Intelligent management of substation assets

Application of artificial intelligence for transformer management

ABSTRACT

Transformers are critical and expensive assets in substations that require meticulous monitoring and control to ensure grid integrity. Various tests that are available can determine the condition of transformer by diagnosing the health of active components such as insulating paper and mineral oil, windings, bushings, tap changers, etc. Some of these tests can be time-consuming, expensive, intrusive, and require some level of expertise. They can also lead to accumulation of large volumes of data that may be challenging for the service engineer to process without suitable scientific backing. In this context, artificial intelligence (AI) finds immense popularity among asset holders, researchers and service engineers who are looking to improve transformer performance by efficient and economical means. AI-based methods imitate the human brain in order to process and convert raw data to draw meaningful inferences. They are typically data-driven i.e., they can identify, locate, and eradicate redundancy in input data, thereby reducing the computational burden. When a large fleet containing both new and old transformers is concerned, such tools can be remarkable in prioritizing the grid management strategies and evaluating the cost-effectiveness of various assets. It can also reduce the time needed for knowledge transfer by end-to-end digitization of the utility data and convert it into simple linguistic inference that can assist the service engineer in deciding what are the necessary preventive or corrective actions quickly and efficiently. AI-based tools show tremendous potential in becoming an intelligent alternative for substation asset management despite their challenges. This article is a discussion on such aspects of transformer management in context of AI applications along with its strengths and limitations.

KEYWORDS

transformer management, condition monitoring, artificial intelligence, data-driven modelling, asset maintenance activities

With the upsurge in energy demands and newer deregulation rules, companies are looking forward to the use of intelligent tools for smart grid maintenance

1. Introduction

Substations are the nodal points in electricity transmission and distribution network containing key assets such as transformers, circuit breakers, switch gears etc. Transformers are particularly critical and expensive assets in substations with high performance and life expectancy. Transformer performance diminishes dramatically with deterioration of its insulation health under various operational stresses and it ultimately affects the integrity and reliability of substation grids.

With the upsurge in energy demands, substations are under tremendous pressure to increase the asset utilization and control the maintenance costs without compromising the quality and continuity of power supply. Besides, numerous transformers of varying age and risk levels are present within a fleet, which makes it more challenging to manage.

In this context, the use of qualitative indicators, such as health and risk index, is gaining popularity when it comes to deciding on suitable preventive or reliability centred actions for transformer maintenance. With combined knowledge of condition assessment, transformer data, operational history, and field observations, they are critical for interpreting the true nature of fault and urgency of human intervention before the ultimate loss of asset. As they depend of condition assessment information, there can be an unwanted accumulation of data that may be challenging to process without scientific backing.

Recently, artificial intelligence (AI) based transformer assessment is becoming increasing popular for its impeccable data handling, storage, and analytical capabilities. It can substantially reduce the computational burden and time of index calculation by using algorithms and integrate them with standard recommendations and industry practices. Due to its data centric nature, it does not require previous knowledge on the inner working of transformer fault. Hence, it is easier for a non-expert to conceptualize, customize and utilize the outcomes from such assessments to make quick action plans.

Various artificial intelligence techniques such as neural network, expert systems, fuzzy logic, etc., are successful in evaluating the health and risk indices through suitable algorithms. However, their practical application regarding substation management is scarce due to several data-oriented challenges. This provides a wide platform for further research on improving and integrating AI frameworks that can be suitable for substation transformer management by quick and economic means.

2. Transformer asset management

ISO 55000 [1] defines asset management as the comprehensive activities pertaining to the maintenance and monitoring of economically significant components i.e. assets. While the generic definition of transformer asset management may be arguable in nature, it is still an organized method of improving the reliability of a grid supporting a large fleet of transformers. Typically, transformer asset management comprises of three activities namely, condition monitoring, fault diagnosis, and end-of-life estimation. These activities are critical in deciding the future maintenance and repair/refurbishment work.

Fault diagnosis in transformers stems from condition monitoring of insulation materials through various electrical, physical and chemical diagnostic tests. For example, oil quality analysis can predict the immediate status of insulation, while dissolved gas analysis and furan testing can provide early prediction of internal faults and age of a transformer. When the preventive maintenance is combined with the risk assessment of

Managing large transformer fleets can be challenging by using condition assessment only

For ranking assets in order of their operational status it is necessary to use appropriate qualitative indicators

utility, it leads to reliability centred decisions that can be very beneficial for holistic assessment and management of the assets. To avoid false conclusions based on individual results, it is advisable to convert the quantitative information obtained from various diagnostic tests into qualitative indicators, such as health and risk index, for maximum benefit.

