 [66]. This method provides an analytical framework an impressive increase in reliability and fault detection accuracy in power transformers.

Table I.21: Identify fault with TRT

Fault	type	R1	R1	R3
T > 700°C	T3	1 or 2	0	0 or 1
300°C < T < 700°C	T2	1 or 2	1	0 or 1
150°C < T < 300°C	T1	1 or 2	2	0 or 1
Low temperature thermal T < 150°C	T0	1	/	1
Low partial discharge	PD1	0	1 or 2	0 or 1
High partial discharge	PD1	0	1 or 2	2
High arcingdischarge	D2	0 or 1	0 or 1	2
Low arcingdischarge	D1	1 or 2	2	2
Mix of electrical and thermal fault	DT	2	0 or 1	2

Table I.22 Limit of dissolved gases concentrations for the TRT method application

Gas	H ₂	CH ₄	C ₂ H ₆	C ₂ H ₄	C ₂ H ₂	CO	CO ₂
Limt ppm	100	120	65	50	1	350	2500

I.5.3. graphical methods:

I.5.3.1. Duval triangle method:

The DTM represents the first graphical alternative to traditional ratio-based methods for interpreting dissolved gas analysis. This approach was introduced in 1974 by the Canadian

researcher Michel Duval [67]. It utilizes three gas ratios, R_1 , R_2 , and R_3 , which are plotted as a single point within a triangular graph, as illustrated in Figure II.9. The triangle is divided into seven distinct zones, each corresponding to a specific fault type: PD, D_1 , D_2 , DT, T_1 , T_2 , and T_3 . Fault diagnosis is determined by the zone in which the plotted point falls [68].

Building on this concept, Michel Duval later developed additional triangles, collectively known as the six Duval triangles [69], including Triangle 4 and Triangle 5, which are specifically designed for low-temperature and high-temperature fault conditions, respectively [70], as shown in Figure II.10.

$$R_1 = 100 * CH_4 / CH_4 + C_2H_4 + C_2H_2 \quad (II.2)$$

$$R_2 = 100 * C_2H_2 / CH_4 + C_2H_4 + C_2H_2 \quad (II.3)$$

$$R_3 = 100 * C_2H_4 / CH_4 + C_2H_4 + C_2H_2 \quad (II.4)$$

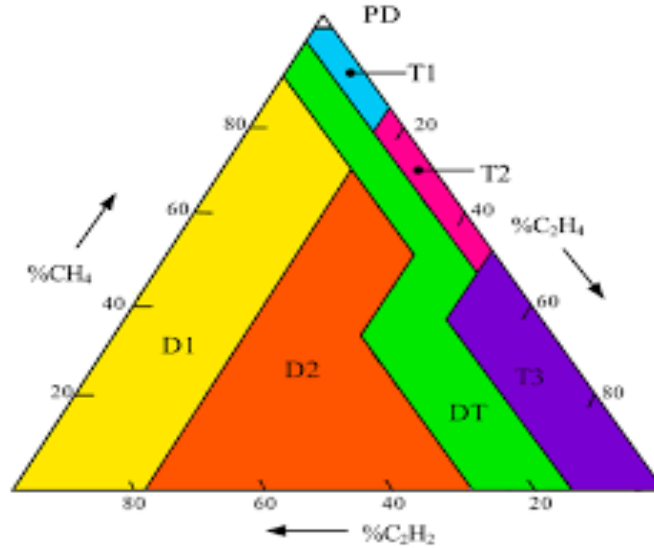


Figure I.9: Duval Triangle 1

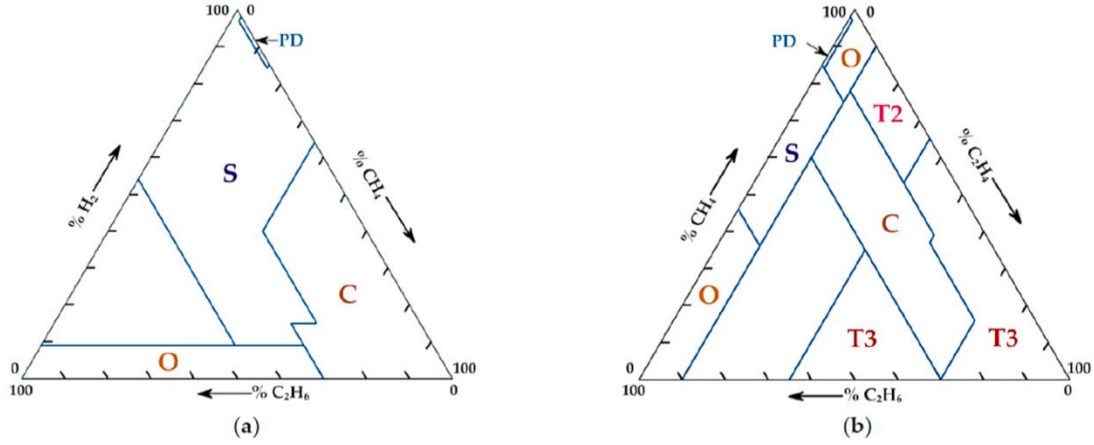


Figure I.10: (a) Duval 4 for a low-temperature fault (b) Duval 5 for a high-temperature fault

I.5.3.2. Duval Pentagon Method:

The Duval Pentagon method, developed by Duval and Lamar [71], offers a graphical approach for interpreting dissolved gas analysis (DGA) results, as illustrated in Figure II.11. This technique employs a pentagonal chart with five axes, each representing the relative concentration of a major fault-indicating gas: hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), and acetylene (C_2H_2), with values ranging from 0% to 100% along each axis.

The pentagon is divided into six distinct zones that correspond to various thermal and electrical faults, along with an additional zone for stray gases. A set of mathematical equations underpins the method, enabling the precise calculation of the pentagon's position and supporting accurate interpretation of the DGA data.

$$\begin{cases} x_0 = \%H_2 \cos\left(\frac{\pi}{2}\right) \\ x_1 = \%C_2H_6 \cos\left(\frac{\pi}{2} + \frac{2\pi}{5}\right) \\ x_2 = \%CH_4 \cos\left(\frac{\pi}{2} + \frac{4\pi}{5}\right) \\ x_3 = \%C_2H_4 \cos\left(\frac{\pi}{2} + \frac{6\pi}{5}\right) \\ x_4 = \%C_2H_2 \cos\left(\frac{\pi}{2} + \frac{8\pi}{5}\right) \end{cases} \quad \begin{cases} y_0 = \%H_2 \sin\left(\frac{\pi}{2}\right) \\ y_1 = \%C_2H_6 \sin\left(\frac{\pi}{2} + \frac{2\pi}{5}\right) \\ y_2 = \%CH_4 \sin\left(\frac{\pi}{2} + \frac{4\pi}{5}\right) \\ y_3 = \%C_2H_4 \sin\left(\frac{\pi}{2} + \frac{6\pi}{5}\right) \\ y_4 = \%C_2H_2 \sin\left(\frac{\pi}{2} + \frac{8\pi}{5}\right) \end{cases} \quad (II.5)$$

$$A = \frac{1}{2} \sum_{i=0}^4 (x_i y_{i+1} - x_{i+1} y_i) \quad (II.6)$$

$$\begin{cases} X_C = \frac{\sum_{i=0}^4 (x_i + x_{i+1})(x_i y_{i+1} - x_{i+1} y_i)}{6A} \\ Y_C = \frac{\sum_{i=0}^4 (y_i + y_{i+1})(x_i y_{i+1} - x_{i+1} y_i)}{6A} \end{cases} \quad (II.7)$$

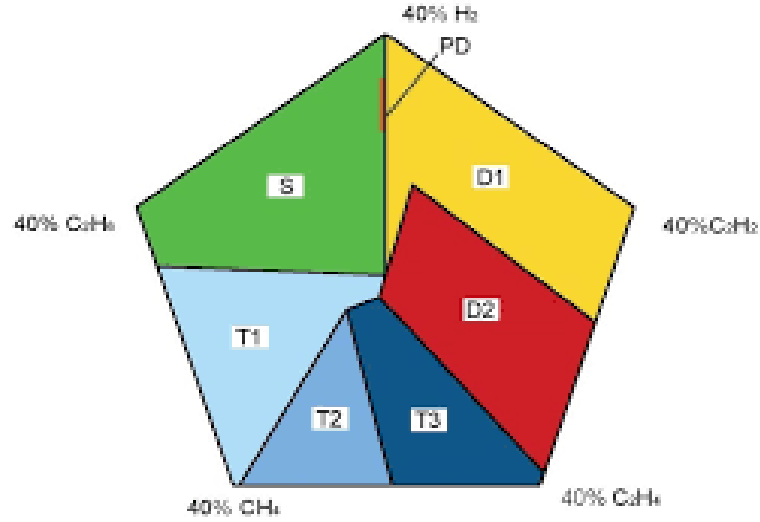


Figure I.11: Duval Pentagon Method

I.5.3.3. Mansour Pentagon Method:

In 2012, Mansour introduced the first graphical fault diagnosis method using a pentagon representation [72]. This approach, later refined in subsequent studies [73], involves plotting a pentagon where each vertex represents the percentage concentration of a specific gas relative to the total gas content.

Similar to the Duval Pentagon, the Mansour Pentagon distinguishes six separate zones corresponding to various electrical and thermal faults. The primary distinction lies in the coding system employed to classify the faults, as illustrated in Figure II.12. The method is supported by a set of equations that define the relationship between gas concentrations and their positions on the pentagon, enabling precise and reliable fault diagnosis.

$$s = \sum_{i=1}^5 P_i \quad (\text{II.8})$$

$$P_{\%i} = \frac{P_i}{s} * 100 \quad (\text{II.9})$$

$$\begin{cases} x_m = \frac{\sum_{i=1}^n P_{\%i} x_i}{P_{\%i}} \\ y_m = \frac{\sum_{i=1}^n P_{\%i} y_i}{P_{\%i}} \end{cases} \quad (\text{II.10})$$

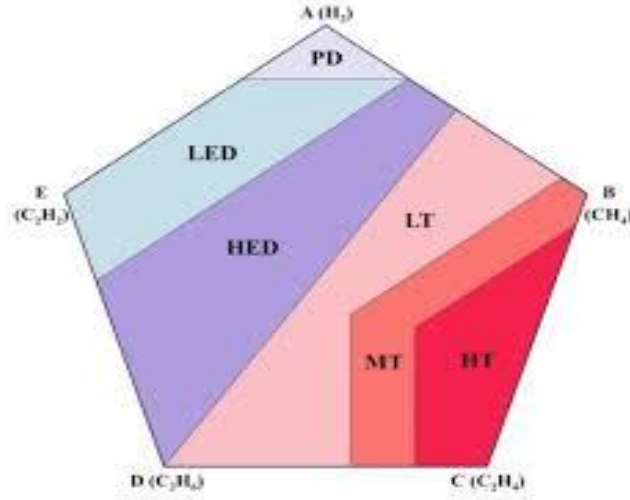


Figure I.12: Mansour Pentagon Method

I.5.3.4. Gouda Triangle Method:

The Gouda Triangle Method (GTM) is an advanced graphical diagnostic technique developed by Gouda and colleagues [74]. It was designed as an enhancement of the Duval Triangle Method, addressing a major limitation of the original approach—its reliance on only three gases for fault detection.

