Digital condition monitoring for smart transformers

Intelligent frameworks for transformer diagnostics

ABSTRACT

A digital transformer is the centrepiece of a smart grid that gives agility to the business model of the power sector. It enables self-measurement, monitoring, analysis, and two-way communication of its condition using various electronic devices in real time. However, big data issues, high cost of sensors, rapidly changing digital technologies, and a lack of standardisation protocol restricts the emergence of a truly digital transformer. This paper describes that a multidimensional approach towards storage, analysis, and safety of condition monitoring data is the key to an integrated platform for complete automation of such purposes.

KEYWORDS

big data, cloud computing, condition monitoring, cybersecurity, digital transformer


Sruti CHAKRABORTY, Marius GRISARU

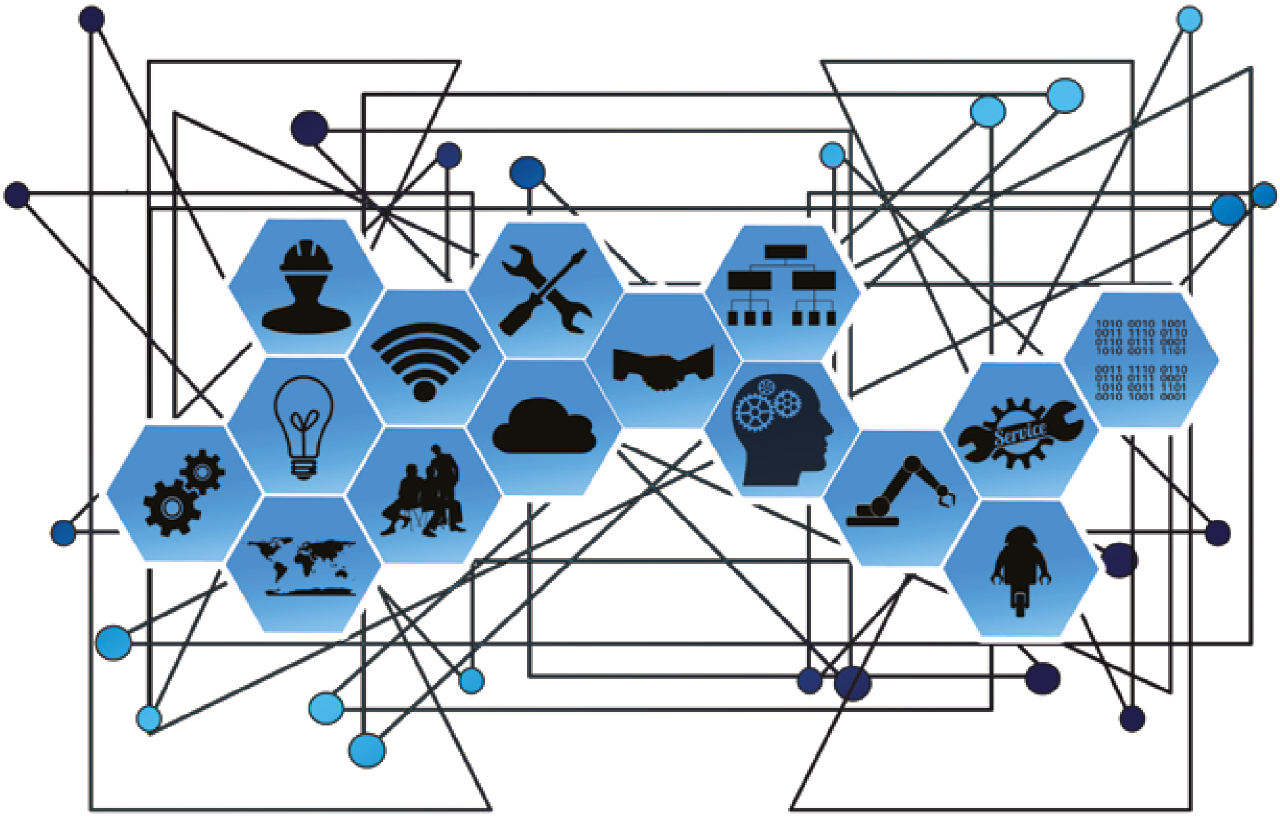
Digitisation of transformers and energy grids can make the business sector agile, cost-effective, and environmentally friendly