2.1. Health and risk index

Health index (HI) is a cumulative assessment of a transformer using condition monitoring data, service history, laboratory and field information, and expert observation. It may include the condition assessment information from various routine and diagnostic tests pertaining the active components e.g. oil and paper insulation, winding, tap changer etc., into a single framework. Typically, transformer HI varies between 0 - 1, 1 - 10 or 1 - 100. By allocating specific meanings to the HI thresholds (within these ranges), identification of parameters that have more involvement in the deterioration varies with the expert opinion as it depends on the industrial recommendations and service history of the transformer. Since it is also an indicator of the asset age, HI evaluation can be helpful in strategizing the routine maintenance of rapidly deteriorating assets in a fleet. Thus, it provides the techno-economical justification for repair, reinstallation or refurbishment of underperforming and risky assets even within a grid.

A transformer is assumed to be at risk when there is a high probability of fault occurrence and consequential failure thereby reducing its performance and life. Risk index (RI) of transformers is a cumulative assessment based on fault diagnosis outcomes and the economic aspects related to these occurrences. It is based on analyzing the true nature of fault and its probability of occurrence along with the cost-benefit analysis of maintenance activates. Besides, it can identify the defective assets to carry out adequate reforming activities in order to avoid complete failure of supply grids [2, 3]. The existing model of health and risk indices uses completely different strategies for calculation purposes. Hence, a combined correlation, empirical or stochastic, is not possible.

2.2. Is it feasible to use a coupled HI-RI model?

It is evident from Figure 1 that health and risk indices of transformers are often evaluated using separate models. It is noticeable that an integrated model containing health and risk indices can be very effective in managing large fleets through cost-effective means. However, it may require a lot of information that can be challenging to process manually. With the evolution of computational intelligence, service providers and asset holders are now looking forward to the smart management of grids and utilities. The state-of-the-art developments in this field are resolving such issues with the help of AI through machine learning (ML) and other data-driven methods. The challenges associated with such an integrated approach (data availability, acquisition, and storage) are constantly addressed by various state-of-the-art methods.

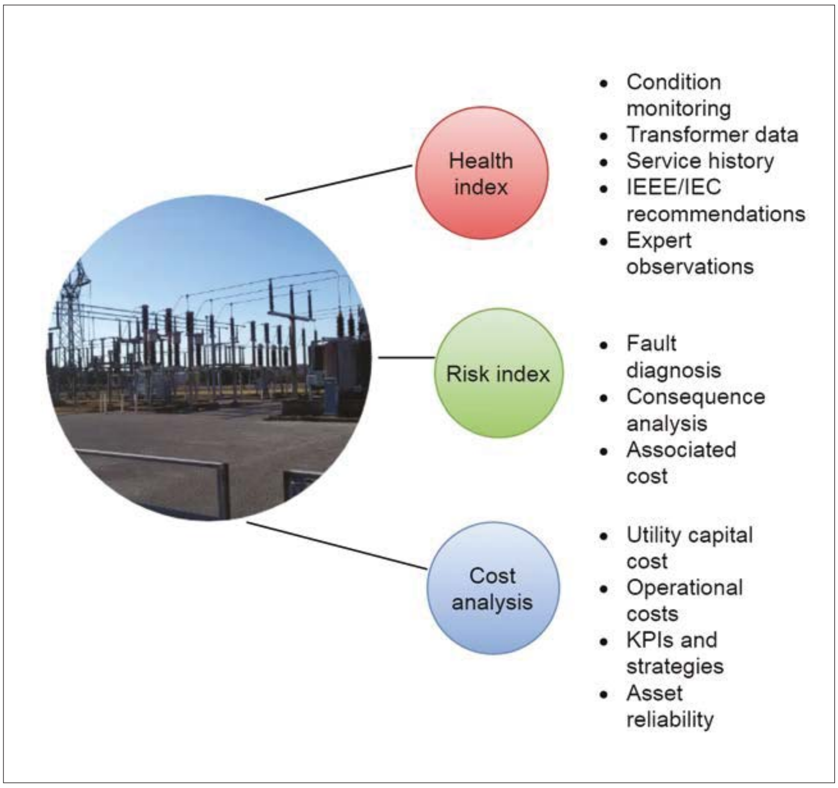

Figure 1. Typical framework of transformer asset management [3]