The GTM improves fault diagnosis by incorporating two additional gases, ethane (C_2H_6) and hydrogen (H_2), into the analysis. In this method, three ratios, R_1 , R_2 , and R_3 , are calculated and subsequently converted into percentages, P_1 , P_2 , and P_3 . Each percentage corresponds to a vertex of a triangle, creating a parallelogram structure. Like the Duval Triangle Method, the GTM employs a triangular graphical representation and defines specific fault zones, as shown in Figure II.10. The inclusion of additional gases provides a more comprehensive and accurate framework for identifying transformer faults.

$$\begin{cases} R_1 = \frac{CH_4}{CH_4 + C_2H_4 + C_2H_6 + C_2H_2} \\ R_2 = \frac{C_2H_2}{H_2 + C_2H_6 + CH_4 + C_2H_2} \\ R_3 = \frac{C_2H_4}{H_2 + C_2H_6 + CH_4 + C_2H_2} \end{cases} \quad (II.11)$$

$$\begin{cases} P_1 = \frac{R_1 \times 100}{R_3 + R_2 + R_1} \\ P_2 = \frac{R_2 \times 100}{R_3 + R_2 + R_1} \\ P_3 = \frac{R_1 \times 100}{R_3 + R_2 + R_1} \end{cases} \quad (\text{II.12})$$

with

$$\begin{cases} x = 100 - P_2 - P_3 \cos\left(\frac{\pi}{6}\right) \cot\left(\frac{\pi}{3}\right) \\ y = P_3 \cos\left(\frac{\pi}{6}\right) \end{cases}$$

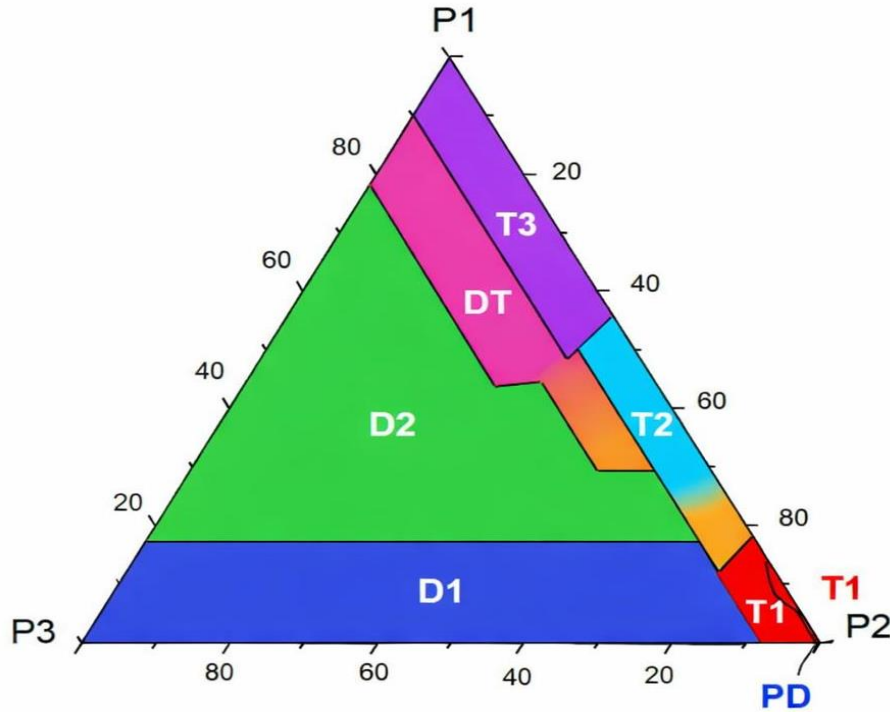


Figure I.13: Gouda Triangle method

I.5.3.5. Gouda heptagon method:

The Gouda Heptagon Method, introduced by Gouda et al. in 2018 [75], is a graphical diagnostic approach designed for detecting faults in oil-immersed power transformers. This method employs a heptagonal chart, with each side representing the proportional percentage of one of seven key gases: hydrogen (H_2), methane (CH_4), ethylene (C_2H_4), ethane (C_2H_6), acetylene (C_2H_2), carbon monoxide (CO), and carbon dioxide (CO_2). The gas percentages are adjusted according to weighting factors detailed in Table II.23 [75].

The method allows for the diagnosis of three levels of cellulose insulation degradation—high concentration (HCCD), medium concentration (MCCD), and low concentration (LCCD)—in addition to the six primary IEC fault types and combinations of electrical and thermal faults. Figure II.14 illustrates the identification of these degradation levels and fault types, demonstrating the method's capability as a comprehensive tool for transformer fault analysis.

Table I.22 Main gas weighting factors in Gouda Heptagon Method

Key gas	H ₂	C ₂ H ₄	C ₂ H ₆	CH ₄	CO ₂	CO	C ₂ H ₂
Weighting factor	3.5	7	5.3846	2.9167	0.14	1	116.6667

$$H_2 = \frac{H_2 \times 3.5 \times 100}{(3.5 \times H_2) + (2.9167 \times CH_4) + (5.3846 \times C_2H_6) + (7 \times C_2H_4) + (116.6667 \times C_2H_2) + CO + (0.14 \times CO_2)} \quad (II.14)$$

$$CH_4 = \frac{CH_4 \times 2.9167 \times 100}{(3.5 \times H_2) + (2.9167 \times CH_4) + (5.3846 \times C_2H_6) + (7 \times C_2H_4) + (116.6667 \times C_2H_2) + CO + (0.14 \times CO_2)} \quad (II.15)$$

$$C_2H_6 = \frac{C_2H_6 \times 5.3846 \times 100}{(3.5 \times H_2) + (2.9167 \times CH_4) + (5.3846 \times C_2H_6) + (7 \times C_2H_4) + (116.6667 \times C_2H_2) + CO + (0.14 \times CO_2)} \quad (II.16)$$

$$C_2H_4 = \frac{C_2H_4 \times 7 \times 100}{(3.5 \times H_2) + (2.9167 \times CH_4) + (5.3846 \times C_2H_6) + (7 \times C_2H_4) + (116.6667 \times C_2H_2) + CO + (0.14 \times CO_2)} \quad (II.17)$$

$$C_2H_2 = \frac{C_2H_2 \times 116.6667 \times 100}{(3.5 \times H_2) + (2.9167 \times CH_4) + (5.3846 \times C_2H_6) + (7 \times C_2H_4) + (116.6667 \times C_2H_2) + CO + (0.14 \times CO_2)} \quad (II.18)$$

$$CO_2 = \frac{CO_2 \times 0.14 \times 100}{(3.5 \times H_2) + (2.9167 \times CH_4) + (5.3846 \times C_2H_6) + (7 \times C_2H_4) + (116.6667 \times C_2H_2) + CO + (0.14 \times CO_2)} \quad (II.19)$$

$$CO = \frac{CO \times 100}{(3.5 \times H_2) + (2.9167 \times CH_4) + (5.3846 \times C_2H_6) + (7 \times C_2H_4) + (116.6667 \times C_2H_2) + CO + (0.14 \times CO_2)} \quad (II.20)$$

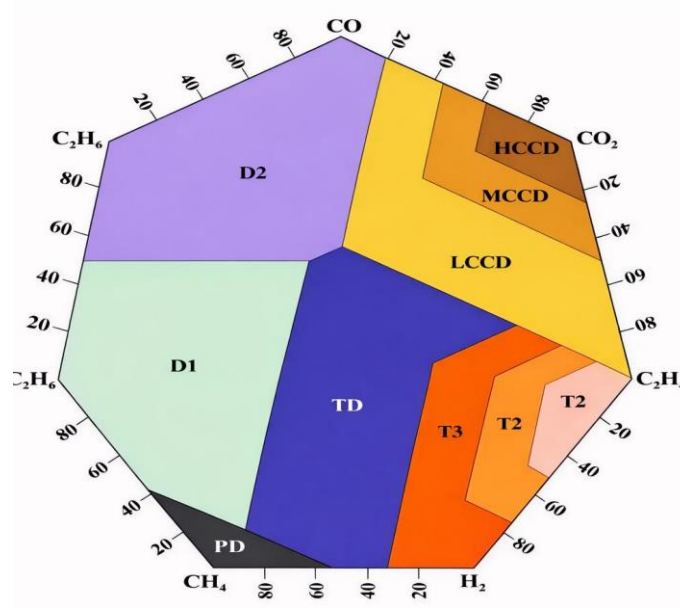


Figure I.14: Gouda's heptagon Method

I.5.3.6. Cartesian graphical method:

The Cartesian Graphical Method [76], developed by Fathallah et al., represents the latest advancement in dissolved gas analysis and is considered a state-of-the-art approach for transformer fault diagnosis. This technique utilizes the concentrations of four key gases: hydrogen (H_2), methane (CH_4), ethylene (C_2H_4), and acetylene (C_2H_2). The method involves calculating three specific ratios that incorporate hydrogen concentrations while also accounting for the influence of ethane (C_2H_6). These ratios are defined as follows.

$$P_1 = \frac{CH_4 + H_2}{2 \times H_2 + 2 \times CH_4 + C_2H_2 + C_2H_4} \quad (II.21)$$

$$P_2 = \frac{C_2H_2 + H_2}{2 \times H_2 + 2 \times CH_4 + C_2H_2 + C_2H_4} \quad (II.22)$$

$$P_3 = \frac{C_2H_4 + CH_4}{2 \times H_2 + 2 \times CH_4 + C_2H_2 + C_2H_4} \quad (II.23)$$

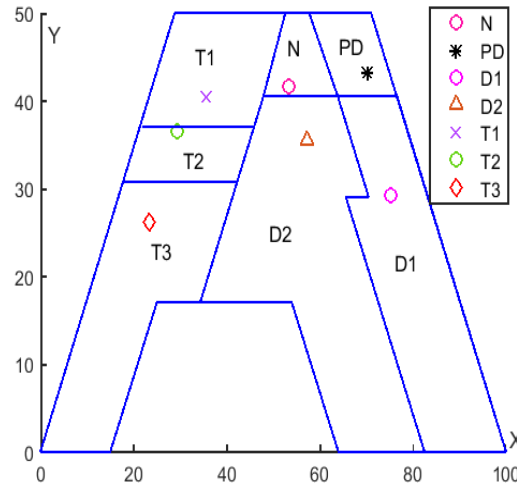


Figure I.15 Cartesian graphical Method

These ratios are subsequently used to determine the Cartesian coordinates (x,y) for graphical representation. The coordinates are computed as follows:

$$x_{\text{point}} = (P_2 + P_1 \times \sin(30^\circ)) \times L \quad (\text{II.24})$$

$$y_{\text{point}} = (P_1 \times \sin(60^\circ)) \times L \quad (\text{II.25})$$

Where L is a scaling factor.

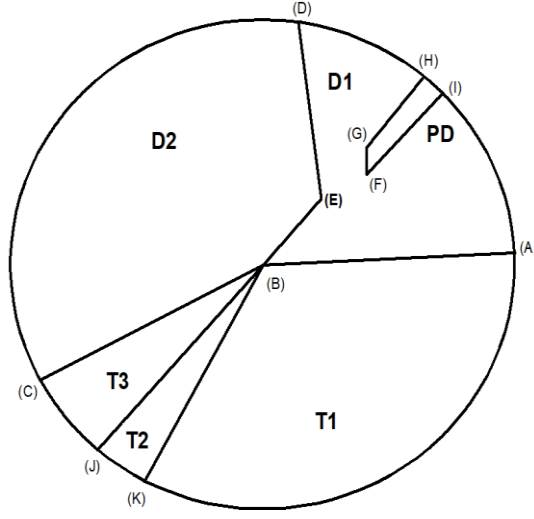
The resulting coordinates allow for the visualization of fault types within a Cartesian graph, as shown in Figure II.12. This graph is split into several zones which represent different fault categories, including partial discharge (PD), low-energy discharge (D1), high-energy discharge (D2), and thermal faults (T1, T2, T3), along with a normal condition (N) zone. This method provides a refined and precise means of diagnosing faults through a straightforward graphical approach.

I.5.3.7. Circle Methods

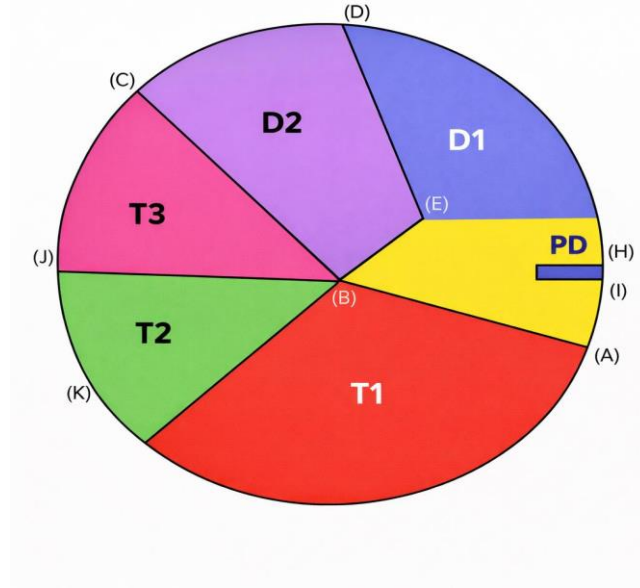
The techniques introduced by Hechifa et al. [24] utilize advanced graphical approaches for diagnosing transformer faults via Dissolved Gas Analysis (DGA). They enhance fault zone delineation by dynamically rotating the axes to achieve the most effective spatial separation of fault data. Metaheuristic optimization methods, including Gray Wolf Optimization (GWO) and Whale Optimization Algorithm (WOA), are employed to find the optimal rotation angles that reduce sample overlap and increase the distance between fault centers. These methods are formalized through equations (25) and (26), improving the discrimination between electrical and thermal faults.

$$x_i = \%H_2 \cos(\theta_1) + \%CH_4 \cos(\theta_2) - \%C_2H_6 \cos(\theta_3) - \%C_2H_4 \cos(\theta_4) + \%C_2H_2 \cos(\theta_5) \quad (25)$$

$$y_i = \%H_2 \sin(\theta_1) + \%CH_4 \sin(\theta_2) + \%C_2H_6 \sin(\theta_3) - \%C_2H_4 \sin(\theta_4) - \%C_2H_2 \sin(\theta_5) \quad (26)$$



(a)



(b)

I.6. Conclusion:

Accurate identification of primary faults in power transformers is essential for developing maintenance strategies that correspond to the actual condition of the equipment. Although conventional diagnostic techniques are widely employed by transformer maintenance professionals, they possess certain limitations, as discussed in the literature reviewed in this chapter. The analysis is organized into four main categories: key gas methods, gas ratio methods, graphical methods, and combined methods. For each category, both the advantages and limitations are critically evaluated, offering a comprehensive perspective on their effectiveness and suitability for transformer fault diagnosis.

