Developments in Online Condition Monitoring of Substation Equipment and the Digital Substation

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SUMMARY

To manage risk and the optimize the availability of substation equipment, online monitoring of substation apparatus is expected to play an essential role in digitalized substations and the power grid of the future. The potential value for online monitoring as a tool used to provide early indication of developing problems or faults, and to further provide information for predictive maintenance of substation equipment has long been recognized.

Historically, some degree of scepticism has limited the wider adoption of online monitoring; due mainly to questions regarding return-on-investment, and challenges associated with managing and analysing the large amounts of data produced from online monitoring.

This paper presents a selection of modern developments in substation online condition monitoring for power transformers and circuit breakers. These advancements include modern online monitoring systems that enable data correlation for more effective diagnostics, integrating online monitoring data in asset health scores, digital twin modelling equipment to estimate real-time operational capability, and the implementation of Artificial Intelligence and Machine Learning for diagnosis of equipment problems or faults. With these developments, many problems associated with data management and analytics to online monitoring data can be alleviated, while improving efficiencies in condition assessment and maintenance planning.

KEYWORDS

Substation monitoring, online condition monitoring, Power Transformers, Circuit Breakers, Digitalization

INTRODUCTION

The purpose of online monitoring systems of substation equipment is to collect data for analysis and inform operational and maintenance decisions [1]. Commonly cited benefits for online monitoring include enabling condition-based maintenance (instead of traditional time-based maintenance), extending the life of equipment while managing risk using online monitoring, and enabling the operation of equipment under controlled overloading conditions [2]. The most valued operational benefit from condition-based online monitoring is from providing early detection of developing fault

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conditions and many economic analyses justify installation of online monitoring on substation equipment by focussing on a cost-benefit analysis for improved reliability with reduced risk by having online monitoring installed, versus without [3, 4].

The projected future power grid is aimed toward having a more sustainable model oriented around decarbonization and decentralization. This will be achieved through increased integration of renewable energy sources and distributed generation. To further achieve ambitious zero-emissions targets, the power system will also be required to support new energy demands associated with growth in electric transportation and electric heating and cooling. It is therefore anticipated that these changes to the power system will impose new operating conditions, and new stresses to transmission substation equipment. Frequent load cycling due to renewable energy from variable sources, may subject equipment to temperature fluctuations and increased thermal stress [5, 6]. For example, equipment such as transformer load tap-changers may be required to operate more frequently to maintain system voltage causing increased wear-and-tear and increase maintenance or risks of premature failure. Given the dynamic nature of the future power grid, equipment availability and the pressures to minimize downtime for equipment maintenance or forced outages will be of critical importance; thus, increasing the importance for substation online condition monitoring. Industry trends toward digital transformation within substations and alignment with the IEC 61850 Standard, will drive greater opportunities for the analysis and diagnostics of data produced from online condition monitoring.

In this paper, a selection of modern developments in online monitoring, and utilization of online monitoring data are presented. Sections are devoted to a range of topics including holistic transformer online monitoring and correlation of online monitoring data for more effective diagnosis, implementing digital twin models based on online monitoring data for calculation of operational capabilities, integrating online condition monitoring data with offline diagnostic test data for asset health scores and condition indices, and the use of AI and ML for more efficient and effective analysis of online monitoring data. Applications for power transformers and circuit breakers will be discussed, however an emphasis will be placed on power transformers. Due to their complexity, cost, criticality, and failure rate, more recent developments in online monitoring of power transformers are available for discussion.

HOLISTIC TRANSFORMER MONITORING AND DATA CORRELATION

The most common online monitoring systems installed on large power transformer are dissolved gas-in-oil detectors. These devices are effective in detecting thermal and electrical defects within the main transformer tank. Other common online monitoring systems for power transformers include leakage current monitoring for the transformer bushings, and DGA monitoring of on-load tap changers (LTCs). These components including the main tank/windings, transformer bushings and the LTC, are the cause of most in-service failures [7]. Therefore, an effective holistic online monitoring solution for power transformers should combine targeted monitoring systems for these components. For a holistic solution, integrating multiple online monitoring systems for the windings, bushings and LTC, effectiveness at detecting transformer problems can be greatly improved if the data from the online monitoring systems can be correlated. Developing faults are often correlated in one or more monitored parameters or the operating conditions. For example, gassing within the main tank could be correlated to loading and top-oil temperature. Similarly, the power factor in a transformer bushing (determined from the leakage current) may be correlated with temperature and/or internal partial discharges.