3. AI applications for transformer management

As discussed earlier, reliable condition monitoring and fault diagnosis of electrical transformers can significantly improve the techno-economical performance of substation grids. In order to achieve this, it is necessary that the service engineers have sufficient information on the asset health in order to identify the nature of fault and predict the necessary preventive or corrective actions. With the developments in online sensors, information concerning some condition monitoring parameters such as gas in oil, water content etc., are perpetually available. However, such information is available in the form of digital signatures that requires expert assistance to understand.

Despite the evolution of various HI and RI models, the complications related to assimilation of data from various sources, its effective storage and processing is still present. As an example, the existing fault diagnosis method requires an in-depth understanding of the fault mechanism and sufficient experience in handling faulty utilities. Besides, it is imperative that the expert can assimilate necessary data from various sources to draw meaningful inferences. Such computations may be complicated, risky, and may induce a delay in knowledge transfer between the asset and the engineer. It can also increase the economic burden on the service providing companies and/or other stakeholders. Therefore, there is an additional need for immediate end-to-end digitization of utility data to convert it into meaningful information that can provide assistance regarding quick and effective planning of the grid maintenance activities.

With AI application, transformer asset management is evolving in a suitable way to meet the needs of emerging smart grids [4, 5]. AI refers to the software implementation of biological capabilities used to perform cognitive functions such as learning, reasoning, and planning of activities to resolve a given problem. Vast availability of asset information, various state-of-the-art technologies, reformed utility philosophies and internet have changed the asset maintenance strategies tremendously, particularly by using artificial intelligence and machine learning. The change has been particularly impeccable in challenges related to data acquisition, storage, and handling. The existing research on this topic is relatively new and offers a lot of research scope to the stakeholders and asset provides, particularly when it comes to integration of various maintenance strategies. This article discusses some of the popular methods of AI implementation in context of transformer asset management in the following sub sections.

3.1. Artificial Neural Network

An artificial neural networks (ANN) refers to a computational model containing a web of several neurons in a hierarchical order. The information exchange through *neurons* (or nodes) occurs through specific channels or *synapses* and passes through an activation function to produce the desired outcomes. When multiple neurons or nodes of similar nature combine, they become a layer. The network topology of an ANN model depends on availability of information across these neurons. In order to develop a suitable ANN model, it is necessary to train the algorithm using a vast knowledge base to initiate self-learning within neurons.

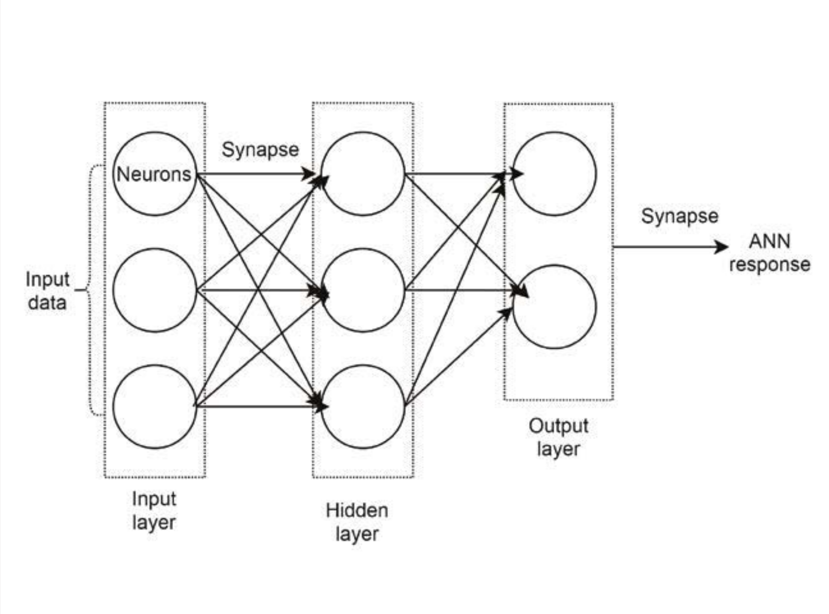

Figure 2. Simple representation of ANN architecture

Intelligent transformer management tools can provide quick estimation of the asset value and can be easy to use even for a non-expert

Figure 2 shows the primary architecture of ANN containing input, hidden, and output layers. As the name suggests, the input and output layers contain incoming information and outgoing response of the model respectively, and hence there cannot be more of them than one. However, multiple hidden layers may exist where the true processing of data happens.