1. Introduction

The decentralisation of power generation sources, strict environmental laws, and various techno-economic regulations are driving the power sector towards optimisation of the existing business model. As a key asset, power and distribution transformers endure severe operational stresses that gradually deteriorate their lifespan and often lead to irreversible damages. Conversely, meticulous condition monitoring of operational transformers can maximise their availability and reliability by optimising the maintenance efforts. It is also the key to stabilise the ageing infrastructure and transformer population by reinforcing effective asset management decisions.

In this context, digitisation of transformer and energy grids can make the business agile, cost-effective, and environment friendly. In fact, a digital transformer enables self-measurement, monitoring, diagnosis, and two-way communication of its condition using various electronic devices in real-time. The interoperability of smart grids using digital transformers can effectively avoid failure occurrence, unwanted downtime, and consequential market backlash.

A primary challenge for energy utilities right now is to control the operational costs of energy transmission without compromising on asset availability. In this context, a digital transformer is an optimum response to such challenges making the whole process agile, compact, and even intelligent enough to accelerate asset management decisions. Modern-day transformers, bushings, and tap changers contain various built-in electronic devices for self-monitoring purposes. However, interpretation of the data from such devices to achieve a conclusive decision or action plan requires vast knowledge and experience on diagnostic matters. Furthermore, a limited number of human experts and lack of



> **Digitisation of transformers and energy grids can make the business sector agile, cost-effective, and environmentally friendly**

knowledge preservation makes the process tedious, costly, and partially inaccessible. A truly digital transformer that can mitigate the said limitations is yet to emerge. Hence, upgrading the analytical platforms by integrating data collection and storage channels, and maximising diagnostic efforts using artificial intelligence and machine learning can be the optimum solution.

This paper brings a discussion on the existing state and evolution of transformer condition monitoring and systems with respect to digital technologies. It also answers some of the basic yet crucial questions related to transformer maintenance and long-term management. However, it primarily focuses on various challenges and opportunities surrounding the construction of an intelligent framework that can assimilate multiple channels of data measurement, collection, storage, and analysis. Finally, it highlights the potential implementation risks on a digital transformer along with possible recommendations.

2. Transformer condition monitoring and systems

Transformer condition monitoring systems (TCMs) is a collective reference to various methods that help in analysing the internal condition of an asset to optimise its availability. The primary objective of TCMs is to pinpoint the severity of a dielectric, thermal and / or mechanical fault, including detection and classification of the identified fault to plan suitable corrective actions.

An acute diagnostic platform contains three TCMs components, i.e., hardware, software, and analytics. Due to the growing interest towards continuous monitoring, modern-day transformers, bushings, and tap-changers contain various built-in sensors, intelligent electronic devices (IEDs), and transducers for online monitoring of the asset. These hardware components enable measurement and monitoring of deterioration parameters using capacitive probes (e.g., moisture sensors), fibre optics (e.g., temperature sensors), and other signal processing technologies (e.g., partial discharge, leakage current, voltage, phase measurement). It may redirect the data in the form of processed signals to a host containing diagnostic software and / or a data integration platform. The transmission of this data may be local or global depending upon the utility requirements. Nevertheless, the data accumulation from these components in case of large transformer fleets can be overwhelming.

The lifespan of some of these devices may be half of that of transformers, and their occasional replacement can be an additional cost. Nevertheless, such factors should not undermine their significance for online condition monitoring of digital transformers. The real challenge in this aspect is the continuous need to upgrade diagnostic methods within the context of integrated platforms due to rapidly changing digital technologies and relatively ambiguous standards.