Chapter II:

Artificial Intelligence (AI)



II.1 Introduction:

The theoretical underpinnings of machine learning are firmly grounded in mathematical disciplines, particularly statistics, probability theory, linear algebra, and optimization. These mathematical foundations are crucial for analyzing and interpreting the behavior of classification and regression models, especially when handling high-dimensional or nonlinear datasets that are challenging to represent using conventional analytical methods.

In diagnostic and classification contexts, machine learning techniques have proven highly effective in improving predictive accuracy by identifying latent structures and intricate relationships within data that traditional rule-based approaches often fail to detect. Research indicates that data-driven models provide superior flexibility and adaptability, particularly under complex and dynamic operating conditions. Owing to these strengths, machine learning has become an essential pillar of intelligent diagnostic and decision-support systems, facilitating the shift from manual or graphical analysis toward automated, data-centric frameworks. This transition enhances the reliability of decisions while reducing reliance on subjective human judgment, particularly in sophisticated engineering applications.

Artificial Intelligence (AI) is widely recognized as one of the most significant branches of modern computer science and a driving force behind current technological advancement. Its primary objective is to develop computational systems capable of emulating human cognitive functions and executing tasks that typically require human intelligence, such as learning, reasoning, problem-solving, decision-making, language comprehension, and environmental interaction. As defined by Encyclopaedia Britannica, AI refers to the capacity of machines to perform tasks commonly associated with human intelligence, including experiential learning, adaptation to new information, and complex data analysis.

The formal establishment of AI as a scientific discipline can be traced back to the Dartmouth Conference in 1956, where John McCarthy introduced the term “Artificial Intelligence.” This milestone signified a transformative vision aimed at evolving computers from simple calculation devices into systems capable of reasoning and knowledge processing. Since that time, AI has progressed through multiple developmental phases, beginning with symbolic and rule-based paradigms and advancing toward contemporary data-driven approaches that leverage large-scale datasets and sophisticated statistical methodologies. This

progression has considerably strengthened AI's capacity to solve complex problems within dynamic and uncertain environments.

Fundamentally, AI is built upon several core principles, including the central role of data in constructing intelligent systems, the utilization of algorithms to extract meaningful patterns from data, and the concept of learning from experience, which allows systems to enhance performance autonomously over time. Moreover, AI is inherently interdisciplinary, integrating insights from mathematics, statistics, neuroscience, and cognitive science, thereby extending beyond the boundaries of traditional programming.

This continuous theoretical and technological evolution has facilitated the deployment of AI across diverse sectors, including healthcare for diagnostic support, industry through intelligent automation, and the digital economy via recommendation systems and behavioral analytics, in addition to applications in security, smart transportation, and natural language processing. As a result, artificial intelligence has become a cornerstone of digital transformation. Nevertheless, its rapid expansion also introduces significant ethical and legal concerns, particularly regarding data privacy, algorithmic bias, and accountability in automated decision-making, underscoring the need for robust regulatory and ethical frameworks to ensure responsible and transparent AI implementation.

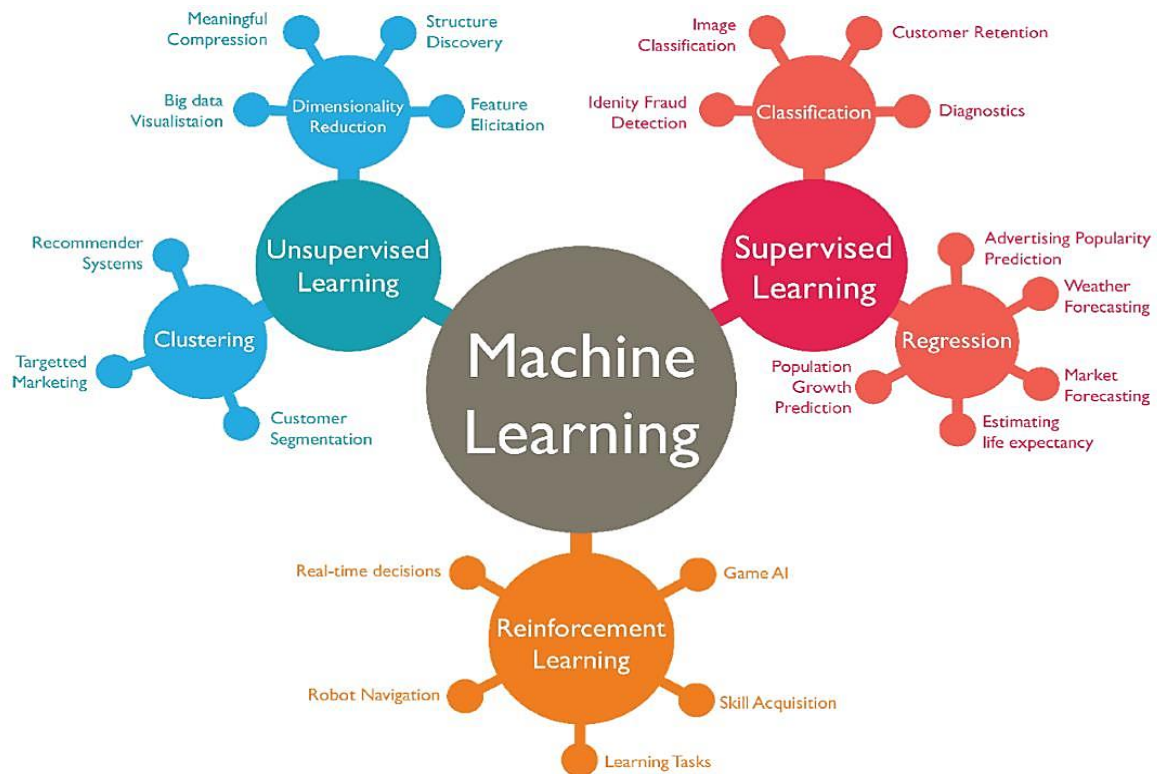


Figure II.1: General Classification of Machine Learning Algorithms and Their Core Models

Through this diagram, we will address the concepts of Machine Learning and Neural Networks. We will also focus on explaining the following algorithms: SVM, XGBoost, Random Forest, and KNN.

II.2 Foundations of Machine Learning (ML)

Machine Learning (ML) represents a specialized branch of artificial intelligence concerned with the design of computational algorithms that enable systems to enhance their performance on specific tasks through experience. In contrast to conventional programming paradigms, where explicit instructions are manually defined for every possible situation, machine learning approaches rely on data-driven mechanisms to discover underlying patterns and relationships. Through this process, models become capable of performing tasks such as prediction, classification, and decision-making without being explicitly programmed for each case.

The theoretical framework of machine learning integrates mathematical modeling, statistical inference, optimization methods, and computational principles to develop models that can extend learned knowledge beyond the training data. This capacity for generalization is a

defining characteristic of machine learning systems and differentiates them from simple memorization processes or rigid rule-based approaches.

From a mathematical perspective, many machine learning problems are formulated as optimization tasks, either constrained or unconstrained. The training phase typically involves minimizing a predefined loss (or cost) function that measures the discrepancy between predicted outputs and true values. To prevent overfitting and enhance model robustness—especially in the presence of noisy or limited data—regularization strategies are introduced to control model complexity and improve generalization performance.

Overall, the theoretical foundations of machine learning establish the essential mathematical and algorithmic basis required to construct intelligent, data-driven models. These foundations empower ML techniques to handle high-dimensional feature spaces and nonlinear relationships effectively, thereby making them particularly suitable for complex diagnostic systems and advanced decision-support applications.

II.2.1 Types of Machine Learning

II.2.2.1. Supervised Learning Concept

Supervised learning constitutes one of the fundamental paradigms in machine learning, where models are developed using datasets that contain both input variables and their corresponding target outputs. In this setting, the algorithm learns to approximate the mapping function between features and labels by leveraging the annotated examples provided during training. The presence of labeled data serves as a guiding mechanism, offering explicit feedback that enables the model to iteratively adjust its parameters and improve predictive performance. As a result, the trained model acquires the ability to generalize learned patterns to previously unseen instances.

From a practical perspective, supervised learning offers a solid theoretical and methodological basis for the development of intelligent diagnostic and decision-support systems. Because it relies on structured and labeled datasets, it facilitates the construction of models with high predictive reliability and, in many cases, enhanced interpretability. These characteristics make supervised learning especially well suited for classification-oriented applications, such as fault detection and condition assessment in complex engineering environments.

II.2.2.2. Unsupervised Learning

Unsupervised learning represents a fundamental approach in machine learning in which algorithms are trained using datasets that do not contain predefined output labels. In this setting, the target values y_i are unknown, and the model is not provided with explicit corrective feedback during training. Instead, the learning process relies solely on the input features x_i , allowing the algorithm to autonomously analyze the data and uncover intrinsic structures, statistical regularities, or latent relationships.

Unlike supervised learning, which aims to learn a direct mapping between inputs and known outputs, unsupervised learning concentrates on revealing hidden patterns, identifying clusters, extracting meaningful representations, or estimating the underlying data distribution. The objective is not prediction in the traditional sense, but rather structural understanding and knowledge discovery.

Unsupervised techniques are extensively applied in numerous domains, such as market segmentation and customer behavior analysis, image and text representation, anomaly and fraud detection, and large-scale data organization. These methods are particularly valuable when labeled datasets are scarce, costly, or impractical to obtain. Consequently, unsupervised learning serves as a powerful framework for exploratory data analysis and for gaining deeper insights into the internal organization of complex and high-dimensional systems.

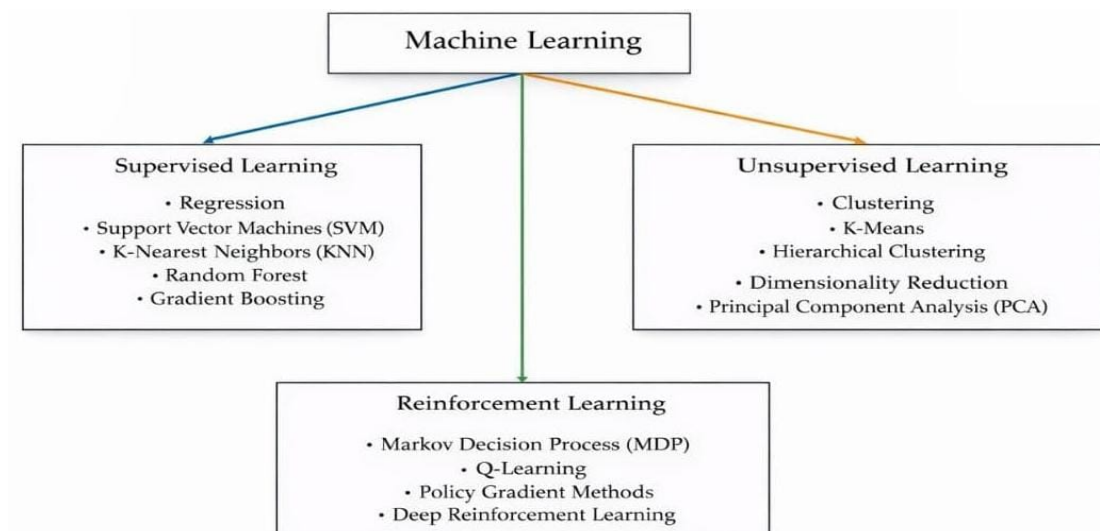


Figure II.2 Taxonomy and Paradigms of Machine Learning Methods

II.2.2 Applications of Machine Learning

Machine learning has become one of the most transformative technologies in recent years, finding applications across a wide range of industries. In healthcare, machine learning algorithms are used to analyze medical images, assist in diagnosing diseases, predict patient outcomes, and recommend personalized treatments. In the finance sector, machine learning supports fraud detection, credit scoring, algorithmic trading, and risk assessment by identifying patterns and anomalies in large datasets. E-commerce platforms utilize machine learning for recommendation systems, personalized marketing, and predicting customer preferences to enhance user experience and increase sales. In transportation, machine learning powers autonomous vehicles, traffic prediction, and route optimization, improving safety and efficiency. Other applications include natural language processing for chatbots and translation services, predictive maintenance in manufacturing, and anomaly detection in cybersecurity. The versatility and scalability of machine learning allow organizations to process vast amounts of data, extract meaningful insights, and make data-driven decisions that were previously impossible with traditional analytical methods. As technology continues to advance, the impact and adoption of machine learning across different domains are expected to grow exponentially.

II.3 Deep Learning

Deep Learning is a branch of Machine Learning that relies on multi-layered artificial neural networks designed to process data and automatically discover complex patterns. It is characterized by its ability to extract important features and representations from data without human intervention, making it highly effective for large and complex datasets such as images, text, and videos.

II.3.1 Ensemble Learning

Ensemble Learning is a machine learning approach that improves the performance, stability, and generalization ability of models by combining multiple individual models, known as base learners. The main idea is that while a single model may have errors or biases, aggregating several models can reduce both bias and variance, resulting in more reliable predictions.