The confidence of ANN prediction varies with the number of neurons and hidden layers, nature of transfer function, number of training iterations, etc. Accurate decision on the optimum number of hidden layers can be deciding factor for the performance of ANN model. Hidden nodes (existing within hidden layers) have an indirect relationship with the input and output nodes and their number depends on the nature of problem itself. Therefore, unnecessary addition of multiple layers can certainly increase the complexity of ANN model, thereby increasing the computational cost and burden.

3.2. Fuzzy systems (or fuzzy logic)

One of the primary disadvantages of ANN is the need for a vast knowledge base to enable self-learning based on algorithm training. While it has impeccable pattern-recognition strength, such models are ill equipped to deal with various data uncertainties. Moreover, decision making on the basis of imprecise or uncertain data using such methods may lead to false conclusions thereby producing catastrophic results. Therefore, it is necessary to use fuzzy systems that can approach the problem with an approximate reasoning instead of adhering to crisp definitions.

Fuzzy logic (FL) is a subset of fuzzy system that allows decision making through the development of various membership functions and rules using the available data. A membership function (MF) refers to the graphical representation

AI based tools are logical, user-friendly, cognitive, and function according to the nature of input data

of variable behaviour within definable boundaries. Fuzzification refers to the conversion of crisp data into imprecise information using suitable MF to explain the uncertainty. Moreover, fuzzification is simpler in comparison with de-fuzzification of data that converts imprecise information into crisp quantities. Figure 3 shows the popular transfer function used as MF during fuzzification and de-fuzzification of data. On the other hand, Figure 4 gives typical process-flow in a FL-algorithm.

Various applications of ANN are available for fault detection, condition monitoring, and health index evaluation of power transformers [6 - 8]. Similar applications using FL based algorithms are also available for power transformer management through various aspects [5, 9, 10]. While these algorithms are certainly smart, they face persistent problems pertaining to data uncertainty, extraction, optimization, and redundancy. In order to overcome this, the integration of optimization methods such as genetic algorithm (GA) and swarm intelligence (SI) can be very beneficial. These methods are biologically inspired and extremely helpful in optimizing the algorithm for quick and accurate prediction by creating an inductive set of the most useful data points only. Some interesting application of GA and swarm optimization (SO) for determining transformer HI using various sensor data is also available [11, 12].

3.3. Other alternatives

Recent evolutions in AI techniques have introduced several improvements including machine learning and other data-driven methods for higher precision and accuracy. Machine learning (ML) is particularly interesting and shows a promising future for transformer asset management purposes. An organized computational method such as ML can be of variable type depending upon the nature of data as shown by the figure below. These tools can be helpful in reducing the dimensionality of complex assessment problems by selecting and/or extracting crucial information from the available dataset. It can simultaneously optimize the learning route and quickly perform the allocated tasks with less computational burden. Various applications of ML algorithms to improve AI performance by integrating data classification and clustering frameworks are available in various research works. The primary aim of such contributions is to improve the fault prediction accuracy, condition assessment, and overall health index estimation in transformers [13-15].

Conclusion

With the upsurge in energy demands and newer deregulation rules, various companies are looking forward to the use of intelligent tools for smart grid maintenance. In this context, AI has been able to provide quick and reliable prediction of the true status of transformers by systematic analysis of the utility data. Although AI shows promising results regarding the improvement of the substation performance, there is a scope of further research to resolve various challenges pertaining to data uncertainty, availability, and extraction of the best data for effective analysis. It is also evident that single AI tool may not be sufficient in solving such problems. Therefore, it is necessary to integrate various (suitable) AI tools to overcome diagnostic problems e.g., fault classifi-

