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REVIEW ARTICLE

A review of power system protection and asset management with machine learning techniques

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Abstract
Power system protection and asset management have drawn the attention of researchers for several decades; but they still suffer from unresolved and challenging technical issues. The situation has been recently exacerbated in the wake of the ever-changing landscape of power systems driven by the growing uncertainty and volatility subsequent to the vast renewable energy integration, more frequent natural extreme events due to climate changes, increasing malicious cyberattacks, and more constrained transmission systems as the result of load growth and limited investments. On the opposite side, the proliferation of advanced measuring devices such as phasor measurement units, emerging electric and non-electric sensors, and Internet of Thing (IoT)-enabled data gathering platforms continually expand/nourish the databases; they hence offer unprecedented opportunities to take the advantage of data-driven techniques. Machine learning (ML) as a principal class of artificial intelligence is the perfect match solution to this need and has newly revoked many researchers' interests to tackle the problems excluding their exact/detailed models. This paper aims to provide an overview on applications of ML techniques in power system protection and asset management. This paper elaborates on issues pertaining to (1) synchronous generators, (2) power transformers, (3) transmission lines, and (4) special and system-integrity protection schemes. In addition to the opportunities offered by the ML techniques, this paper discourses on the barriers and challenges to the wide-spread application of ML techniques in real-world practices.

Keywords Machine learning · Power system protection · Asset management

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1 Introduction

The modern power systems continue to evolve, driven by technological developments, regulatory policy mandates, and climate and environmental issues [1, 2]. Nowadays, power systems are operating close to their nominal ratings, which dictates having access to effective real-time monitoring, powerful control, and fast protection countermeasures to maintain secure operation under incipient contingencies and extreme events [3, 4]. However, power system protection has always suffered from perfect functionalities due to the lack of persistently precise and dependable models, deficiency of the measurement devices, and difficulty of enumerating all possible scenarios. On top of these issues, power system protection is facing new phenomena imposed by intermittent renewable energies, demand-side participation, power electronics influx, and further malicious activities either in the system physical or cyber layer [5]. Such phenomena add to the dynamicity of power systems and render conventional control and protection models inefficient or even vain [5].

Power systems have been broadly renowned for being a capital-intensive industry, which is a genuine judgment since electrical power generators, power transformers, transmission lines (TLs), and distribution networks (DNs) are all extremely pricy assets with considerably long manufacturing/installation processes [6, 7]. The other unique aspect is the obvious expectation to have power system pertinent apparatuses running around-the-clock and for decades! The power outages, even as short as few minutes, are no longer bearable and might engender serious adverse influences on human life and society/community affairs. As a direct result, any approach to monitor, care, and prolong the operation of power system equipment would be of an urgent need and great value. By definition, *power infrastructure asset management* is the combination of sorts of practices and wisdom such as engineering, management, and economics applied to the worthy physical assets of power systems with the main objective of securing the best value level of service for the expenses involved [8]. Asset management spans the entire life cycle of design, construction, commissioning, operating, maintaining, repairing, modifying, replacing, and decommissioning/disposal of equipment [9]. In the operating and maintaining phases, condition monitoring (CM) systems are the main entity in charge to fulfil the early identification of the progressing defects right before the interruption of the service [10, 11]. Ironically and as a matter of fact, the management of physical assets of the power system could be challenging since they are mostly outdoor facilities (transformers, TLs, DNs) and even situated in unguarded terrains (TLs and DNs). They are hence naturally exposed to harsh ambient conditions and external invasions. Furthermore, some of the failure mechanisms of these apparatuses are not thoroughly digested as yet; hence they lack dependable models. This situation pushes us to the boundaries of our classic monitoring, maintenance, and management approaches.

Although a long path has been paved to develop the model-based approaches for power system protection and asset management, machine learning (ML) techniques, in either sort of supervised, unsupervised, or reinforcement learning

Table 1 Machine learning techniques and features

ML Class	Main features
Supervised learning	Labeled Data and Task Driven Classification/Regression Algorithms Suitable for Diagnostics/Prediction Application
Unsupervised learning	Unlabeled Data and Data Driven Clustering/Dimensionality Reduction Algorithms Suitable for Pattern/Structure Recognition
Reinforcement learning	Rewarding/Punishing Mechanism Clustering/Association Algorithms Suitable for Decision Making Process

(Table 1), come up very promising to resolve the associated questionable facets [12, 13]. These data-driven techniques are based on exploratory data analyses, involving computational statistics and data mining [14, 15]. Supervised learning uses labeled training data to perform function mapping between system inputs and outputs. Training performance would be satisfactory if training data covers enough scenarios to address various credible conditions. In real-world implementations, it can be challenging for training data to cover these scenarios without relying on simulation tools. Artificial neural networks (ANN) are a supervised learning technique that has been used widely to detect/classify faulty conditions [16]. Unsupervised learning uses datasets that are neither labeled nor classified. It looks for similarities and differences in the dataset and can cluster the data into distinct classes. Intuitively, unsupervised learning can also detect anomalous data that does not belong to an existing category [17]. Support vector machine (SVM), although is basically recognized as a powerful method for classification (supervised learning), is found as an efficient and conducive approach for clustering (unsupervised learning) as well [18]. Reinforcement learning is applied if the decision-making environment is uncertain or complex. In order to reinforce its learning, the machine uses reward/penalty functions to guide decision making, without relying on labeled input/output pairs [19, 20].