II.3.2 Diversity Mechanism

Base learners are the individual models that form the ensemble. They can be homogeneous, meaning the same type of model is used repeatedly (e.g., multiple decision trees), or heterogeneous, combining different model types such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and decision trees. Choosing diverse base learners is crucial to improving the ensemble's overall performance.

II.3.3 Aggregation Strategy

The aggregation strategy determines how the outputs of base learners are combined to produce the final prediction. Common methods include majority voting for classification tasks, averaging for regression tasks, or using a meta-learner in stacking ensembles. This final combination leverages the strengths of each model and reduces the weaknesses of individual learners.

II.3.4 Ensemble Learning Strategies

Ensemble learning techniques are generally divided into three main strategies:

- Bagging (Bootstrap Aggregating), such as Random Forest, which reduces variance by training multiple models on different subsets of the data.
- Boosting, such as XGBoost, where models are trained sequentially, with each new model focusing on correcting the errors of the previous ones.
- Stacking, which combines multiple base models through a higher-level meta-learner, allowing the system to learn the optimal way to integrate predictions.

Ensemble Learning has proven highly effective in practice, particularly in competitions and applications where accuracy and stability are critical, as it combines the strengths of multiple models while mitigating their individual weaknesses.

II.3.5 Evaluation Metrics for Ensemble Models

This section focuses on how to evaluate the performance of ensemble models using metrics such as Accuracy, F1 Score, AUC-ROC, or Mean Squared Error (MSE) for regression tasks. It may also include comparisons between ensemble models and individual models, highlighting the importance of selecting appropriate metrics to analyze the model's effectiveness.

II.3.6 Advantages and Limitations of Ensemble Learning

This section discusses the strengths and weaknesses of ensemble learning. Key advantages include improved accuracy, reduced variance and bias, and enhanced generalization ability. Limitations include increased computational complexity, higher resource requirements, and the difficulty of interpreting certain strategies such as Stacking or complex Boosting methods.

II.4 Study of Proposed Classification Algorithms

II.4.1 k-Nearest Neighbors (k-NN)

The k-Nearest Neighbors algorithm (commonly abbreviated as K-NN) is one of the supervised learning algorithms in the field of Machine Learning. This algorithm is based on the principle of similarity between data points, where a new sample is classified or its value is predicted according to the k nearest samples in the training dataset using a specific distance metric, such as the Euclidean distance.

The algorithm operates by computing the distance between the sample to be classified and all samples in the dataset, and then selecting the k closest neighbors. The final class of the new sample is determined based on the majority class among these neighbors in classification problems, or by calculating the average of their values in regression problems.

The K-NN algorithm is characterized by its simplicity and ease of implementation, and it does not require a complex training phase. However, its performance may be affected by the size of the dataset, the choice of the parameter k, and the distance metric used.

This can be mathematically expressed as:

$$y^{\wedge} = \operatorname{argmax}_c \sum_{j=1}^k I(y_j = c)$$

where I is an indicator function that equals 1 if the class label y_j matches c and 0 otherwise. The distance between points is often measured using Euclidean distance:

$$d(x, y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2}$$

This method enhances the classification process by extending the nearest neighbor concept, allowing the algorithm to leverage more information from multiple nearby points during the d

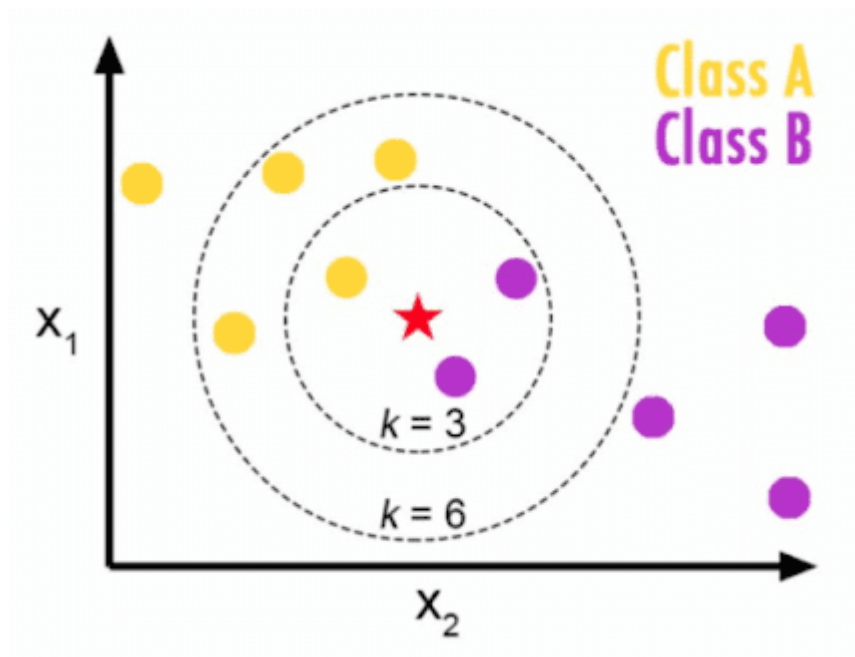


Figure II.3: Principle of KNN algorithm with different k value

II.4.2 Support Vector Machine (SVM)

Support Vector Machine (SVM) is considered one of the most powerful classification techniques in the field of machine learning. It was introduced based on the theoretical work of Vladimir Vapnik during the 1990s. The main objective of this algorithm is to construct an optimal decision boundary, known as a hyperplane, which effectively separates data points belonging to different classes.

SVM achieves high classification accuracy by maximizing the separation margin between classes. This margin represents the distance between the hyperplane and the closest data points from each class, which are referred to as support vectors. Due to its strong generalization capability, SVM performs well in both linear and nonlinear classification problems, making it widely used in data mining and complex data analysis applications.

The decision function of the SVM model can be expressed as:

$$f(x) = w^T x + b \quad \text{for all } i$$

The objective is to maximize the margin $2/(||w||)$ between the classes, subject to the constraints:

$$w^T x_i + b \geq 1$$

Furthermore, the effectiveness of SVM strongly depends on the selection of an appropriate kernel function. The kernel function allows the transformation of the original input space into a higher-dimensional feature space, enabling the algorithm to perform linear separation even when the data are not linearly separable in the original space.

This transformation is implemented using the Kernel Trick, which can be expressed as:

$$K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$$

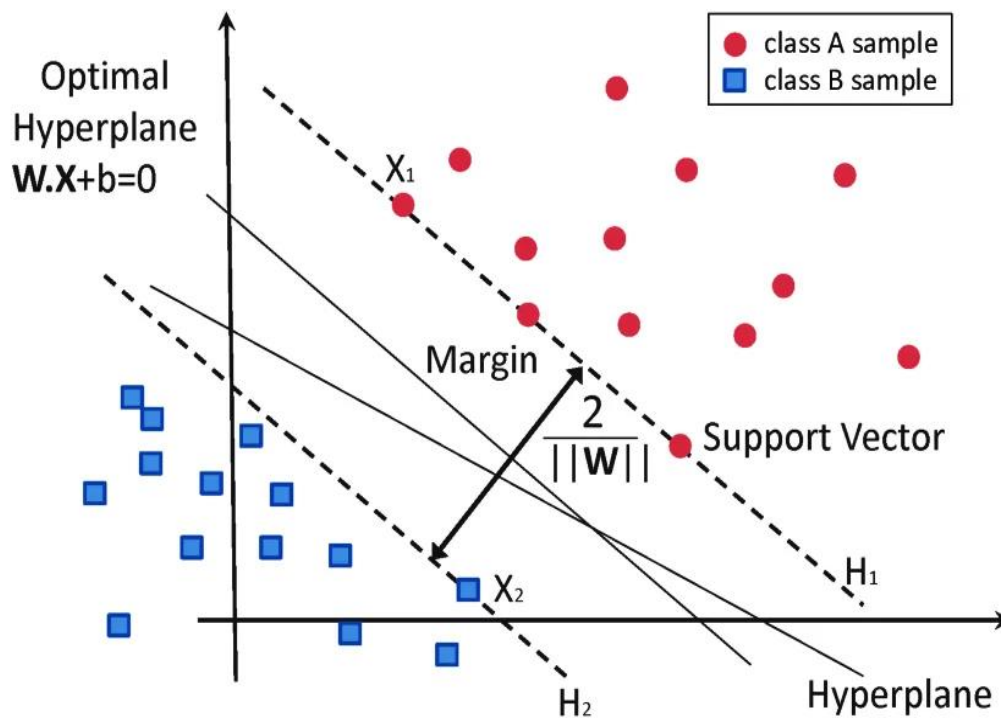


Figure II.4: Enhanced Hyperplane Optimization in SVM for High-Dimensional Data Classification.

II.4.3 Random Forest Algorithm

Random Forest is a machine learning algorithm proposed by Leo Breiman in 2001. It is an ensemble learning technique that constructs multiple decision trees during the training process instead of relying on a single tree.

1. **Bootstrap Sampling:** Subsets of the training data are randomly drawn with replacement to train each tree on a slightly different dataset.

2. **Random Feature Selection:** At each node, a random subset of features is chosen for splitting, which increases tree diversity and reduces correlation among them.

Mathematical Formulation of the Random Forest Algorithm for Classification

Suppose we have a training dataset:

$$\{(x_i, y_i)\}_{i=1}^n = D$$

where:

- $x_i \in \mathbb{R}^p$ represents the feature vector of each sample,
- $y_i \in \{1, 2, \dots, C\}$ is the class label of the sample,-
- C is the number of possible classes.

The Random Forest algorithm constructs B independent decision trees, each trained on a bootstrap sample drawn randomly from D . For each tree b the prediction function is :

Final Decision Rule (Majority Voting)

For classification, the predicted class label of a new sample x is determined using the majority voting rule:

$$\hat{y}(x) = \arg \max_c \frac{1}{B} \sum_{b=1}^B \mathbf{1}(h_b(x) = c)$$

Where:

$\hat{y}(x)$ is the predicted class label

$h_b(x)$ is the prediction of tree b

- $\mathbf{1}(\cdot)$ is the indicator function, equal to 1 if the condition is true and 0 otherwise.

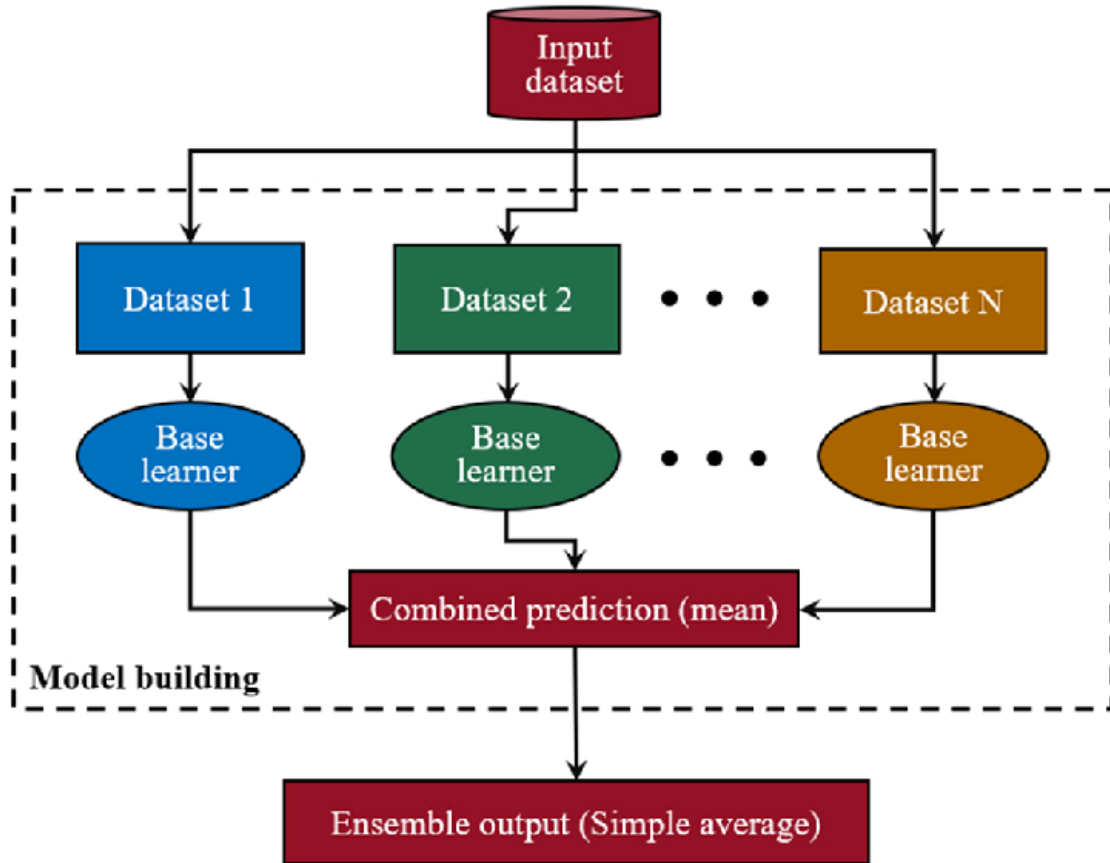


Figure II.5: Structure of Bagging

II.4.3. XGBoost:

XGBoost (Extreme Gradient Boosting) is an advanced machine learning algorithm based on the principle of Gradient Boosting, designed to build strong and accurate predictive models. It works by combining a series of weak learners, usually small decision trees, where each new model focuses on correcting the errors of the previous ones, gradually improving prediction accuracy.