A modern holistic online monitoring system which integrates DGA monitoring main tank/LTC, bushing leakage currents, and online partial discharges along with operating conditions (e.g. load, temperature data etc.) is described in [8]. A modern transformer online monitoring system can enable convenient correlation of data in software, so that faults can be diagnosed at their incipient stages, preventing permanent damage or failure. Figures 1 and 2, show two example case studies that demonstrate early detection capabilities using the modern online monitoring system from [8], using correlation tools available in the system software.

Figure 1 shows a detection of an early fault condition in a 345kV, OIP, transformer bushing. The correlation of partial discharges occurring at the same moment as a step increase in bushing capacitance leakage current in the bushing, detects the exact moment that condenser layers within the bushing became shorted. For many bushing defects leading to faults by this mechanism, the relative change in capacitive leakage current may be less than <1%. With such a small change in capacitance it can be difficult to confirm the faulty condition by offline power factor testing. Offline testing can have inaccuracies greater than 1% due to operator error, instrument accuracy, or differences in the bushing temperature. Therefore, the detected correlation by the online monitor between high magnitude partial discharges and change in capacitance is essential to give greater confidence in the faulty diagnosis.

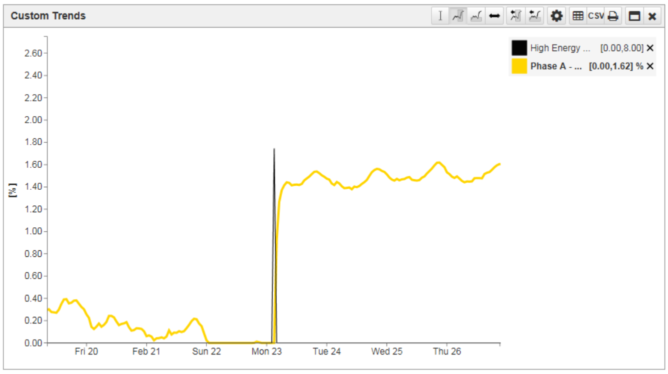

Figure 1: Early online detection of a bushing fault using correlated change in capacitance leakage current and high energy partial discharge events.

In a second example demonstrating online fault detection using correlated online monitoring data, Figure 2 displays the detection of an electrical arcing event inside the main tank of a 300 MVA, 500 kV autotransformer. The arcing events are intermittent, occurring over the course of two weeks. It is clear from the correlated data that at the same moment as high electrical discharges occur, step increases in acetylene also occur.

In both examples from Figure 1 and 2, the correlation of online monitoring data from multiple systems; online PD, bushing leakage current, and DGA, has the potential to provides earlier indication of internal problems and increase confidence for immediate diagnosis. Confirmation of the diagnosis by offline testing to the transformer or delays for confirmation by laboratory DGA become unnecessary.

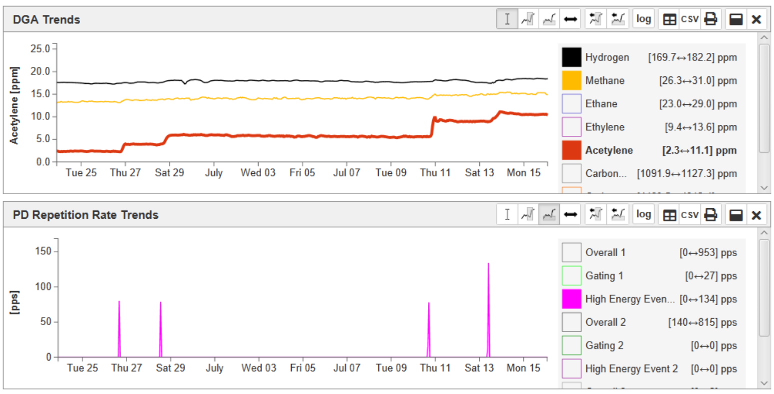

Figure 2: Online monitor detection of a fault in transformer winding insulation using correlated high energy partial discharge events with cumulative increases in acetylene from DGA monitoring.

The effective use of data correlation in transformer online monitoring provides clear operational benefits for a digital substation. If the diagnostics were carried out by the online monitor, acting as an 'edge' device, it could provide more immediate alerting to faulty conditions to swiftly prevent the risk of in-service catastrophic failure. Alternatively, if the correlation analysis was implemented at the station level, then a CMMS could be programmed to provide prescriptive actions for outages and/or maintenance. Other benefits are possible for potential enhancements to monitoring and artificial intelligence and machine learning AI/ML implementations. For example, a failure mechanism observed in one transformer could train monitoring systems to identify similar faults occurring in other transformers within the power system.