Most recent advances in the ML domain, including less-supervised and unsupervised machines to relieve the human interventions as well as deep learning algorithms suited for highly nonlinear systems, portray a more promising future for successful implementation of ML algorithms. Deep learning imitates the way humans gain certain types of knowledge and utilizes a hierarchical level of ANNs to effectively carry out the process of ML in a complex abstraction. Each level of abstraction is created with knowledge that was gained from the preceding layer of the hierarchy [21].

Fuzzy logic, as a powerful means to capture the expert knowledge with linguistic variables and to tackle the uncertain and imprecise situation with co-occurring inference rules, has now become an indispensable part of ML in real-world applications [22]. A fuzzy inference system uses fuzzy set theory to map a system's inputs (called "features" in classification problems) to its outputs (called "classes" in classification problems). To do so, the membership functions of linguistic variables are defined and if–then rules are extracted to map all credible combinations of input variables with one or more output variable. A set of if–then rules is then leveraged to explore possible scenarios for the output variables. The defuzzification process eventually produces a specific value for each output variable. In this process, fuzzy sets and corresponding membership degrees, result in a quantifiable crisp result. As it uses multiple rules per any situation, fuzzy logic theory is intrinsically robust against noise/errors in input variable measurements [23, 24].

With the spotlight on industrial electronics solutions and seamless communication capabilities, the landscape of power system measurement, particularly at the distribution level, is evolving to benefit from the abundance of smart meters, intelligent electronic devices (IEDs), phasor measurement units (PMUs), and various sorts of emerging sensors mainly enabled by the internet of things (IoT) technology [25, 26]. These facilities and platforms enrich the power system control centers in terms of data availability and accessibility and gradually realize ML techniques applications. ML approaches bring forth unprecedented opportunities for developing adaptive and reinforcing solutions for power systems problems. Just to name a few, ML techniques were successfully used to predict load curves [27, 28], schedule outages [29], predict photovoltaic and wind power outputs [30, 31] and energy management implementations [32], forecast spot electricity prices [33], make decisions in electricity markets [34], run contingency analysis [35], specify the impact of hurricane on power system components [36], and develop adaptive emergency control schemes to solve system uncertainties and variations [37].

This paper scrutinizes the inadequacy of analytical methods and available models in addressing protection and asset management of modern power systems and elaborates the emerging techniques enabled by ML science. Various sorts of applications ranging from component protection algorithms, system-wide protection schemes, anomaly detection methods to visualization and early alarming techniques are investigated. Furthermore, the technical and non-technical barriers to having widespread real-world applications of ML-based protection and asset management techniques are discussed here. Therefore, this paper can be considered as a high-level overview on the huge and endless domain of ML applications.

In the remaining, we first focus on the opportunities of ML techniques in power system protection and asset management. Section 2 elaborates associated applications for synchronous generators (SGs), Section 3 for power transformers, Section 4 for TLs, and Sect. 5 for special and system integrity protection schemes (SIPS). In Sect. 6, we discuss the challenges and barriers against broad deployment and implementation of ML techniques in power system protection and asset management. Section 7 summarizes the paper.

2 Synchronous generator (SG)

2.1 Background

SGs are exposed to the multiple electrical faults, which are shown in Fig. 1. Therefore, both protection schemes and CM systems are significantly important.

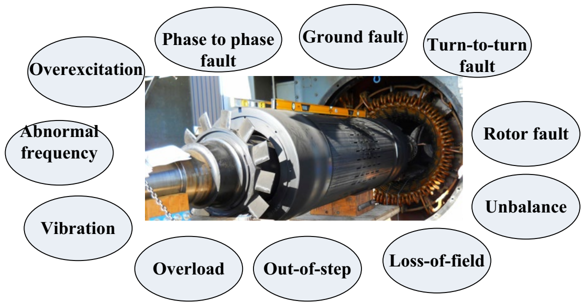


Fig. 1 Different fault types in the SG

To quickly detect faulty conditions in a turbine-generator unit and also to decrease the number of the corresponded relay maloperations, it is necessary to develop a reliable protective scheme. In addition, CM of the SGs plays a critical role to prevent unexpected failures. The main differences between the protective relays and CM systems are the severity of faults. When the fault severity becomes endanger, protection relays issue trip command. However, CM systems prevent damages at the beginning of the fault progress.

Nowadays, the protection of the SG is accomplished by a variety of philosophies. Figure 2 shows a traditional protection scheme that is usually adopted in power plants. During some faulty conditions, more than one protective function may issue the trip command and thus the fault discrimination may not properly be granted. In addition, there are some sorts of faults that the traditional protection schemes cannot absolutely address. Accordingly, ML techniques can considerably enhance these deficiencies. In addition, ML can offer unique opportunities to be exploited in the SG CM systems.