XGBoost is known for its high speed and efficiency thanks to parallel processing, and it can handle large and complex datasets while adapting to missing values without requiring prior preprocessing. Additionally, it incorporates regularization techniques to control overfitting and enhance the model's generalization ability, making it a popular choice in both competitive machine learning challenges and real-world applications that demand reliable and high-performance predictions.

II.4.3.1. XGBoost Model (Ensemble of Trees)

In XGBoost, the model is expressed as a sum of weak learners (small decision trees):

$$\hat{y}_i = \sum_{t=1}^T f_t(x_i), \quad f_t \in \mathcal{F}$$

Where:

$\hat{y}_i$ is the model's prediction for sample i ,

T is the total number of trees,-

f_t represents a weak decision tree from the tree space $\mathcal{F}$ -

x_i is the feature vector of sample i -

II.4.3.2. Classification Decision for Binary Classes

After computing $\hat{y}_i$, the sigmoid function is used to convert it into the probability of belonging to class 1, followed by class assignment:

$$\left. \begin{array}{l} \text{if } p_i \geq 0.5 \\ \text{if } p_i < 0.5 \end{array} \right\} = \begin{array}{l} \text{class } 1 \\ \text{class } 0 \end{array}, \frac{1}{e^{\hat{y}_i} + 1} = \sigma(\hat{y}_i) = p_i$$

p_i is the predicted probability of class 1,-

$\hat{y}_i$ is the final predicted class,-

$\sigma(\cdot)$ is the sigmoid function- .

$$\text{Precision} = \frac{TP}{TP+FP}$$

- **TP (True Positives):** Correctly predicted positives
- **FP (False Positives):** Incorrectly predicted positives

Interpretation:

- High precision → Most of the predicted positives are correct.
- Low precision → Many predicted positives are actually negative (false alarms).

Recall (Sensitivity): The proportion of positive samples correctly classified out of all actual positive samples:

$$\text{Recall} = \frac{TP}{TP+FN}$$

- **TP (True Positives):** Correctly predicted positives
- **FN (False Negatives):** Positives that the model missed

Interpretation:

- High recall → The model catches most of the actual positives.
- Low recall → The model misses many positives.

II.5.3 ROC Curve and AUC

Plots True Positive Rate (TPR / Recall) vs False Positive Rate (FPR) at various thresholds.

Shows the model's performance across all possible thresholds, not just a fixed one.

Formulas:

$$\text{TPR} = \frac{TP}{TP+FN} \quad (\text{Recall})$$

$$\text{FPR} = \frac{FP}{FP+TN}$$

- TPR = fraction of actual positives correctly detected
- FPR = fraction of actual negatives incorrectly classified as positive

AUC (Area Under the Curve): Represents the model's ability to discriminate between classes. The closer the AUC is to 1, the better the model performance.

Important Notes on Metric Selection

- **Balanced datasets:** Accuracy is usually sufficient.
- **Imbalanced datasets:** F1-Score or AUC is preferred.
- **High cost of false negatives (e.g., disease detection):** Focus on **Recall**.
- **High cost of false positives (e.g., spam detection):** Focus on **Precision**.

II.5.4 F1-Score

The harmonic mean of precision and recall, particularly useful when dealing with **imbalanced classes**:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

II.5.5 Accuracy

Represents the proportion of correctly classified samples out of the total samples:

$$\text{Accuracy} = \frac{TP}{TP + TN + FP + FN}$$

- Where:
- **TP (True Positives):** Positive samples correctly predicted as positive
- **TN (True Negatives):** Negative samples correctly predicted as negative
- **FP (False Positives):** Negative samples incorrectly predicted as positive
- **FN (False Negatives):** Positive samples incorrectly predicted as negative
- **Interpretation:**
 - High accuracy → Most predictions (both positive and negative) are correct.
 - Low accuracy → Many predictions are wrong.
 - Suitable for balanced datasets, but may be misleading in the case of **imbalanced classes**.

II.6.CONCLUSION

This chapter lays out the theoretical and mathematical underpinnings of Artificial Intelligence (AI) and Machine Learning (ML), with a strong focus on classification techniques for intelligent decision-support systems. The transition from symbolic AI approaches to data-driven learning models represents a significant shift toward optimization-centered and statistically informed computational intelligence.

Within this framework, Machine Learning is formalized through empirical risk minimization, where predictive models are derived by optimizing a loss function while applying regularization to maintain generalization. Striking the right balance between model complexity and predictive accuracy forms the fundamental principle behind modern classification algorithms, particularly in high-dimensional and nonlinear problem spaces.

The chapter explores the main learning paradigms, highlighting supervised learning as the most appropriate for discriminative classification tasks due to its reliance on labeled data, which allows for explicit decision boundary construction and measurable performance evaluation. In contrast, unsupervised learning and reinforcement learning are discussed in the contexts of structural inference and sequential decision-making, respectively.

Advanced modeling techniques are analyzed to demonstrate their role in enhancing predictive reliability. Deep Learning is presented as a hierarchical framework for nonlinear function approximation capable of capturing complex feature representations. Ensemble Learning is interpreted through the lens of the bias–variance tradeoff, showing how aggregation methods improve generalization and reduce overfitting.

The chapter also positions several key algorithms—Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest (RF), and XGBoost—based on their structural characteristics and optimization strategies. SVM is described as a convex, margin-maximizing classifier with kernel-based nonlinear extensions. KNN is introduced as a non-parametric, distance-based local decision model. Random Forest is framed as a stochastic ensemble that lowers variance through bootstrap aggregation and random feature selection, while XGBoost is analyzed as a regularized gradient boosting framework performing sequential functional optimization to enhance accuracy and convergence stability.

Finally, a comprehensive evaluation framework is presented, including metrics such as Accuracy, Precision, Recall, F1-score, and ROC-AUC, emphasizing the importance of

choosing metrics according to dataset characteristics and risk sensitivity to ensure robust and statistically sound comparisons.

In conclusion, this chapter provides a well-structured analytical foundation that integrates statistical learning theory, optimization principles, ensemble strategies, and discriminative evaluation metrics, establishing the theoretical groundwork for experimental validation and performance assessment of the proposed classification models.

Chapter III:

Application and Evaluation of AI Technique for Diagnosis



III.1. Introduction

The reliable diagnosis of incipient and developed faults in oil-immersed power transformers remains a critical requirement for ensuring operational continuity, asset protection, and maintenance efficiency in electrical power systems. Among the available diagnostic approaches, dissolved gas analysis (DGA) has long been recognized as one of the most informative and widely adopted techniques, owing to its ability to reflect the internal physicochemical degradation processes occurring under thermal and electrical fault conditions. The characteristic gases generated in the insulating oil provide indirect but highly valuable evidence regarding fault type, severity, and progression.

Despite the diagnostic importance of raw gas concentrations, their direct use does not always provide the most suitable representation for intelligent classification. For this reason, substantial attention has been devoted to feature engineering strategies capable of transforming DGA measurements into more informative diagnostic descriptors. In conventional transformer diagnosis, two major directions have been widely employed for this purpose. The first relies on gas ratios, which express proportional relationships between key gases and have historically formed the basis of several established interpretive methods. The second relies on graphical diagnostic approaches, in which gas compositions are projected into geometric spaces or diagnostic coordinates that facilitate fault discrimination through spatial representation.

Within the context of artificial intelligence, the effectiveness of a diagnostic model is not determined solely by the choice of classifier, but also by the quality of the feature space used as model input. This makes the comparison between ratio-based and graphical feature representations particularly relevant, since both originate from the same DGA measurements yet encode diagnostic information in substantially different ways. Accordingly, the present chapter investigates how these two feature construction strategies influence the classification of transformer faults when integrated with machine learning techniques.

To this end, the chapter develops a comparative experimental framework based on DGA samples associated with six transformer fault categories: partial discharge (PD), low-energy discharge (D1), high-energy discharge (D2), and three levels of thermal faults (T1, T2, and T3). Starting from the five key gases commonly used in transformer diagnosis, two parallel feature sets were generated: a compact 12-dimensional ratio-based representation and a 12-dimensional graphical representation derived from several established diagnostic diagrams. These two

feature spaces were then evaluated using four AI classifiers, namely KNN, SVM, Random Forest, and RUSBoost.

The objective of this chapter is therefore twofold. First, it seeks to assess the diagnostic performance of the selected AI models under each feature representation. Second, and more importantly, it aims to determine which feature engineering strategy provides the most discriminative and operationally appropriate representation for transformer fault diagnosis. The chapter is organized around the experimental setup, comparative results, and analytical discussion of the observed performance differences, with particular attention to classification accuracy, class separability, agreement metrics, and the practical implications of the results for intelligent DGA-based diagnostic systems.

III.2. Experimental setup for AI application for DGA

Figure IV.22 illustrates the overall experimental workflow adopted in this study for intelligent transformer fault diagnosis based on dissolved gas analysis (DGA). The proposed framework starts from the occurrence of an internal fault in the power transformer, which leads to the decomposition of the insulating oil and the generation of characteristic dissolved gases. These gases are then measured and organized into a diagnostic dataset. Subsequently, two different feature extraction strategies are applied, namely ratio-based feature construction and graphical feature construction. The resulting feature sets are separately integrated with artificial intelligence (AI) classifiers in order to evaluate their respective suitability for transformer fault diagnosis. The entire framework is designed to compare the diagnostic effectiveness of the two feature representations under the same classification and evaluation conditions.

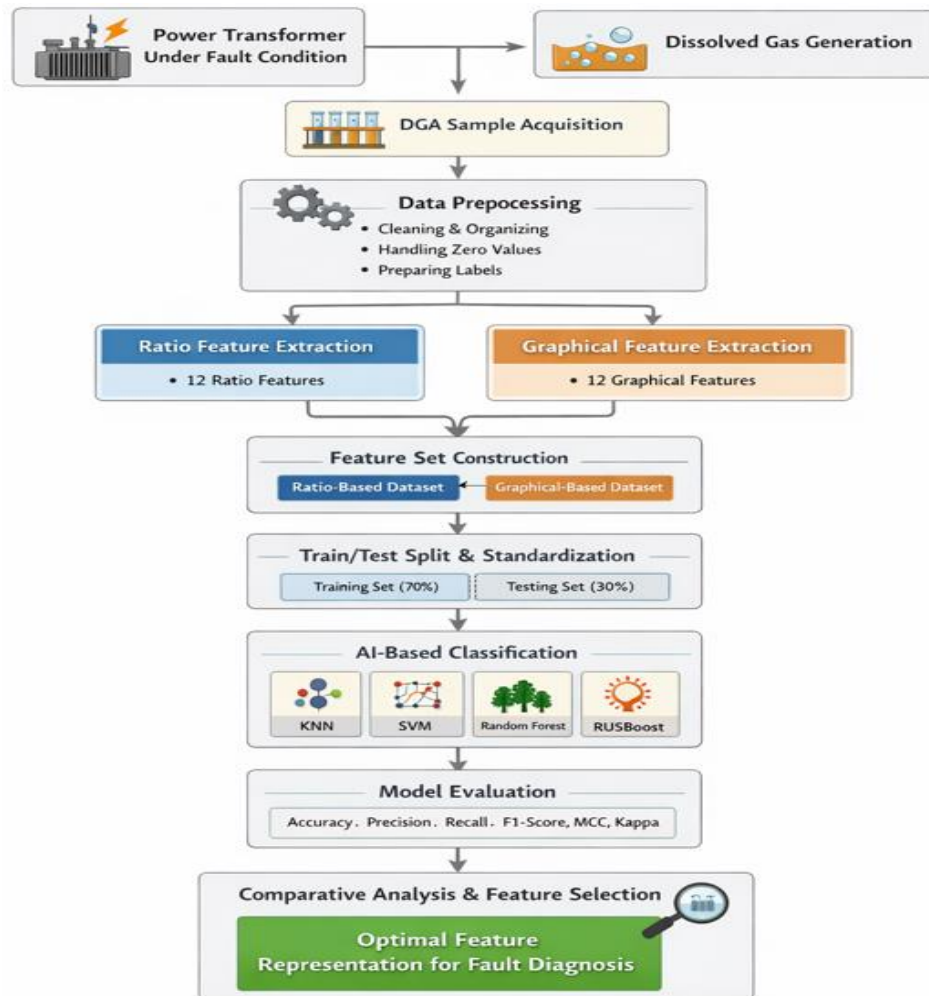


Figure III.1: General experimental workflow for DGA-based transformer fault diagnosis using ratio and graphical features integrated with AI classifiers.