DIGITAL TWINS AND ANALYTICAL MODELS

Online monitoring data can also be used in real-time operating decisions. With modernizing of the grid and a focus on renewable generation, the dynamics of transformer loading patterns are expected to be different from present day where many transformers are base loaded during industrial peak hours, and lightly loaded at night. Renewable generation may also impose pressures to reduce downtime and may require more temporary overloading on transformers to make up intermittent renewable generation.

Building a digital twin model in the transformer online monitor enables functionality to operate under controlled overloading conditions without risk to the transformer. Online monitoring of parameters, such as transformer load, top oil temperature, cooling performance, and moisture-in-oil, enables a digital twin model to be used in the estimation of hot spots and the bubble formation temperature. From this information it is possible for the digital twin model to calculate temporary overload capability and a safe duration of overload conditions on the transformer in real-time.

The digital twin model is also be used to estimate aging of the transformer cellulose insulation. This is a useful parameter to track because the condition of the transformer paper is essential to determining the transformer reliability, and its ability to sustain system disturbances. An estimate of the solid insulation remaining life is also important for life cycle management and planning for transformer replacements or spares.

Figure 3 below shows a schematic representation of algorithms used in the digital twin model to estimate overloading capacity and transformer ageing. The model utilizes factory acceptance testing data, loading, moisture-in-oil, and operating temperature parameters in its calculations.

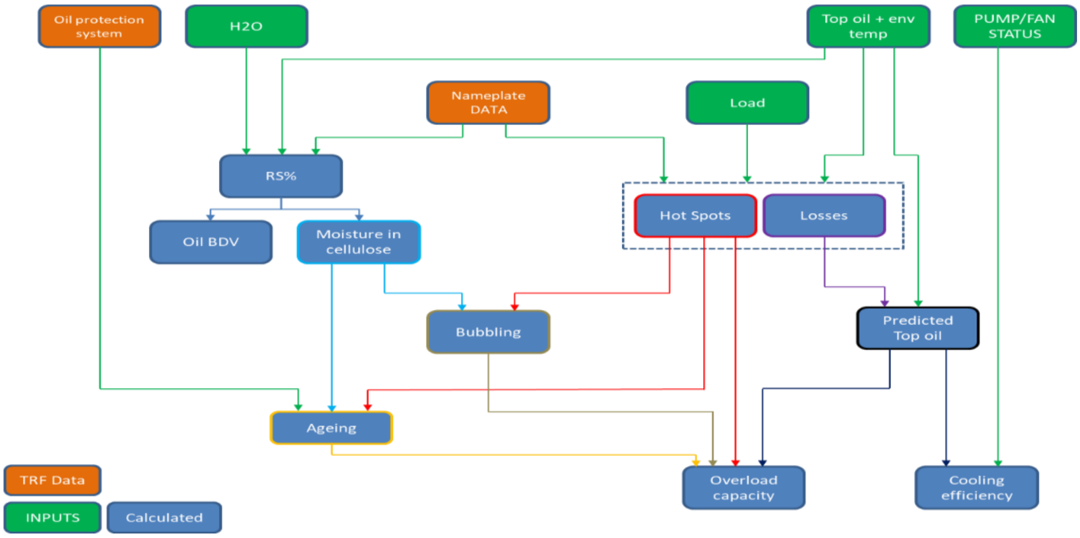

Figure 3: Schematic representation of a transformer digital twin model used for estimation of overload capacity, transformer aging, and cooling efficiency.

INTEGRATION OF ONLINE MONITORING DATA FOR HEALTH INDICES

Utility calculation of health scores or indices for substation assets are typically based only on offline diagnostic test data and visual inspections. Online monitoring can provide valuable insight into the asset condition since the assets are exposed to stresses from operating conditions which are not present during offline testing.

However, online monitoring data are not commonly considered in asset health scores or condition indices. The exclusion of online monitor data in many cases are due to uncertainty with how to interpret and assess some online data, e.g. partial discharge data. In other instances, it may be due to uncertainty with integrating the online data for transformer fleet assessment.