A. A. Faults, the Corresponded Industrial Protections, and ML Applications

1. 1. Stator short-circuit fault

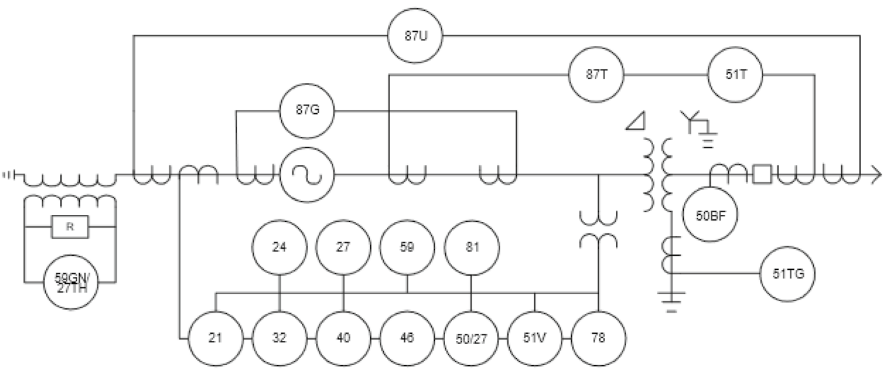


Fig. 2 Typical protection scheme of the SG [38]

These types of faults can occur due to insulation failure of the stator windings. Different types of stator windings faults are as follows.

Ground fault The ground fault is one of the most prevalent short-circuits in SGs. A high magnitude ground fault current results in an excessive amount of dissipated energy at the fault point which can damage core laminations [39]. In such a case, to repair the SG, there is needed a considerable amount of capital and time to remove all the stator windings and replace the damaged parts. Since the ground fault results in imposing destructive damages to the generator, the neutral point of the SG is connected to the ground grid through a high impedance to limit the magnitude of the ground fault current. This issue results in existing protection schemes being desensitized; they hence cannot appropriately detect this fault.

Phase-to-phase fault This fault may occur at the end portion of the stator coils or in slots if the winding involves two coil sides in the same slot. Although phase-to-phase faults are less common, the fault current is considerably high and is not limited by the impedance located at the neutral point. Therefore, it is highly crucial to detect this type of fault rapidly and properly.

Turn-to-turn fault This type of fault, although is rare, involves a significant fault-loop current. Ironically, the traditional SG protection systems would be blind to detect this type of fault.

The main protective function against the aforementioned faults is the differential function (ANSI code 87). However, this function has some limitations for detecting turn-to-turn faults and also the ground faults near the neutral [40]. In addition, the security of this function during current transformer (CT) saturation, inrush current, and over-excitation conditions may become endangered. In practice, there are several backup stator ground fault protection schemes to improve the mentioned deficiencies, including:

59N The neutral fundamental frequency over-voltage scheme generally performs well for detecting faults up to 90–95% of the stator winding. Protection of the remaining 5–10% of the winding toward the neutral point is challenging due to low induced neutral voltage during fault conditions.

64S The sub-harmonic voltage injection scheme may protect 100% of the stator winding. However, its application depends on accurate identification of the SG capacitance to ground [41].

27TH To protect 100% of the stator windings, the third-harmonic schemes are used along with the 59N scheme [42]. In some SGs, the third harmonic voltages at the generator neutral and terminal vary due to generator loading, power factor variation, and system disturbances. These variations make the third-harmonic schemes to be insecure.

Differential split phase In the case of a machine with several branches per phase, the turn-to-turn fault can be detected by employing the differential split-phase relaying scheme. However, for SGs with a different configuration, an alternative solution is needed.

Phase distance This function measures the impedance on the terminal side. It should be noted that function 51 V is another method of providing a backup protection scheme. The sensitivity of these functions is insufficient to completely detect turn-to-turn and also the ground faults near the neutral.

To cope with the mentioned drawbacks, the use of ML techniques is proposed in the literature. Fault detection in SGs is one of the areas of intensive application of ANN because of their superior learning, generalization features, and fault-tolerance capabilities. Neural network principal component analysis (PCA) has been successfully used as a pattern classifier [43]. This technique makes the decision based on the current signature verification, which is more accurate than the traditional method. Optimal probabilistic neural network (PNN) has also been adopted as the core classifier to discriminate between inrush and internal fault [44]. A novel approach based on a decision tree (DT) for discrimination between inrush and the internal fault with better accuracy was presented in [45]. Three parallel ANNs were used in [27] for classifying three aforementioned different fault cases. Another scheme was offered in [28], where two separate ANNs are used for fault detection and fault classification. An advanced version of this method using both fuzzy logic and ANN has been shown in [46].

2. 2. Rotor short-circuit fault

Ground faults in the rotor side of SGs cannot cause any damage to the machine because the corresponded circuit is ungrounded [47]. However, if a second fault occurs, a part of the rotor will be short-circuited, which results in vibrations and also stator voltage unbalance. In addition, locating the ground fault is usually a costly and laborious process. Locating rotor ground faults needs the generator to be removed from service and, then, the rotor to be extracted. Adopting ML techniques for detecting and also locating rotor faults would be an interesting idea in this context.