III.2.1 DGA data collection and fault class distribution

The first stage of the proposed framework consists of collecting dissolved gas analysis (DGA) data corresponding to different transformer fault conditions. DGA is one of the most widely adopted diagnostic techniques for oil-immersed transformers, since the decomposition of insulating oil and solid insulation under abnormal thermal or electrical stresses leads to the generation of characteristic gases. The type and concentration of these gases provide valuable information about the nature and severity of internal faults.

In the present study, the dataset is composed of samples associated with six transformer fault classes, namely partial discharge (PD), low-energy discharge (D1), high-energy discharge (D2), and three levels of thermal faults (T1, T2, and T3). The complete dataset contains 407 samples distributed across these classes. This distribution is summarized in Table IV.

Table III.1. Distribution of DGA samples by fault type

	PD	D1	D2	T1	T2	T3	Total
No of Samples	32	59	99	86	48	83	407

The diagnostic input data were initially defined by the concentrations of five key dissolved gases commonly used in transformer fault diagnosis, namely hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), and acetylene (C_2H_2). These five gases constitute the raw chemical basis from which the two feature representations used in this study were derived.

III.2.2. Construction of ratio-based feature vectors

To construct the first feature representation, the raw gas concentrations were transformed into diagnostic ratios derived from well-established conventional DGA ratio techniques. These include the Dornenburg ratios method, Rogers four-ratio method, IEC ratio method, ETRA ratio method, Hyosung Corporation ratios, and the Three-Ratios technique. Since several of these approaches share repeated or overlapping ratios, the extracted quantities were consolidated into a compact and non-redundant set of twelve unique ratio features.

Accordingly, each transformer sample was represented by a 12-dimensional ratio-based input vector defined as:

$$X_{\text{ratio}} = [R_1, R_2, R_3, R_4, R_5, R_6, R_7, R_8, R_9, R_{10}, R_{11}, R_{12}]$$

where the adopted ratio features are expressed as follows:

$$\begin{aligned}
 R_1 &= \frac{CH_4}{H_2} \\
 R_2 &= \frac{C_2H_2}{C_2H_4} \\
 R_3 &= \frac{C_2H_4}{C_2H_6} \\
 R_4 &= \frac{C_2H_2}{CH_4} \\
 R_5 &= \frac{C_2H_6}{CH_4} \\
 R_6 &= \frac{C_2H_2}{C_2H_6} \\
 R_7 &= \frac{H_2}{CH_4} \\
 R_8 &= \frac{C_2H_2}{H_2} \\
 R_9 &= \frac{C_2H_6}{C_2H_2} \\
 R_{10} &= \frac{C_2H_4}{CH_4} \\
 R_{11} &= \frac{C_2H_6 + C_2H_4}{H_2 + C_2H_2} \\
 R_{12} &= \frac{CH_4 + C_2H_2}{C_2H_4}
 \end{aligned}$$

This ratio-based representation aims to capture the relative relationships among dissolved gases rather than relying solely on their absolute concentrations. Such relationships are often more informative for discriminating among transformer fault mechanisms, since different fault types produce distinct gas proportion patterns.

III.2.3 Construction of graphical feature vectors

In parallel with the ratio-based representation, a second feature representation was developed using graphical diagnostic methods. These methods are widely used in transformer diagnostics because they transform gas composition information into geometric coordinates or representative points that reflect fault regions in diagnostic diagrams.

In this study, twelve graphical features were extracted from six graphical diagnostic approaches, with each method contributing two features. The resulting graphical feature vector can be written as:

$$X_{\text{graphical}} = [F_1, F_2, F_3, F_4, F_5, F_6, F_7, F_8, F_9, F_{10}, F_{11}, F_{12}]$$

The graphical features were derived as follows.

a) Duval Triangle Method

$$F_1 = x = 100 - \%C_2H_2 - \%CH_4 \cos\left(\frac{\pi}{6}\right) \cot\left(\frac{\pi}{3}\right)$$

$$F_2 = y = \%CH_4 \cos\left(\frac{\pi}{6}\right)$$

b) Gouda Triangle Method

$$F_3 = x = 100 - \%R_2 - \%R_3 \cos\left(\frac{\pi}{6}\right) \cot\left(\frac{\pi}{3}\right)$$

$$F_4 = y = \%R_3 \cos\left(\frac{\pi}{6}\right)$$

c) Duval Pentagon Method

$$F_5 = X(1) = \frac{1}{6} \frac{\sum_{i=0}^4 (x_i + x_{i+1})(x_i y_{i+1} - x_{i+1} y_i)}{\frac{1}{2} \sum_{i=0}^4 (x_i y_{i+1} - x_{i+1} y_i)}$$

$$F_6 = X(2) = \frac{1}{6} \frac{\sum_{i=0}^4 (y_i + y_{i+1})(x_i y_{i+1} - x_{i+1} y_i)}{\frac{1}{2} \sum_{i=0}^4 (x_i y_{i+1} - x_{i+1} y_i)}$$

d) Mansour Pentagon Method

$$F_7 = x_m = \frac{\sum_{i=1}^n m_i x_i}{100}$$

$$F_8 = y_m = \frac{\sum_{i=1}^n m_i y_i}{100}$$

e) Cartesian Graphical Method

$$F_9 = x_{\text{point}} = (P_2 + P_1 \sin 30^\circ) \times L$$

$$F_{10} = y_{\text{point}} = (P_1 \sin 60^\circ) \times L$$

f) Circle Method

$$F_{11} = x_i = \%H_2 \cos(\theta_1) + \%CH_4 \cos(\theta_2) - \%C_2H_6 \cos(\theta_3) - \%C_2H_4 \cos(\theta_4) \\ + \%C_2H_2 \cos(\theta_5)$$

$$F_{12} = y_i = \%H_2 \sin(\theta_1) + \%CH_4 \sin(\theta_2) + \%C_2H_6 \sin(\theta_3) - \%C_2H_4 \sin(\theta_4) \\ - \%C_2H_2 \sin(\theta_5)$$

These graphical features provide a geometric abstraction of the DGA patterns and are expected to preserve diagnostic information from the original graphical methods while making them directly usable as numerical inputs for machine learning classifiers.

Table III. 2. Graphical feature extraction methods and corresponding equations

Graphical method	Extracted features
Duval Triangle	F_1, F_2
Gouda Triangle	F_3, F_4
Duval Pentagon	F_5, F_6
Mansour Pentagon	F_7, F_8
Cartesian graphical method	F_9, F_{10}
Circle method	F_{11}, F_{12}

III.2.4 Data preprocessing and feature standardization

Before training the classification models, the extracted features were subjected to a preprocessing stage. For the ratio-based dataset, very small constant values were used to replace zero concentrations whenever necessary in order to avoid undefined divisions during ratio computation. This step is essential because several ratio expressions involve denominators that may become zero in some transformer samples.

After feature construction, the class labels were converted into categorical form so that they could be handled appropriately by the multiclass classification algorithms implemented in the study. Subsequently, feature standardization was performed separately for the ratio-based and graphical datasets. The standardization process relied on the mean and standard deviation calculated from the training subset only, and the same transformation parameters were then applied to the corresponding testing subset. This procedure prevents information leakage from the testing data and ensures a fair evaluation of model performance.

III.2.5 Training and testing data partitioning

To assess the classification performance under an independent validation protocol, each dataset was partitioned into training and testing subsets using the holdout approach. Specifically, 70% of the samples were used for model training, whereas the remaining 30%

were reserved for testing. This partitioning strategy was applied independently to the ratio-based dataset and the graphical-feature dataset.

The training subset was used to fit the classification models, while the testing subset served to evaluate their generalization capability on unseen samples. This setup makes it possible to compare the diagnostic utility of the two feature representations under the same overall experimental protocol.

III.2.6 AI classifiers and implementation settings

To investigate the effectiveness of the extracted DGA features in transformer fault diagnosis, four artificial intelligence classifiers were implemented, namely K-nearest neighbors (KNN), support vector machine (SVM), random forest (RF), and random undersampling boosting (RUSBoost). These classifiers were selected because they represent complementary learning mechanisms, including distance-based classification, margin-based learning, ensemble bagging, and imbalance-aware boosting.

The implementation settings of the four classifiers were defined according to the MATLAB code used in this study. The adopted hyperparameters are summarized in Table IV.26.

Table III.3. Hyperparameter settings of the implemented AI classifiers

Classifier	Hyperparameter	Value
KNN	Number of neighbors	5
KNN	Distance metric	Euclidean
KNN	Internal standardization	False
SVM	Kernel function	Radial basis function (RBF)
SVM	Kernel scale	Auto
SVM	Box constraint	1
SVM	Internal standardization	False
Random Forest	Number of trees	200
Random Forest	Learning mode	Classification
Random Forest	Out-of-bag prediction	On
RUSBoost	Number of learning cycles	100
RUSBoost	Base learner	Decision tree
RUSBoost	Maximum number of splits	20

III.2.7 Performance evaluation criteria

The diagnostic performance of the developed models was evaluated using several complementary metrics in order to obtain a comprehensive assessment of classification quality. These metrics include the confusion matrix, accuracy, precision, recall, F1-score, specificity, Matthews correlation coefficient (MCC), and Cohen's Kappa coefficient.

Accuracy was used to quantify the overall proportion of correctly classified samples. Precision and recall were considered to evaluate the reliability and sensitivity of the models for each class. The F1-score was used to provide a harmonic balance between precision and recall, whereas specificity was adopted to assess the ability of the model to correctly reject non-target classes. In addition, MCC and Cohen's Kappa were included because they offer more robust evaluation in multiclass problems, especially when class distributions are not perfectly balanced.

The confusion matrix was particularly useful for identifying which fault classes were well recognized and which classes were more likely to be confused. This class-level analysis is important in DGA-based diagnosis because some fault categories may exhibit similar gas generation patterns.

III.2.8 Comparative framework between ratio-based and graphical features

The final objective of the proposed experimental setup is not limited to the evaluation of classifier performance alone, but extends to the comparison of two different feature representations derived from the same raw DGA data. For this reason, each classifier was trained and tested twice: first using the 12 ratio-based features and then using the 12 graphical features. The resulting performances were subsequently compared under identical evaluation criteria.

This comparative framework makes it possible to determine which feature representation is more discriminative and more suitable for intelligent transformer fault diagnosis. If the ratio-based features produce superior results, this would indicate that the relative relationships among gases carry stronger diagnostic information. Conversely, if the graphical features perform better, this would suggest that the geometric transformation of gas patterns provides a more effective representation for fault classification. Therefore, the proposed framework serves as a

systematic benchmark for evaluating the diagnostic relevance of ratio and graphical DGA features when integrated with machine learning models.

III.3. Results and Discussion

This section presents the comparative performance of the proposed DGA-based diagnostic framework using two alternative feature representations, namely ratio-based features and graphical features, in combination with four artificial intelligence classifiers: K-nearest neighbors (KNN), support vector machine (SVM), random forest (RF), and RUSBoost. The analysis is developed progressively, beginning with the global comparison of classification accuracy, followed by confusion matrix interpretation, cross-metric evaluation, model-wise performance analysis, integrated ranking across all indicators, and statistical significance assessment. The purpose of this section is not merely to identify the best-performing classifier, but more fundamentally to determine which feature representation provides the most discriminative and operationally suitable description of transformer fault conditions.

III.3.1 Global comparison of classification accuracy

The first level of analysis concerns the overall classification accuracy achieved by each classifier under the two investigated feature representations. The comparative results are summarized in Table IV.27 and visually illustrated in Figure IV.23.

Table III.4. Comparative analysis of ratio-based and graphical feature representations in terms of classification accuracy

Model	Ratio Accuracy (%)	Graphical Accuracy (%)	Δ (Ratio – Graphical)
KNN	60.66	91.80	-31.15
SVM	64.75	93.44	-28.69
RF	93.44	94.26	-0.82
RUSBoost	90.16	95.90	-5.74
Average	77.25	93.85	-16.60

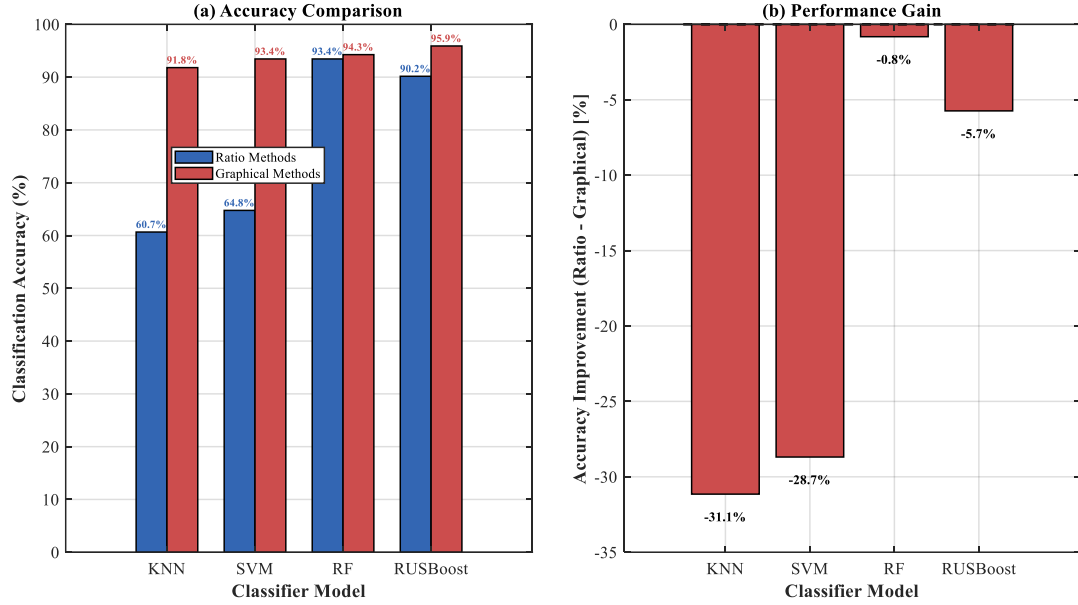


Figure III.2. Accuracy comparison and performance gain obtained with ratio-based and graphical feature representations.