In [9] an analytical method for computing transformer health indices using both online monitoring data and offline test data for power transformers is described. The method evaluates a condition index score based on offline diagnostic test data and online monitoring data. For transformers that do not have online monitoring installed, a condition index is calculated based on the available offline data. From the perspective of integrated online monitoring within digital substations, this approach to integrate online monitoring data into condition health scores for fleet asset management provides multiple benefits. One benefit is that that the condition for a fleet of assets can be monitored in a consistent way utilizing a centralized database or data historian that is populated by online monitoring data continuously and translated into a condition score or index for all monitored assets. Visual inspection information and/or offline test data can also be integrated and automatically populated into the calculation of a hybridized condition index which factors online with offline data. For fleet asset management, this type of system would provide the up-to-date current data for maintenance planning, and life cycle management planning for transformer replacements or spares.

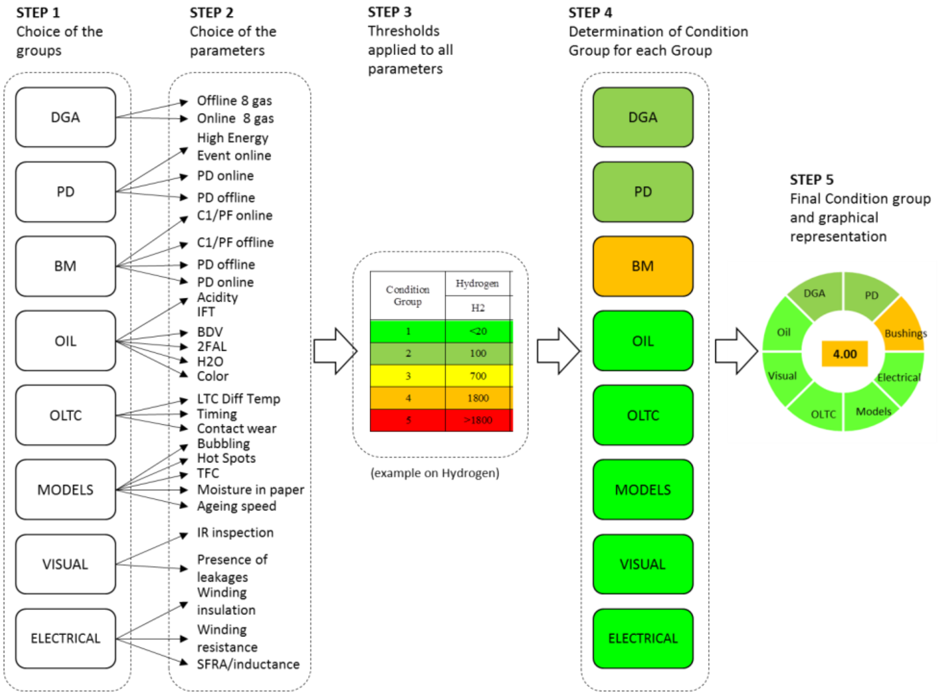

Figure 4: Schematic representation for an integrated condition group (health score) calculation in power transformers based on offline diagnostic tests and online monitoring.

ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

Artificial Intelligence (AI) and Machine Learning (ML) methods are well suited for analysis of online monitoring data on substation equipment. AI and ML methods are particularly effective at processing substantial amounts of data and providing a diagnostic assessment on the data. However, the accuracy AI diagnostic assessment and its ability to correctly identify fault conditions from the online monitoring data depends on how closely the data aligns with training data that the ML algorithm was developed from, and how distinguishable (separable) the monitoring data values are for the different failure modes and fault types.

For DGA in power transformers, a range of DGA diagnostic methods are available in industry standards (e.g. Duval, IEC, Rogers, and Key Gas, etc.). For most transformer defects and faults, diagnostic methods will provide consistent assessment for the fault-type. However, DGA does not always produce consistent assessment according to various industry diagnostic methods, which can make diagnosis of the transformer fault type unclear, and prescriptive actions uncertain.

In the left portion of Figure 5 below, a graphical representation of an AI for DGA diagnostics is shown. This type of AI can be characterized as an 'augmented intelligence,' which by definition, is an AI is designed to aid human intelligence (i.e. the DGA subject matter expert). Within the digital substation environment, this tool functions at the station database or data historian layer and for the large volume of DGA results that have a clear diagnostic result with consistency among multiple DGA diagnostic methods, the AI can perform automatic assessment. For the DGA results with unclear assessment the AI can alert the attention of SMEs. Based on estimated accuracy for various diagnostic methods, and alignment to AI training data, the system can return confidence estimates for the various fault type assessments as shown in the right of Figure 5. Given this information, the SME can also review offline test data, or request additional follow-up tests to further aid assessment.