Furthermore, interpretation of hardware data requires additional efforts in the form of quantitative representation and analysis. Diagnostic software based on explicit programming for fault detection, maintenance and planning, and asset risk management can be partially useful. Unfortunately, additional challenges such as high procurement / renewal cost, perpetual maintenance, the prior need of diagnostic knowledge, and restricted access make such options redundant for a non-expert and particularly small-scale user. In fact, open-access software for such purposes does not exist due to limited inter-compatibility of hardware devices and variable company goals and functions.

Current diagnostics practices also vary with structural and behavioural limitations of transformers. Recent developments in dielectric materials alongside design improvements impose constant revision of the classical diagnostic methods. Diagnostic software can often be quite elaborate and may have predefined domain applications, most of which may be unnecessary for a non-related or non-expert user. Hence, the development of a robust, intelligent, and justifiable analytical platform can be extremely beneficial from a user's perspective, interested only in having a simple, quick, and reliable interpretation of the diagnostic data. Such solutions must be in line with the user's interest in either immediate maintenance based on the fault analysis or long-term management based on health assessment. Furthermore, they must be scientifically developed in such a way that experts worldwide can correlate their opinions alongside predictive solutions.

3. Fault diagnosis versus health assessment

As mentioned earlier, TCMs vary with company goals and functions. For example, an isolated asset owner may be particularly interested in early detection and correction of faults to optimise the transformer lifespan. However, a grid owner knows that comprehensive health assessment of transformers is the key to optimise asset management activities, especially in case of large fleets. A primary concern of utilities worldwide is that frequent fault occurrence increases the risk of the ultimate failure of transformers leading to severe consequences. Qualitative and valuable expertise needs to distinguish between the triggers from faulty and non-faulty phenomena, even at the most basic assessment level. After all, it is the key to evaluate condition severity and asset ranking for repair / refurbishment decisions. Ambiguity in decision making pertinent to such matters can be particularly distressing for a non-expert user.

Intelligent and integrated diagnostic framework is the key to address the existing transformer monitoring challenges

Industry professionals use a subsidiary tool called health index (HI) as a well-communicated and often self-conceptualised protocol to evaluate overall health, immediate and long-term risks of an operational transformer. It is a combination of diagnostic information, service history, field experience, and expert observation on dynamic behaviour anomalies. The most interesting part is that the big data (obtained from various online sensors) may contain redundant and irrelevant information that requires extraction and optimisation of key information for the suitable representation of asset health. This can be quite challenging without the expertise and computational advantage. Besides, the general lack of standardisation protocols does not allow a universal method of HI computation.

Current practices for evaluating transformer health index depend on the quantitative value of the routine diagnostic tests. A particularly popular choice among industry professionals is the standard score-weight (SW) matrix method. It involves the allocation of numerical score to the deterioration assessment parameters and weighing their importance from "very poor" to "very good." The numerical range of such scales may be 0 - 10 or 0 – 100, such that the lower value represents an already degraded transformer. Nevertheless, the scale subdivides into specific ranges that denote the "wellness" of transformers containing simple linguistic remarks [1, 2].

The division of score and weight in the above method depends on the experience of the diagnostic expert and vastness of the database. It may be available to the end-user as value addition in the diagnostic software or upon consultation. Nevertheless, it may or may not be available as a real-time service that can merge diagnostic and analytical services on a single platform. Recent advancements in artificial intelligence (AI) technologies may be helpful in the designing of such an integrated framework for the smart diagnosis of operational and somewhat digital transformers.

4. Integrated frameworks for smart diagnosis

Industry professionals often use various expert system-computational intelligence (ESCI) tools as a subset of AI-technique to achieve their diagnostic objectives. Primarily, ESCI-tools contain rule (knowledge)-based or statistical algorithms. A classic example of such a system in the transformer industry is the rule-based translation of DGA data into fault interpretation that stems from experience and knowledge of the diagnostic expert. An expert system that uses fuzzy logic (FL) for similar purposes codifies human knowledge into facilitating an approximate but practical diagnostic statement.