The results demonstrate a consistent and unambiguous superiority of the graphical representation across all classifiers. The most substantial differences are observed for KNN and SVM, for which the use of graphical features leads to accuracy gains of 31.15% and 28.69%, respectively. Such improvements indicate that the graphical transformation yields a much more informative and structurally separable feature space for classifiers whose behavior is highly dependent on geometric proximity or nonlinear class boundaries.

By contrast, the difference becomes considerably smaller for RF, where both representations achieve high classification performance and the gain in favor of graphical features is limited to 0.82%. This suggests that tree-based ensemble learning retains a strong capacity to extract class-discriminative patterns even from ratio-based descriptors. Nevertheless, graphical features still maintain the highest accuracy. A similar tendency is observed for RUSBoost, where the improvement remains clearly favorable to the graphical representation, although less pronounced than in KNN and SVM.

From a global perspective, the average accuracy rises from 77.25% with ratio-based features to 93.85% with graphical features, corresponding to an overall gain of 16.60%. This result establishes, at the most direct level of comparison, that the graphical feature representation offers a markedly more effective basis for transformer fault classification.

III.3.2 Confusion matrix-based interpretation of class discrimination

Although overall accuracy provides a first indication of predictive performance, it does not fully capture the way in which each model distributes its errors across the six fault classes. For this reason, the confusion matrices were examined in detail, as presented in Figure IV.23.

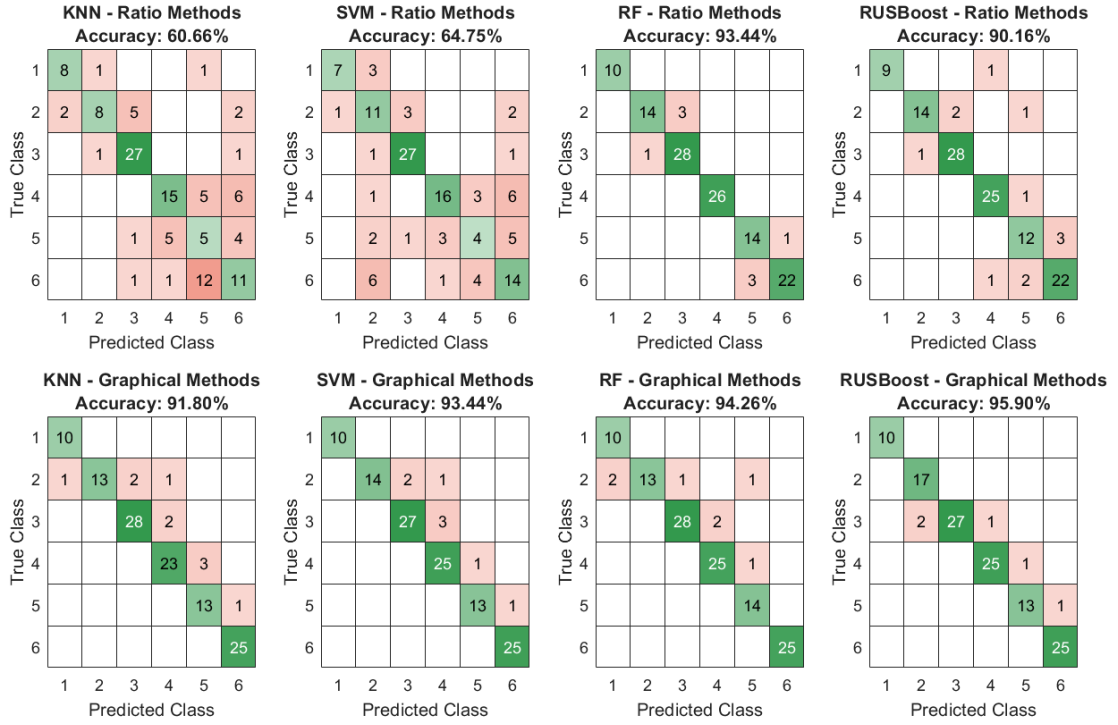


Figure III.3. Confusion matrix comparison for ratio-based and graphical feature representations across the four classifiers.

A close inspection of the confusion matrices reveals that the superiority of graphical features extends well beyond a simple increase in the number of correctly classified samples. Under ratio-based features, KNN and SVM display substantial off-diagonal dispersion, reflecting recurrent confusion among several fault classes. These misclassifications are particularly visible for intermediate discharge and thermal fault categories, which indicates that the ratio representation does not provide a sufficiently compact structure for reliable boundary formation in these two classifiers.

Once the graphical representation is adopted, the confusion matrices become markedly more diagonal-dominant. This shift is especially clear for KNN and SVM, where misclassification patterns are drastically reduced and the correct identification of fault classes becomes substantially more stable. The implication is that graphical features improve not only

classification strength in aggregate terms, but also the internal separability of classes within the feature space.

RF and RUSBoost exhibit stronger confusion matrix structures under both representations, which is consistent with their higher accuracies even when ratio-based features are used. However, the graphical representation still yields cleaner diagonals and fewer off-diagonal assignments, confirming that its benefit remains present even for already robust classifiers. Accordingly, the confusion matrix analysis confirms that graphical features generate a more discriminative encoding of DGA information, with a direct effect on class-level fault recognition.

III.3.3 Comparative analysis across overall evaluation metrics

To avoid reducing the comparison to accuracy alone, the two feature representations were further evaluated using a broader set of performance indicators, including precision, recall, F1-score, specificity, Matthews correlation coefficient (MCC), and Cohen's Kappa. The average values of these metrics across all classifiers are reported in Figure IV.25.

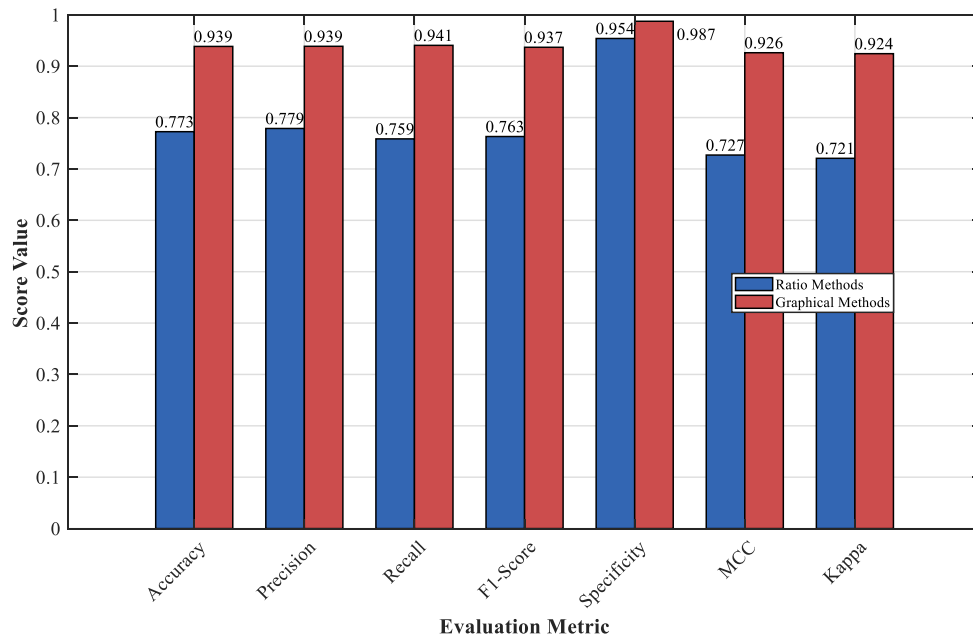


Figure III.4. Overall performance metrics comparison averaged across all classifiers

The cross-metric comparison confirms that the advantage of graphical features is systematic rather than isolated. In addition to the marked improvement in accuracy, graphical features yield higher precision, recall, and F1-score, indicating a more balanced relationship between predictive exactness and sensitivity. This is particularly important in multiclass

transformer fault diagnosis, where a high-performing model must not only maximize the number of correct decisions but also minimize the likelihood of class-specific confusion.

The superiority becomes even more meaningful when examining MCC and Cohen's Kappa, two metrics that provide a more rigorous evaluation of multiclass classification quality. Their substantial increase under graphical features indicates that the observed gains are not merely superficial improvements driven by dominant classes, but rather reflect a genuine strengthening of class agreement and decision reliability across the full diagnostic problem. Specificity also remains higher with graphical features, suggesting a stronger capacity to reject incorrect class assignments and reduce false positive tendencies.

Taken together, these results indicate that the graphical representation enhances not only predictive effectiveness but also the structural coherence of the classification process. In other words, the gain associated with graphical features is broad-based, extending simultaneously to discrimination strength, error balance, agreement quality, and class exclusion capability.

III.3.4 Model-wise performance behavior

To identify how each learning paradigm reacts to the two feature spaces, the results were analyzed at the individual classifier level. Figure IV.26 presents the detailed per-model comparison in terms of accuracy, precision, recall, F1-score, and specificity, together with the corresponding difference heatmap and accuracy improvement plot.

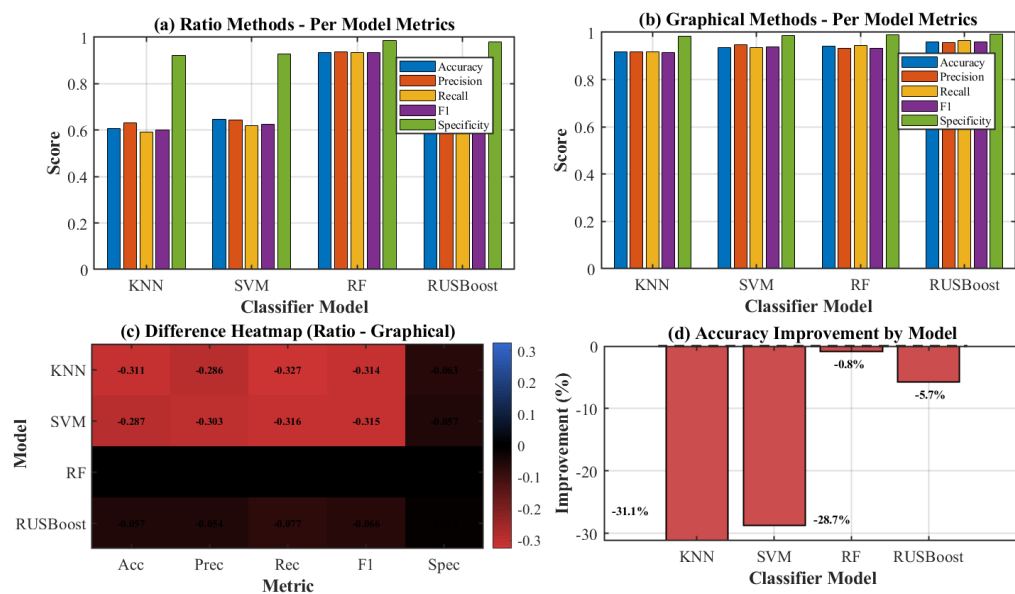


Figure III.5. Detailed per-model performance analysis for ratio-based and graphical feature representations.

The model-wise analysis reveals a clear gradient of sensitivity to feature representation. KNN and SVM emerge as the classifiers most affected by the choice of input features. Under ratio-based descriptors, both models remain well below the performance level required for highly reliable diagnostic deployment. However, once graphical features are introduced, their performance rises sharply across all principal indicators. This behavior strongly suggests that graphical features produce a feature topology that is significantly more compatible with distance-sensitive and boundary-sensitive learning mechanisms.

RF, in contrast, appears comparatively stable across both feature representations. Its performance is already high with ratio-based features and becomes only marginally higher with graphical features. This stability reflects the intrinsic robustness of ensemble tree models, which are less dependent on global feature-space geometry and more capable of constructing localized decision rules from heterogeneous inputs. Even so, the graphical representation still yields the best outcome, indicating that enhanced feature structure remains beneficial even for flexible ensemble architectures.