3. Loss-of-field (LOF)

LOF detection is one of the functions of SG protection. LOF is experienced due to interruption of the field DC source, subsequent to abnormal events, e.g., field open-circuit, field short-circuit, accidental tripping of the field/exciter breaker, failure of the regulator control system, and loss of AC supply of the excitation system [48]. An LOF event can result in: (i) stator winding excessive currents, (ii) induced AC voltage/current in the field winding, (iii) electro-mechanical oscillations of the turbine-generator shaft system, (iv) stator end-core overheating, and (v) voltage instability due to excessive reactive power absorption by the generator [49, 50]. Therefore, it is imperative to rapidly and securely detect LOF conditions and activate appropriate countermeasures to prevent adverse effects.

Although there are some approaches to detect LOF, they exhibit sensitivity to severe power system disturbances. Existing LOF functions may not provide comprehensive security during system disturbances, and the NERC report [24] has indicated that they resulted in a number of LOF relay mal-operation during the North American blackout event. Smart and intelligent approaches based on the ML algorithms such as ANN and DT [51], fuzzy logic [52], SVM [53, 54] would be outstanding approaches to robustly detect LOF. The mentioned tools are constructed over a comprehensive list of operational and topological scenarios.

Unlike the traditional relay, these methods can distinguish between the stable power swings and actual LOF conditions. The merit of the ML algorithms depends on the feature selection and robust classification.

4. Out-of-step (OOS)

Subsequent to a disturbance, the power system equilibrium is disturbed which results in the acceleration/deceleration of the rotating shaft of each turbine-generator unit. If a rotor angular speed becomes temporarily larger than the others, its angular position relatively advances. If the short-circuits near the generator terminal occur and last longer than the critical clearing time, the generator loses its stability and moves into an asynchronous mode of operation. During minor abnormalities, the SG keeps its stability; however, the one is usually followed by a stable power swing emergence. Angle instability results if the system cannot absorb the kinetic energy corresponding to these rotor speed deviations and this phenomenon is referred to as OOS condition [55]. The OOS condition can lead to severe oscillations in voltage, current, torque, position, and speed of the unit, while such oscillations will be also experienced by other turbine-generator units within the system. Therefore, it is imperative to detect OOS conditions and activate appropriate countermeasures to prevent instability.

The use of an impedance relay which includes blinders in the impedance plane and a timer is a prevalent industrial approach to detect OOS [56]. Disadvantages of this approach are: i) blinder and timer settings require information of the fastest power swing and the power system configuration, and ii) the OOS condition is detected after the fact, i.e., after its occurrence without provision to predict it in advance. Use of ANN, fuzzy logic, and DT methods are proposed in [57–59]. Reference [60] has suggested a method based on the K-means clustering pattern recognition technique. A method based on a heuristic algorithm that uses a load angle and angular speed of the generator is shown in [61]. The main advantage of these methods is their capability to predict the OOS condition and thus successfully distinguishes between the stable and unstable conditions. In addition, these approaches can provide considerable time to make an accurate decision before the rotor angle noticeably grows. This achievement significantly lessens the damaging stresses imposed on the SG during OOS conditions. Furthermore, the chance of the relays mal-operation in other parts of the network declines.

5. Volts/Hertz limiting

The Volts/ Hertz limiter measures generator terminal voltage and frequency. Since the SG flux density is proportional to the ratio of the terminal voltage and frequency, the aforementioned quantity would be measured. Excessive magnetic flux results in core overheating or failure in insulation between the core and laminations. This protective function maintains and limits generator flux density at the appropriate levels. The main challenge is obtaining the permissible time that

SGs can tolerate over-excitation. ML as a salient technique can represent a reasonable solution for this challenge.

6. Abnormal frequency

Load rejection (LR) and loss of generation events lead to the operation of SGs at the off-nominal frequencies, which can result in blade resonance and fatigue damages in the turbine unit [62]. Since control action during over-frequency may restore SG speed to the normal case, the concern about over-frequency is less than that of the under-frequency. Although load shedding schemes are adopted to restore frequency to the normal condition during under-speed scenarios, the amount of load shedding might be insufficient, which can impose destructive damages to both steam or gas turbines. This results in imposing destructive damages to both steam or gas turbines. Therefore, it is recommended that both under-frequency and over-frequency protections are adopted for the aforementioned turbines.

In this context, one of the interesting applications of ML is predicting the frequency behavior of the SG during system disturbances. Accelerating generator tripping for the severe disturbances can result in experiencing less off-nominal frequency conditions in comparison with the exiting protection methods, which are based on just frequency threshold and time delay.

7. Miss-coordination between SG and network

Mal-operations of the SGs protection during power system disturbances have highlighted the need for secured coordination with the power system. In addition, it is necessary to coordinate between the generator control and other control strategies of the power system in order to avoid system collapse. The coordination of the SG protection and control presents a number of challenges. One challenge is due to the method commonly used to determine SG protection settings, which is based on static characteristics representing generator capability, control limits, or even protective relay characteristics. The other challenge is that this coordination is performed offline. Doing online and dynamic coordination using ML techniques such as ANNs, fuzzy logic, and pattern classifications can provide an outstanding enhancement. In addition, these techniques are very effective for improving the performance of the power system protection.