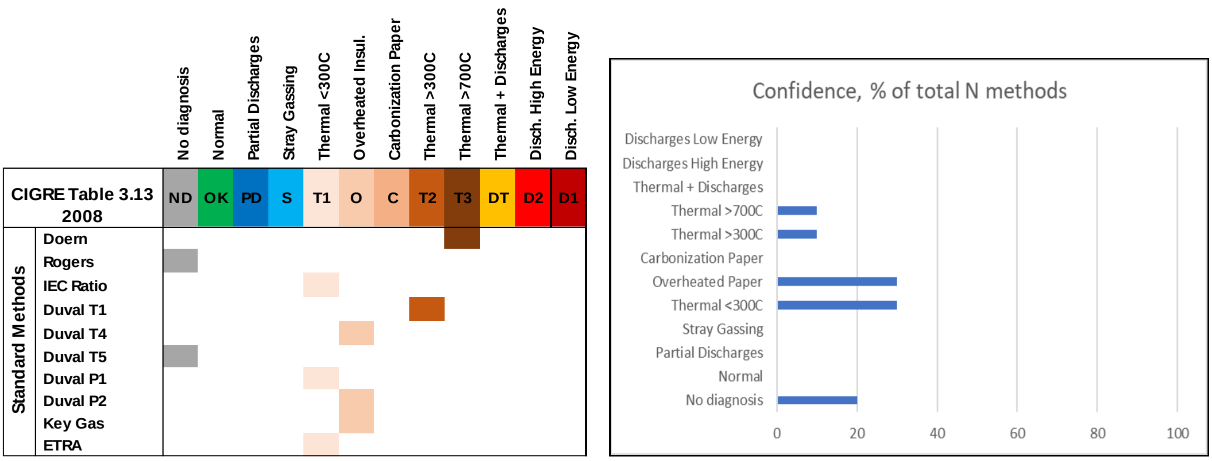

Figure 5: DGA Matrix with Machine Learning evaluation of probable diagnostics

Artificial Intelligence and Machine Learning are also well suited to online monitoring applications in circuit breakers. One effective online monitoring diagnostic for circuit breakers examines the trip coil current profile [10]. This diagnostic method is most effective at diagnosing breaker operations after the breaker has been in a closed position for an extended period prior to operation. By inspecting for anomalies in the trip coil current waveform during a trip operation, it is possible to detect circuit breaker problems associated with the operating time, close and trip coil integrity, auxiliary contacts, or operating mechanism. Trip profiling can detect up to 80% of circuit breaker problems.

Similar to DGA in power transformers, AI and ML methods are well-suited for analysing trip coil profile data on circuit breakers. In Figures 6 and 7, images of a ML interface for trip coil current analysis is displayed. Most normal trip operations appear as shown in Figure 6, with the characteristic in the trip profile waveform falling within statistically normal tolerances. In these instances, the AI monitoring system will indicate normal breaker operation. In Figure 7, we see the AI detecting an anomalous operation with a delayed opening of the operating mechanism, and fluctuations on the plateau which may indicate an issue with the auxiliary contacts. The AI flags the potential issues and can provide prescriptive actions for further inspection or maintenance. With digitalization and integration of online monitoring to a centralized data historian and computerized maintenance management system, the process of identifying an anomalous breaker trip operation, diagnosing the problem, and providing prescriptive actions can be automated.