However, it is rather difficult to state the exact relationship between the condition monitoring parameters and transformer health, particularly outside the context of a rule-based system. It can be a perplexing and time-consuming task. Although FL may ensure local membership functions between some parameters, complex and simultaneously active fault mechanisms may not allow appropriate inference of all diagnostic issues. Additionally, difficulty in acquiring expert knowledge, insufficient experience, and inadequate translation of rules can make such tools relatively imperfect.

Conversely, the use of statistical methods can ensure a data-driven statement rather than an ambiguous opinion. Artificial neural network (ANN) and machine learning (ML) can overcome such limitations by extracting the hidden relationships by the statistical distribution

> **Digitisation of transformers with contemporary communication devices can expose the asset to cyber vulnerabilities**

of knowledge over the network of input and output parameters. In fact, ANN and FL are the most popular AI-based tools among industry professionals for fault diagnosis and health indexing of transformers. Many reputed organisations use such tools as a value addition to their diagnostic services.

Artificial intelligence (AI) refers to a computer's ability to learn and act like a human. One of the key objectives for using AI-based method is that it delivers a reliable diagnostic statement even when there is the limited or poor quality of data. For example, the cost of online hydrogen monitors is relatively lower than the conventional DGA devices leading to its popularity [3]. Although a single gas can diagnose only so much in a transformer, yet AI can provide added value to the end-user by improving the accuracy of its diagnostic statement.

Various efforts by CIGRE are currently in practice for AI-based fault diagnosis and health index assessment that is widely popular among the industry professionals [4-7]. The bases of these models are rigid rules (mathematical models), diagnostic opinion (fuzzy logic), pattern recognition (regression), or a combination of the above. Technical insights leading to such parturition on some of these methods are available elsewhere [8].

Another interesting example of the AI-application is the use of machine learning (ML) as a statistical method that allows iterative learning from data to predict the outcomes and reduce the dimensionality of complex problems. Various ML-based models are available for predictive assessment of transformer health and faults. Classic examples include the use of support vector mechanism (SVM), radial basis function (RBF), Bayesian network, k-nearest neighbour (kNN), regression algorithms, etc. A comparison of these methods is beyond the scope of this paper. Nevertheless, all learning methods need improvement using various evolutionary algorithms (EA) such as particle swarm (PS), cuckoo-search (CS), ant colony (AC) optimisation, etc. In fact, computational intelligence is the collective ability of machines to learn and perform tasks using such statistical or mathematical methods, unlike the expert systems.

Vast information is available on the application of coupled ML - EA systems for the prediction of unknown parametric values from the available data, fault diagnosis, and health-index assessment of transformers as an improvement of traditional practices. They do not necessarily require costly know-how or substantial historical data on the asset. However, smaller sample size and significant difference between training and testing samples can impose serious concerns for such solutions. Furthermore, a well-communicated protocol that can define the requirements and techniques to obtain predictive statements in real time by the integration of multi-channel data into a coupled ML - EA analytical platform does not exist.

The key to the integration of monitoring channels with analytical diagnostic platforms lies in the handling of data. An intelligent framework should be able to identify and remove noise from online data before redirecting it to analytical platforms. It should be dynamic and sensitive to the incremental changes in the data or knowledge base. It must be flexible instead of relying on outdated and rigid guidelines that may lead to erroneous decisions. It should be able to integrate multiple channels of historical data, field observations, and other offline diagnostic reports for general health assessment. It should rely more on pattern recognition to remember past trends and forecast a reliable future of transformer behaviour.

An internet-of-things (IoT)-based gateway must be available for the real-time transmission of diagnostic data to the analytical platform that may be present as an in-premise or cloud solution. Due to the proven benefits such as low carbon emission, low energy consumption, cost-effectiveness, and real-time access, a cloud-computing solution must be in place to assist with the diagnostic statements. Lastly, two-way communication using internet protocol and secure wireless communication must be present between the asset and the user for the remote administration of the now-digitised smart transformer. Conclusively, an intelligent and integrated transformer diagnostic framework can overcome many limitations of classical HI-models and software.