2.2 CM systems and ML applications

CM is an effective method for improving the reliability and lifespan of SGs, which in turn can decrease the downtime and maintenance cost. There are two types of CM approaches including [63–65]:

(i) *Model-based* This approach relies on the comparison of a mathematical model of the SG and the measured parameters [66]. Based on the model, fault diagnosis algorithms are developed to monitor the consistency between the measured outputs of the practical systems and the model-predicted outputs. The main issue with this approach is that it cannot detect some of the faults at various operating conditions [49–67].

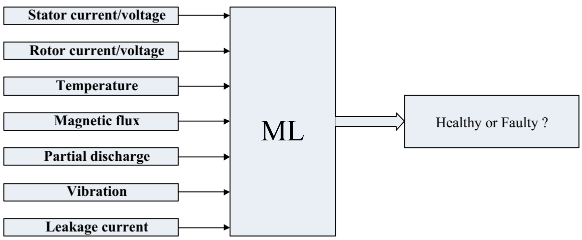
(ii) *Signal-based* This approach relies on the extracted fault signatures from the measured signals for CM. This approach itself can be categorized into twofold groups: (a) invasive, (b) non- invasive. The feature signals to be extracted for pattern analysis can be either time domain (e.g., mean, trends, standard deviation, phases, slope, and magnitudes such as peak and root mean square) or frequency domain (e.g., spectrum). Indeed, signal-based methods utilize measured signals rather than explicit input–output models for fault diagnosis. The faults in the process are reflected in the measured signals, whose features are extracted, and a diagnostic decision is then made based on the pattern analysis and prior knowledge of the patterns of the healthy systems. If sensors such as search coil or flux probe are inserted inside of the SG, the method is referred to as invasive type; otherwise, it is non-invasive. The measured signals are terminal current/voltage, exciter field current/voltage, core vibrations, field current, search coil voltage, partial discharge, and leakage current.

In this context, smart and intelligent approaches based on the ML algorithms such as ANN, fuzzy logic, and SVM reveal outstanding capability in accurately monitoring SG. To do this, the whole measured signals can be injected as input data to the ML process. After the training process, the ML tool can properly predict failures. Figure 3 shows a block diagram of the ML technique for this issue. In addition, there are some research works in the literature to monitor SG via ML. In [68], a time-based CM system using combinational ANN and fuzzy logic is developed to monitor SGs. The developed system is applied to predict the fault types of the mechanical system. In [69], the SG model is developed based on a memory matrix of the SG dataset. ANN is implemented to determine the condition of the SG by considering trends of parameter deviation during healthy and faulty scenarios.

2.3 Future trends

Based on the above explanations, ML can be used to enhance both protection and condition monitoring of the SGs. The ML system will offer instant diagnosis, which can help cut down on operational costs and improve the lifetime of SGs. In summary, some of the ML future trends are as follows:

Fig. 3 Block diagram of the ML technique for CM [24]



- *Model-Free Protection* Some protection schemes are based on SGs model. Indeed, to protect the SGs against a specific fault, there is needed to know the SG model. Based on input–output data, the ML algorithms including ANN, DT, and SVM, are able to offer a black-box model to be used as a model-free protection scheme.
- *Setting-Free Protection* One of the major challenges of the conventional protection schemes is to set the corresponded protection functions. This issue may result in decreasing both security and dependability of the protection system. Based on the ML system, it is possible to provide an intelligent protection scheme without needing any settings, i.e., to be setting-free.
- *Intelligent CM* The ML application can provide this opportunity to adopt both signal-based and model-based CM approaches. This issue results in increasing both accuracy and sensitivity of the CM process.

3 Power transformers

Power transformers are among critical and costly components in the global power delivery chain from power generating units to end-users [70]. Nowadays, the management of these assets is more important than ever before, and this can be due to several reasons. First, a vast number of transformer fleets in the world are approaching their end of expected life, i.e., they are aged, and this has raised the probability of transformer failures [71]. Second, the expenditure needed for their repair or replacement is extremely high. The profit losses because of outages in the time of transformer repair or replacement, which can even be up to a couple of days, should be added to this expenditure. It can be imagined that a power plant cannot operate due to the failure of its step-up transformer. Third, the consumers' expectations for more reliable services has been raised. On the other hand, the replacement costs of aged transformers are not affordable for many grid management companies. In such a circumstance, the strategy is to extend the transformer life as much as possible, and this can only be accomplished through advanced asset management of power transformers [72].

In transformer asset management, two important tasks have to be achieved. The first one is to predict a failure before its occurrence. This decreases the repair time and costs significantly and lets the operator perform a planned outage for corrective actions. The second task is the life prediction of a transformer. It is essential to anticipate the replacement time of a power transformer couple of years ahead. In this sense, the grid manager can plan the replacement and its associated costs. These two tasks are not straightforward, and this is where ML schemes can help. The following subsections give more details about the complexity of these tasks and the role of ML techniques.