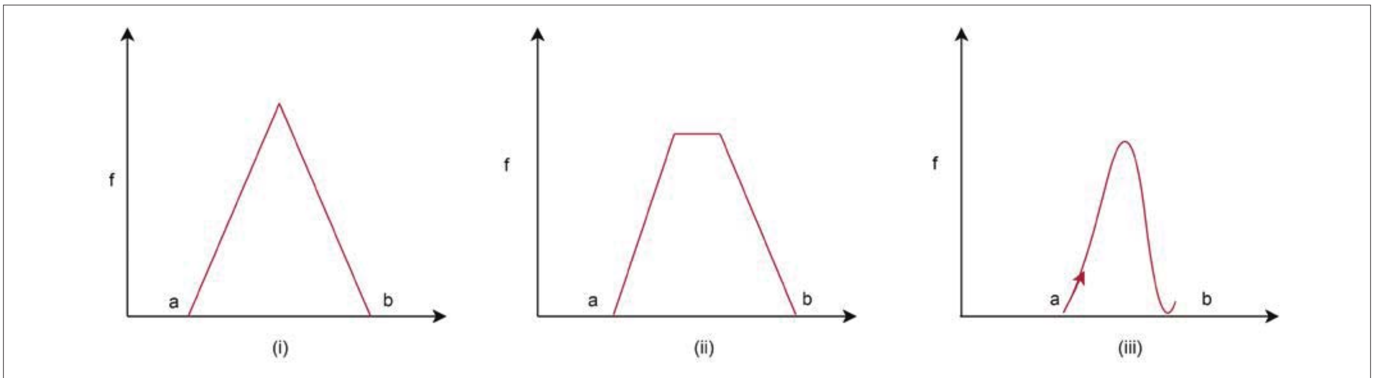

Figure 3. The data function (f) has boundaries (a, b) and can be (i) triangular, (ii) trapezoidal or (iii) Gaussian in nature

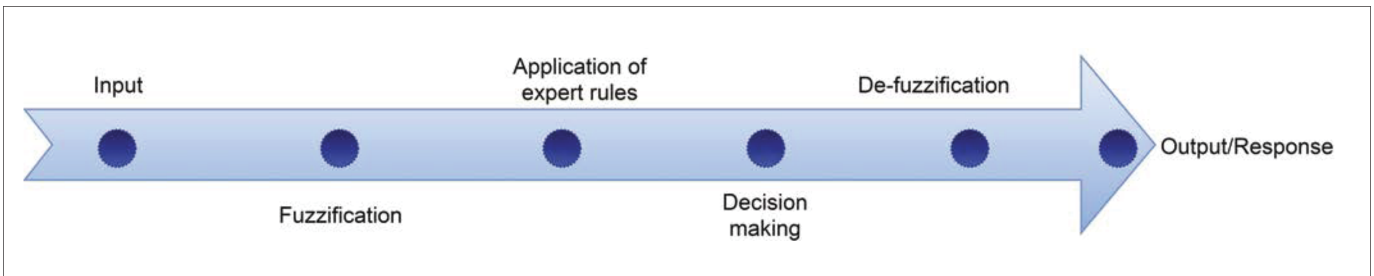

Figure 4. Process flow within a fuzzy system

cation, for an overall assessment of the health and status of transformers.

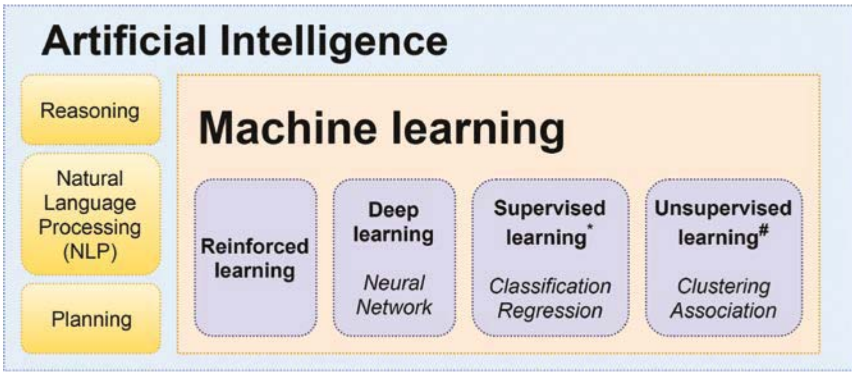

Figure 5. Various aspects of machine learning (Algorithm is *affected and #not affected by the difference in actual and targeted output values)

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