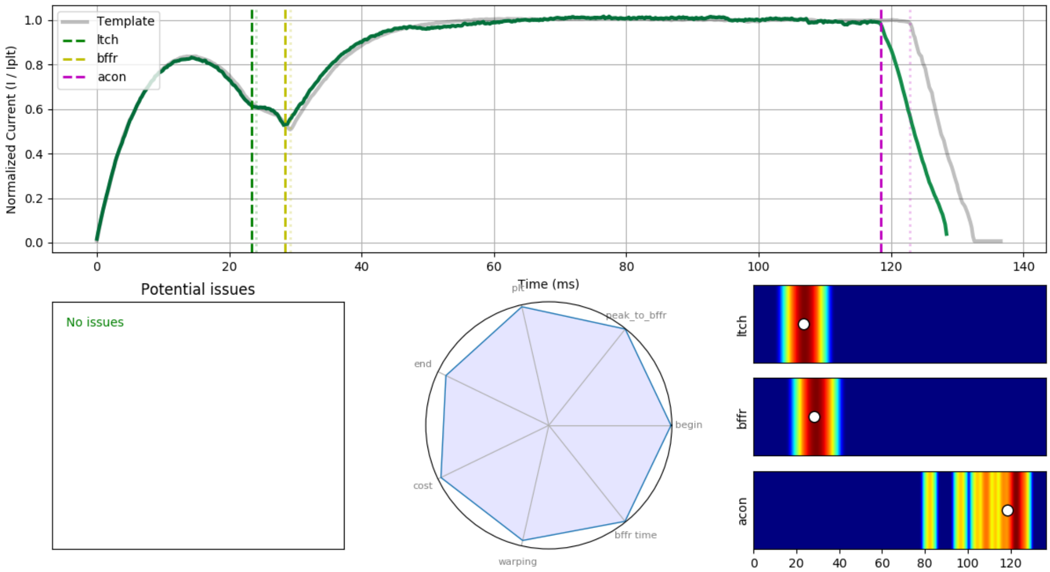

Figure 6: Augmentened Intelligence monitoring system for circuit breakers using trip coil current profiling. AI diagnostic analysis detected no issues during a normal breaker operation.

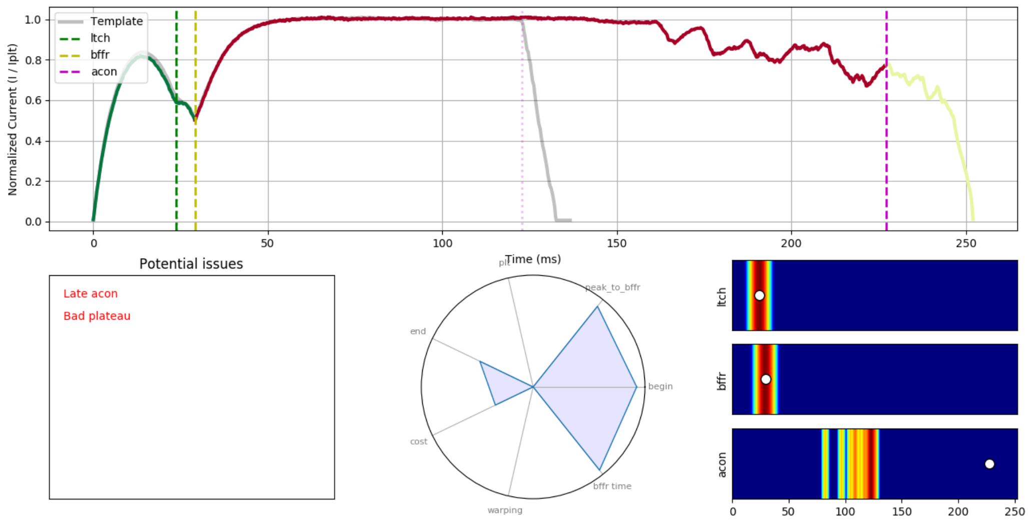

Figure 7: Augmentened Intelligence monitoring system for circuit breakers using trip coil current profiling. AI diagnostic analysis detected issues with the late interruption, and abmornal oscillations in the waveform during an abnormal circuit breaker operation.

CONCLUSION

Modern developments in online condition monitoring for substation equipment are enhancing the capabilities and value these systems provide within the power grid. Future trends/changes with increased onboarding of renewable generation, along with trends toward digitalization and digital substations, will only reinforce the necessity of online monitoring systems for substation equipment. The capabilities and future integration of online monitoring systems within digital substations is becoming clearer with advancements in modern online monitoring systems.

A modern online monitoring system for power transformers which provides a holistic online condition monitoring approach including DGA monitoring, bushing leakage current monitoring, and continuous online PD monitoring has been described. The combination of these system into an integrated holistic solution allows for the correlation of data with operating conditions for improved diagnostics and earlier detection of fault conditions. In addition to functional benefits for reliability, modern online monitoring for transformers can also be used in a digital twin model of the power transformer to enable for controlled overloading, and to estimate remaining insulation life.

From the perspective of asset management, integration of online condition monitoring data in asset health scores provides benefits for fleet asset management. Online monitoring data can be used in asset health indices and condition assessment to aid in asset management and maintenance, or life-cycle asset planning for replacements or spares.

Developments in the application of AI and ML demonstrate strong potential for increasing efficiencies in data management and diagnostic analysis. For DGA in power transformers and trip coil current profiling in circuit breakers, AI can be used to process large volumes of data and can automate the identification of anomalous readings. These systems can identify likely fault conditions or defects, and the system can provide prescriptive maintenance actions.

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