3.1 Health monitoring

Transformer, as a very complex engineering system, has numerous subsystems depending on the size and type. Predicting failures and their diagnosis is a delicate, difficult, and challenging procedure. In a transformer, different phenomena, including mechanical stresses, chemical reactions, and electrical field stresses, can cause defects in a power transformer. Indeed, all of these phenomena might contribute to failure. Therefore, it is a dilemma to predict a failure reliably [73]. While a false prediction leads to unnecessary outages along with the possibility of damages during internal inspections, a lack of a proper alarm may be followed by a catastrophic failure.

There are multiple attempts in the literature to diagnose the transformer faults via simple models. For example, tables, thresholds, ratios of two or three parameters are used in standards for transformer diagnosis [74–76]. However, these methods are inaccurate and incapable of considering several factors simultaneously. Therefore, they go through revisions when new versions of relevant standards are released.

ML techniques can help to overcome this issue. They can be trained based on data from previous failures. The input can be of multiple natures, while the existing ML algorithms have applications in diagnosis based on only one category of results. A simple instance is an algorithm trained on the dissolved gases in several transformers [77]. Certainly, the failure data of these transformers are also needed, which is itself a challenge for ML techniques. The result is a trained algorithm, which can analyze further dissolved gas data to raise an alarm before failures in the early stages [78]. Although no simple model or function can be established from a large amount of failure data, the ML methods can succeed in this task by their complex learning algorithms. After the training phase, the machine can predict failures. Applying fuzzy sets and membership functions can be used to describe the evaluation of various test values in order to establish a multifactorial condition assessment model [79, 80]. For instance, suppose an expert system that analyzes several data types such as transformer moisture, temperature, loading, dissolved gas data, physical characteristics of the transformer oil such as the interfacial tension, chemical byproducts in oil, etc. to predict a fault. Such a complex environment cannot be modeled by simple linear systems, and advanced ML algorithms are in an urgent need.

Some other assessment methods are more complicated, and using ML for their evaluation is more reasonable and beneficial. For instance, the frequency response analysis (FRA) gives the transfer function of the transformer in the 20 Hz–2 MHz frequency range [81]. A change in the transfer function is an indicator of a fault, namely mechanical faults or shorted turns. However, the interpretation of such changes is a dilemma since the transfer function is different from case to case, while each fault type can also have diverse effects on the transfer functions [82]. Despite such complexity, ML algorithms can interpret the FRA results not only to indicate the existence of faults but also to determine the fault type or even the fault location [83]. Results of different fault cases provided from experiments or models are fed into a machine. This system is then trained based on the available data and can detect the next fault within FRA results. Accuracies of more than 98% are claimed in FRA interpretation based on ML techniques [67].

ML can also help to establish various models for monitoring the transformer status and predicting its capacity. Thermal models are a commonly used example of this case. The purpose of a thermal model is to predict the transformer temperature distribution in order to monitor its situation and define its overloading capacity. Several empirical factors and design-dependent parameters are needed for an advanced thermal model, which are unknown since they are not provided by manufacturers

[54]. Therefore, these parameters and factors have to be estimated. ML plays an important role here since ML techniques can estimate the unknown parameters from the temperature and loading data measured in the normal operation of the transformer [84]. The ML approach can also establish direct models in which the aforementioned parameters are not necessary. These models estimate the desired parameters, such as the overloading capacity, from the input parameters after a training phase [85].

3.2 Remnant life assessment (RLA)

Another complicated task is assessing the remnant life of a power transformer. Several factors contribute to the aging of a transformer. First, the temperature causes degradation of insulation material, especially the cellulose. Second, the moisture breaks the cellulose chain and participates in several chemical reactions. Third, oxygen leads to oil oxidation, which in turn starts secondary degradation reactions. Fourth, mechanical stresses weaken the paper and pressboard strength. Fifth, different acids or other corrosive materials take part in degradation phenomena. In the presence of these factors, it is not easy to define the remnant life since all these factors have interdependent relations, where some of them are still unknown [86].

There are some models for predicting transformer life. The main ones introduced in standards are only based on the transformer temperature, i.e., they assume that merely the heat degrades the insulation system. These models do not consider other effective factors. More advanced methods use the health index [87]. Here, a weight function is defined to consider the effect of several factors. However, the effects of aging factors are more complex than a simple weight function. Instead, a health index based on ML techniques is proposed in the literature as a superior approach [88, 89].

ML can consider all the aforementioned aging factors. Figure 4 shows such an expert system. All the effective data such as transformer moisture, temperature, acids, oxygen content, furanic compounds, and mechanical stresses (mainly short circuit events) serve as the input of the model [90]. Some of these data have integrating nature, i.e., their history is also needed for analyzing the remnant life. For instance, the history of the hot-spot temperature from the past up to now can give a prediction of the remnant life. In the first phase, the data of other transformers, which have reached the end of life, are used to train the system. In the second phase, the data of existing transformers are fed into the system to predict a remnant life. A ML algorithm can also combine the results of existing models for the RLA. For example, the output of several physical models, including the thermal aging models proposed in IEC and IEEE standards, can be combined in an expert system, which considers all of the important parameters [91]. To summarize, the ML algorithm can either establish the relations for RLA from scratch or combine the existing models for RLA.