5. Cybersecurity and privacy threats

Broadly speaking, digitisation of transformers with contemporary communication devices can expose the asset to cyber vulnerabilities. Virtual attack on metering devices may increase the risk of data tampering and reduce computing capacity. It can leak temporal information about the asset and hence revoke its access. Similarly, malicious manipulation of IEDs can disrupt the normal operation of the grid by reducing the accuracy of relayed information and can be particularly distressing for the operator. To mitigate some of these challenges, dedicated efforts are in place to improve the temporal information relays using phasor measurements units (PMU) and forensic technologies. Transaction gateways are becoming more secure with the help of various fraud detection algorithms to protect user information and data from breaches [9, 10].

As mentioned earlier, the quantitative storage and analysis of big data is the key to an intelligent diagnostic framework. However, there is a perpetual risk of the security breach and privacy error between the analysing algorithms and end-to-end communication channels. Although communication protocol such as IEC 61850 is quite popular for synchronising the control and automation devices in a smart-grid over a wireless network, there is still a general lack of well-documented messaging protocols to integrate built-in devices with AI / ML platforms and communication routers.

6. Discussions

It is evident by now that this paper is exploring opportunities and challenges in digitisation of TCMs that requires

an elaborate and multidimensional approach. There is a general inclination among various end-users towards aggressive procurement of hardware components while raising concerns over their costs and accessibility of diagnostic software, particularly for small-scale and non-expert users. Even for a so-called digital transformer containing various hardware components, offline / laboratory testing and field experiences are pivotal for factual verification of online monitoring results. Similarly, there is also an ominous need to upgrade the existing diagnostic practices that are still somewhat outdated by using advanced data analytics tools.

To ensure that a "digital" transformer can self-diagnose, it requires a sustainable platform for the integration of various digital, analogue, and intelligence technologies, preferably as a safe cloud-computing solution in real-time. With the explosion of AI technologies, it is the right time to encourage the transformer industry to think beyond their over-reliance on outdated practices and motivate them towards smart innovation. For example, AI-based maintenance schemes can analyse and adjust the loading profile of transformers by interpretation of online and digitally processed offline data. For grids that are still in the stage of digital upgrading (particularly in the Asia-Pacific nations), it can allow real-time feedback irrespective of the "digital" status of their assets. This ensures greater visibility and stress avoidance on the entire grid that may be particular to a specific unit.

Cloud computing using AI / ML tools can promote low-cost, real-time and multi-device control and management of digital transformers

Despite the slow evolution of transformer design, the industrial response to changing materials and technologies is relatively dynamic. Decade-old diagnostic protocols are being replaced with upgrades as per class and specification of materials. There is a lot of ongoing effort in improving the hardware and software experience of TCMs; however, an analytical revolution that is sustainable for a smart-grid operation is yet to happen. Obviously, the asset owners need to have a clear vision of their diagnostic goals (i.e., predictive maintenance and asset management) and resources to ensure appropriate selection of method(s) that are compatible with such integrated frameworks. Nevertheless, they must explore the opportunities to rely on a relatively data-driven model rather than a rigid and somewhat outdated rule-based system.

Data scientist, computer engineers, and mathematicians are already contributing towards improving the self-learning abilities of such integrated frameworks with respect to incremental changes in the database. Therefore, active industry professionals and researchers must continue their work on assimilating their technical and market experiences from such initiatives so that the desired standardisation is achievable in future. Besides, digitisation of TCMs is soon going to become a necessity instead of an option.

> **Integration of digital technologies is the key to mitigating the disruption in power supply and distribution network**

Conclusions

Integration of digital technologies is the key to mitigate the ongoing disruption in power supply and distribution network. A digital transformer can support a smart grid that boasts about an efficient and cost-effective operation by becoming an independent and intelligent node in itself. With the increasing number of hardware components, it is necessary to have an integrated and comprehensive platform for management and analysis of the monitoring data. Besides, such efforts can counteract the storage and handling of big data that may be generated due to such measures. There is an ongoing effort to standardise the diagnostic protocols for such integration frameworks partially. However, high cost, ambiguous diagnostic opinion, data uncertainties, privacy, and cyber-security issues threaten such solutions and restrict their large-scale industrial implementation.