RUSBoost occupies an intermediate position. Its ratio-based performance is already strong, yet graphical features still induce a non-negligible improvement. This suggests that imbalance-aware boosting can capitalize on both feature types, while still benefiting from the more expressive geometric abstraction provided by graphical descriptors.

The heatmap of metric differences reinforces this interpretation. The most pronounced negative values (Ratio–Graphical) are concentrated in KNN and SVM, whereas RF shows near-zero differences, and RUSBoost exhibits moderate improvements in favor of graphical features. The model-wise evidence therefore converges on a central conclusion: the more a classifier depends on the internal organization of the feature space, the more decisively it benefits from graphical feature representation.

III.3.5 Integrated ranking across performance metrics

To synthesize the comparative behavior of the two feature representations across all evaluation dimensions, an integrated ranking profile was examined, as shown in Figure IV.27.

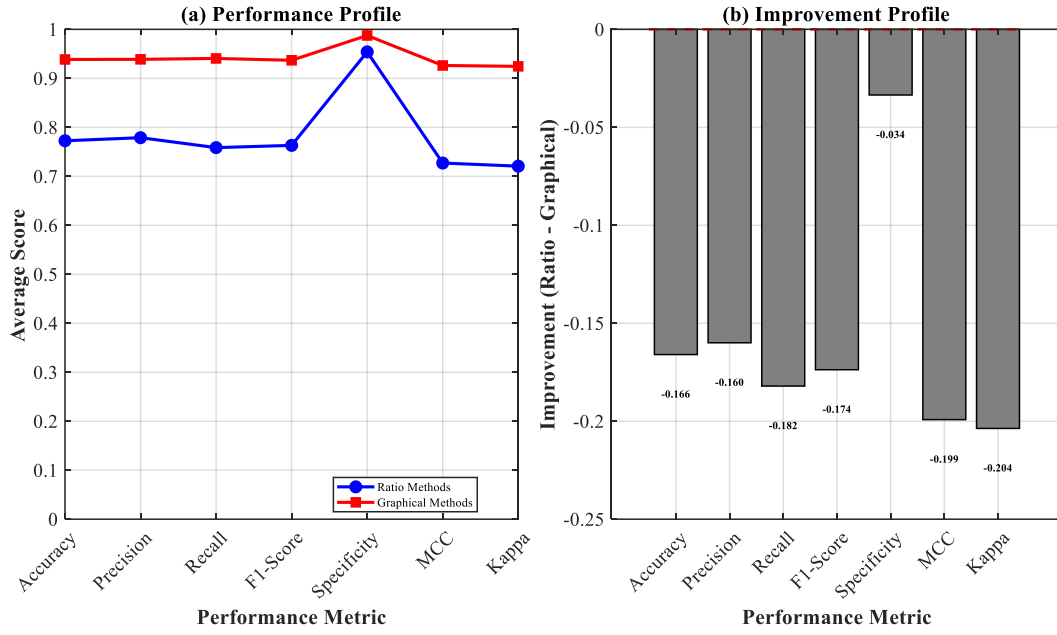


Figure III.6. Performance ranking across all evaluation metrics for ratio-based and graphical feature representations.

The performance profile confirms that graphical features consistently dominate ratio-based features across every metric considered in this study. No individual metric favors the ratio representation, and no reversal appears in any part of the ranking pattern. This consistency is of particular importance because it rules out the possibility that the superiority of graphical features is conditional, selective, or limited to a specific performance perspective.

The improvement profile further shows that the largest relative gains are associated with recall, F1-score, MCC, and Kappa, which are among the most informative indicators for multiclass diagnostic tasks. This suggests that the principal added value of graphical features lies not only in increasing raw predictive success, but more fundamentally in stabilizing class recognition and reducing structurally harmful errors. The comparatively smaller gap observed for specificity does not weaken this interpretation; rather, it indicates that both representations maintain acceptable rejection capability, while graphical features still preserve an advantage.

Hence, the integrated ranking analysis supports a decisive conclusion: graphical features provide a more coherent and consistently effective representation of transformer fault information than ratio-based descriptors.

III.3.6 Statistical significance of the observed improvement

To complement the descriptive and comparative analyses, a paired statistical comparison of the accuracy values obtained under the two feature representations was performed. The results are shown in Figure IV.288.

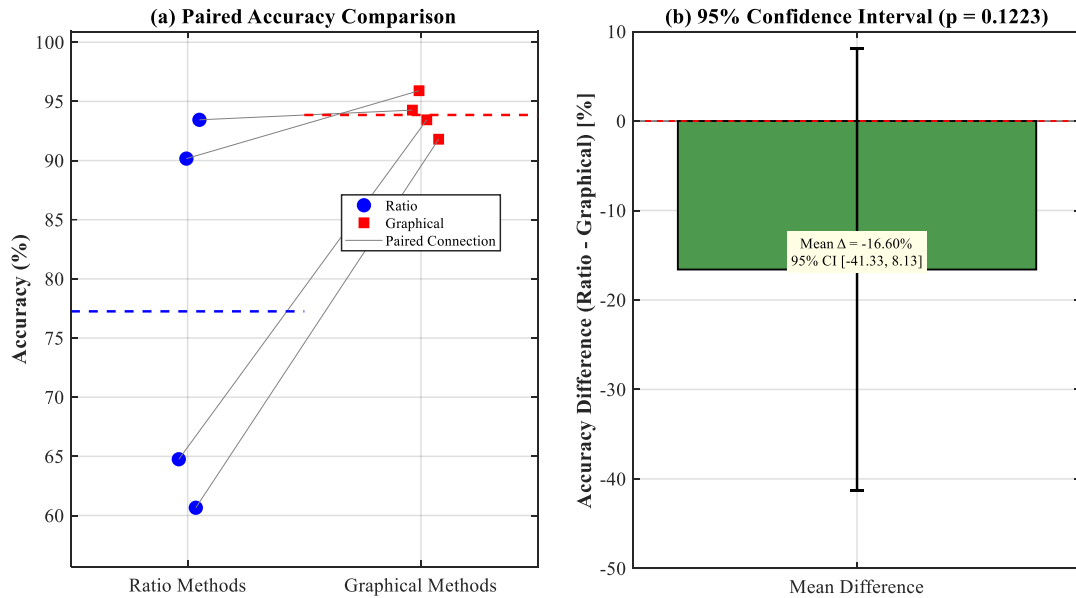


Figure III.7. Statistical significance analysis of the accuracy difference between ratio-based and graphical feature representations.

The paired comparison indicates that the graphical representation yields higher accuracy than the ratio representation for each of the four investigated classifiers. The mean difference reaches -16.60%, which constitutes a substantial practical advantage in favor of graphical features. However, the associated p-value ($p = 0.1223$) remains above the conventional 0.05 threshold, and the 95% confidence interval includes zero. Strictly speaking, this means that statistical significance cannot be formally established at the standard confidence level.

This result should nevertheless be interpreted with methodological caution rather than as evidence against the superiority of graphical features. The paired test is based on only four observations, corresponding to the four classifiers, which substantially limits statistical power. Under such conditions, the absence of significance is largely attributable to sample size constraints at the comparison level rather than to inconsistency in the empirical results. Indeed, the observed improvement is directionally uniform across all models and is repeatedly confirmed by the confusion matrices, the global metrics, and the integrated ranking analysis.

Accordingly, the statistical test does not invalidate the empirical conclusion; rather, it indicates that the inferential confirmation remains limited by the small number of paired model-level comparisons.

III.4 Conclusion

This chapter examined the application of artificial intelligence techniques to transformer fault diagnosis using two distinct feature representations derived from dissolved gas analysis data, namely ratio-based features and graphical features. Starting from the concentrations of five key dissolved gases, a structured comparative framework was established in which twelve ratio features and twelve graphical features were separately constructed and then evaluated using four classification models: KNN, SVM, Random Forest, and RUSBoost. The objective was not limited to identifying the most accurate classifier, but rather to determine which feature representation provides the most suitable diagnostic basis for intelligent fault classification.

The obtained results show that feature representation has a decisive influence on classification performance. Across all tested models, graphical features consistently produced higher diagnostic accuracy than ratio-based features. The most pronounced improvements were observed for KNN and SVM, indicating that graphical descriptors generate a feature space with stronger geometric separability and greater compatibility with classifiers that are highly sensitive to data distribution and decision-boundary structure. Although Random Forest and RUSBoost also performed relatively well with ratio-based features, they still achieved their best results with graphical inputs, confirming that the superiority of graphical features is general rather than model-specific.

This conclusion was further supported by the confusion matrix analysis, which revealed a substantial reduction in inter-class confusion when graphical features were used. In parallel, the comparison across multiple evaluation metrics demonstrated that the advantage of graphical features extended beyond overall accuracy to include precision, recall, F1-score, specificity, Matthews correlation coefficient, and Cohen's Kappa. Such consistency indicates that the observed improvement reflects a genuine enhancement in diagnostic discrimination and multiclass classification reliability rather than an isolated gain in a single performance measure.

From a methodological perspective, the findings of this chapter highlight the central role of feature engineering in AI-assisted DGA diagnosis. While ratio methods remain valuable in traditional transformer diagnostic practice because of their interpretive simplicity, they do not

appear to provide the most effective numerical representation for machine learning in the present multiclass setting. Graphical methods, by contrast, offer a more structured transformation of gas information and preserve diagnostic relationships in a form that is better exploited by intelligent classifiers.

Overall, the chapter demonstrates that graphical feature representation constitutes the most suitable strategy among the two investigated alternatives for transformer fault diagnosis based on DGA data. This outcome provides a clear basis for the subsequent orientation of intelligent diagnostic model development, emphasizing that improved diagnostic performance depends not only on classifier selection, but equally on the manner in which raw DGA information is transformed into machine-readable features. In this sense, the contribution of the chapter lies in establishing a comparative and experimentally supported justification for adopting graphical DGA features as the preferred representation in multiclass transformer fault classification frameworks.

General Conclusion



General Conclusion

This thesis addressed the problem of intelligent fault diagnosis in oil-immersed power transformers through the optimal exploitation of Dissolved Gas Analysis (DGA) as the most effective and reliable technique in the field of predictive monitoring for these critical electrical assets. The work was carried out within a scientific framework aimed at overcoming the limitations of conventional diagnostic methods and advancing toward intelligent systems capable of processing data with high accuracy and efficiency.

The study began with a comprehensive examination of the principal internal faults to which power transformers are susceptible, which were categorized into six main types: partial discharge (PD), low-energy discharge (D1), high-energy discharge (D2), and thermal faults of three severity levels (T1, T2, and T3). It was established that each fault category exhibits a distinctive gas signature reflecting the nature of the underlying thermal or electrical stress, thereby enabling dissolved gas compositions to serve as precise scientific indicators and reliable diagnostic markers.

A key methodological contribution of this study consisted in conducting a rigorous and systematic experimental comparison between two distinct feature extraction strategies derived from DGA data. The first strategy relied on ratio-based features, obtained by computing specific gas ratios from dissolved gas concentrations. The second strategy employed graphical features, derived by transforming gas compositions into geometric coordinates using well-established diagnostic approaches such as the Duval Triangle, the Duval Pentagon, and related graphical methods. This comparative framework was applied to a dataset comprising 407 samples distributed across the six fault categories.

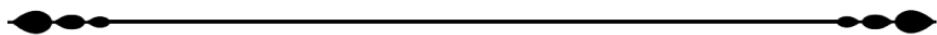
To evaluate both feature representations, four artificial intelligence classifiers were employed: K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest (RF), and Random Under-Sampling Boosting (RUSBoost). The results revealed a consistent and unambiguous superiority of graphical features over ratio-based features across all classifiers and evaluation metrics. The average diagnostic accuracy increased from 77.25% with ratio-based features to 93.85% with graphical features, representing an overall gain of 16.60%. The most substantial improvements were observed for KNN and SVM, which achieved accuracy gains of 31.15% and 28.69% respectively, confirming that the geometric

transformation of DGA data yields a feature space with significantly stronger class separability and greater discriminative power.

These results reinforced a fundamental principle in intelligent diagnostics: the quality of feature extraction and the manner in which raw data are represented are at least as important as the choice of classifier itself. While Random Forest demonstrated relatively robust performance even with ratio-based features — owing to its inherent flexibility in constructing localized decision rules — graphical features consistently produced the best outcomes across all models without exception. This finding offers practically valuable guidance for researchers and engineers engaged in the development of AI-assisted DGA diagnostic systems for power transformers.

In conclusion, this thesis presents a comprehensive scientific contribution that integrates a rigorous theoretical framework with documented experimental validation in a field of considerable strategic importance, namely the preservation of electrical network assets and the assurance of operational continuity. The obtained results open promising avenues for future research, particularly in the direction of developing hybrid diagnostic models that combine graphical features with deep learning architectures, extending the framework to larger and more diverse datasets, and exploring the deployment of such systems within real-time monitoring and condition-based maintenance platforms for power transformers.

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