ML can of assistance for improving the reliability of RLA by evaluating the accuracy of different tests and checking their validity. Moreover, when critical data are missing, the trained machine can produce such results based on other available data.

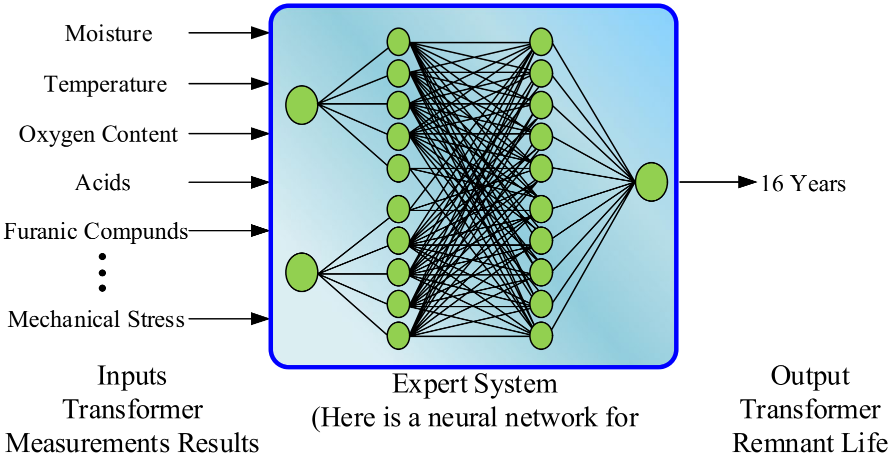


Fig. 4 An example of an expert system for RLA of power transformers

For example, the furanic compounds play an important role in assessing the transformer life. On one hand, there are various errors in its measurement. On the other hand, this parameter is dependent on other parameters such as oil breakdown voltage, water content, acidity, total combustible gases, etc. Therefore, a ML algorithm can be trained to predict the amount of furanic compounds from other parameters [92].

Another area where the machine-learning can have an impact is providing information on the data, which are not available or difficult to gather. As an instance, the degree of polymerization (DP) is a parameter that mainly determines the mechanical life of the cellulose in the transformer. This parameter describes the average number of glucose monomers in the polymeric chain of the cellulose. When this parameter falls below 150–200, the paper does not have enough mechanical strength and may fail in the next shot-circuit event. For measuring DP, it is necessary to drain the transformer oil and take a paper sample from the inside. This procedure can damage the transformer since a person should enter the transformer. Moreover, the DP is more critical in points with higher temperatures, e.g., around the winding conductor, but it is not possible to take samples from a conductor paper as the winding is covered with multi-layer insulation. As a result, even if the sample can be taken, the test result does not reflect the actual state of the transformer. The alternative method is to estimate DP from other parameters that are easier to measure. Some contributions try to reach the DP number via the furanic compounds. However, the results do not show a firm relationship between the furanic compounds and DP. Figure 5 shows the furanic compounds versus 1000/DP gathered from scrapped transformers, which indicates the lack of a consistent relationship between DP and the furanic compounds [93]. The main reason is that several factors influence the DP number [94]. In this circumstance, ML can be a solution since it can consider all the effective parameters in DP and find a relationship to define the DP number based on other available parameters. This helps the mechanical life assessment of the transformer

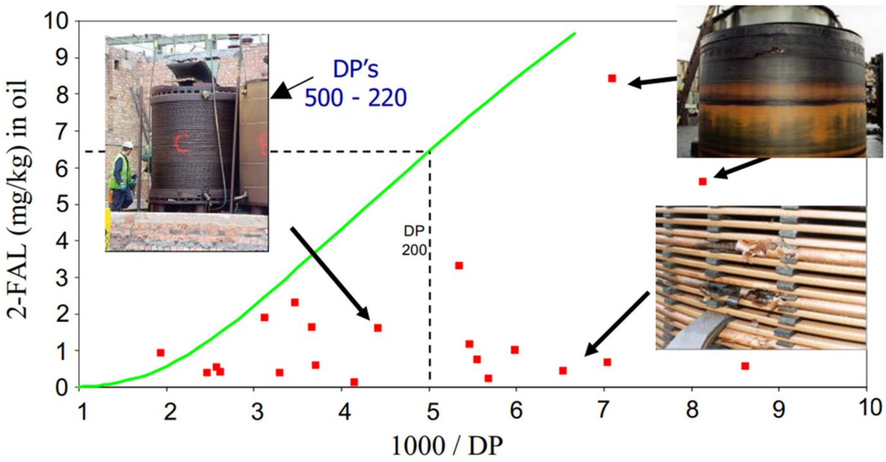


Fig. 5 2-FAL detected in the oil (mg/kg) versus degradation factor (1000/DP) from scrapped transformers [77]

significantly because the DP number is not available for the assessment in many cases.