There is a monotonous reliance on hardware manufacturers and diagnostic server providers. It is a fact that the aggressive sale of hardware devices (for both on- and offline monitoring) drives the present TCMs market worldwide. No third-party or open-access solution exists that can mitigate the diagnostic contradictions from such devices while staying out of the conflict-of-interest of manufacturing and supplier companies. This leads the user to prefer in-house experts and / or digital solutions as per the recommendation of such companies. It drives the users' interest away from obtaining an updated and holistic diagnosis of their assets. Hence, digitisation of transformer condition monitoring and diagnostic systems must be adequate, efficient, low-cost, easy access, and user-friendly.

Acknowledgements

The authors are thankful to Dr. Sushil Chaudhari (Raj Petro Specialties Pvt Ltd., India), Mr. Alberto Zotto (Studio Zotto, Italy), and Mr. Paul Guy (Smart Grid Solutions, Australia) for their valuable inputs as our advisors during the construction of this paper.

Bibliography

[1] A Naderian et al., *An approach to power transformer asset management using health index*, IEEE Electrical Insulation Magazine, Vol 25, No 2, pp. 20-34, 2009

[2] G Brandtzæg, *Health indexing of Norwegian power transformers*, Master's thesis, Norwegian University of Science and Technology, 2015

[3] CIGRÉ Working Group Number A2.47: *DGA monitoring systems*, 2019

[4] CIGRÉ Working Group Number A2.44: *Guide on transformer intelligent condition monitoring*, 2015

[5] CIGRÉ Working Group Number D1.11: *Data mining techniques and applications in the power transmission field*, 2006

[6] P Pitcher et al., *Use of health index and reliability data for transformer condition assessment and fleet ranking*, CIGRE Paris Session, A2-101, pp. 1-9, 2014

[7] M. Zarkovic, Z. Stojkovic, *Analysis of artificial intelligence expert systems for power transformer condition monitoring and diagnostics*, Electric Power System Research, vol. 149, pp. 125-136, 2017

[8] S. Chakraborty, A. Zotto, *Intelligent management of substation assets*, Transformers Magazine- Special Edition, pp. 94-99, 2019

[9] H. Ma et al., *Smart transformer for smart grid- intelligent framework and technique for power transformer asset management*, IEEE Transactions on Smart Grid, vol. 6, No. 2, pp. 1026-1034, 2015

[10] J Liu et al., *Cyber security and privacy issues in a smart grid*, IEEE Communications Survey and Tutorials, vol. 14, No. 4, pp. 981-997, 2012

Authors

Sruti Chakraborty has a PhD in chemical engineering from Malaviya National Institute of Technology in India. She is the technical founder of SeetaLabs (Italy) with a huge passion for developing low-cost solutions for risk management and failure mitigation in industrial assets. She works closely on various issues related to transformer health and performance optimisation. Her research interest includes condition monitoring, alternative dielectric fluids, process modelling, and non-linear control. She has several scientific contributions in various journals and conferences of high repute and is a winner of two academic awards.

Marius Grisaru has an MSc in Electro-Analytical Chemistry from Israel Institute of Technology. He has almost three decades of extensive and worldwide experience on oil sampling, diagnostic testing, planning, treatment, and recommendations. He is responsible for establishing test strategies and procedures for creating acceptance criteria for insulation liquids and materials, based on the current standardisation and field experience. He trains and educates electrical staff on insulation matrix issues from a chemical point of view. He is an active member of relevant working groups of IEC, CIGRÉ and a former member of ASTM. He has made several scientific contributions in various journals, magazines, and conferences of high repute. Currently, he is advising SeetaLabs as a domain expert on transformer diagnostics.