3.3 Future trends

Two main areas can be distinguished as future trends of the application of ML regarding transformers. One of the main challenges for employing ML is that normally, there is not sufficient failure data available to be used for the training phase of the transformers. Therefore, a major effort is put into building reliable models for producing the required data for the training phase. In other words, it is intended to train an algorithm based on simulation data but use it to distinguish failure cases. It is noteworthy to mention that some of these models are made using ML techniques.

The next area is to develop ML algorithms to anticipate a failure ahead of occurrence. To achieve such an algorithm, it is needed to employ all the available data from transformers, which had failures in the past. The algorithm is trained to realize the changes of different parameters before the failure. Due to the complexity of the transformer structure, the effect of some parameters on certain failures is not known. However, an ML algorithm can build up a model based on available data to find situations similar to the pre-failure states of previous transformers and to raise an alarm. If such an algorithm is developed, a significant number of failures can be avoided.

4 Transmission line (TL)

TL protection plays a vital role in power systems not only to minimize equipment damage but also to maintain the system stability. With the restructuring of the electrical utility industry worldwide, today's power systems are utilized at smaller safety margins and, therefore, fast and reliable operation of protection systems has become much more important.

Although modern commercial protective relays are based on microprocessor technology, their basic principles are mostly inherited from traditional electromechanical relays. However, considering the probabilistic nature of the fault conditions, it may not be possible in some situations to definitely distinguish between internal and external faults using conventional algorithms. Indeed, the probabilistic nature that exists in the fault conditions with respect to the fault type, fault resistance, pre-fault load flow, remote-end infeed, etc., could lead to an overlap between the signatures of in-zone and out-zone faults.

Distance protection is the most common protection technique in the transmission network. Conventionally, distance relays estimate the fault loop impedance using local voltages and currents. The measured impedance is proportional to the distance of the relay to the fault point. However, the accuracy of distance relay is adversely affected by fault resistance combined with remote-end infeed, which is not measurable at the relaying point. The fault resistance not only adds a resistive component to the fault loop impedance, but also shifts the measured reactance due to the influence of load and infeed current from the remote bus. Accordingly, the measured impedance would tilt up or down in the impedance plane, resulting in the relay underreach or overreach problems. Moreover, substantial errors in impedance measurement can result from ignoring pre-fault system conditions and shunt capacitance influence, especially for high resistance faults [95].

The impedance measurement using phasors of local waveforms is, indeed, a mathematical problem in which the number of unknowns is more than the number of equations. The problem will become more complex in multi-circuit and other configurations of parallel lines due to the voltage induced by the mutual coupling between parallel lines and multi-terminal lines due to the infeed or outfeed currents from tap points. Meanwhile, the power system dynamics affect the accuracy of the fault distance calculation. Severe overreaches can occur unexpectedly, consequently affecting the selectivity of the protection system [96].

In this respect, ML-based approaches can help improve the protection system selectivity and dependability by providing more effective distinctive features and/or adaptive adjustment of the relay settings. From a general perspective, the ML-based approaches can be summarized in the following categories illustrated in Fig. 6.

4.1 Innovative protection algorithms with non-fundamental frequency components

Most conventional protection algorithms are based on the power frequency components of the measured waveforms. However, in some conditions, the power frequency components of the locally measured signals do not provide sufficient information to distinguish the fault reliably. It is worth considering that the non-fundamental and high-frequency components of the fault signal contain useful information about the fault location and direction [97]. The high-frequency transients, when passing through the substation busbar into other TLs, are affected by the frequency

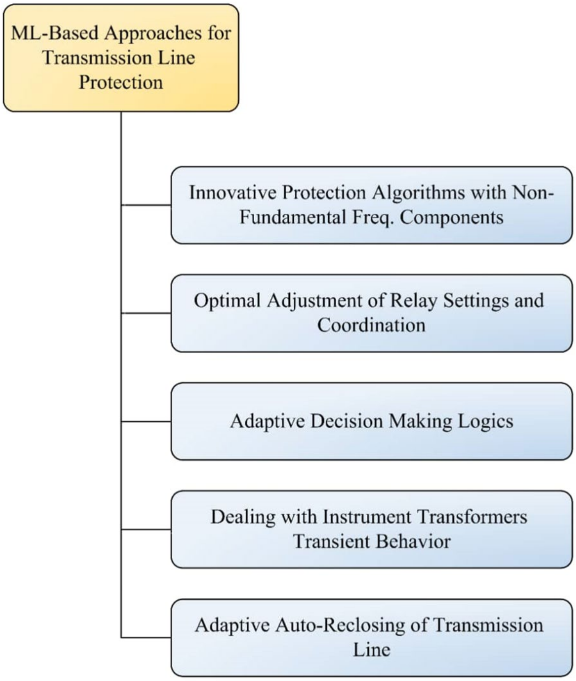


Fig. 6 ML-based approaches proposed for TL protection

characteristics of the line traps and busbar equipment, which can further help identify the faulty section. These components are commonly filtered-out by conventional algorithms. While it is difficult to apply some set of rules and criteria to disclose the extensive information contained in the non-fundamental frequency components of the fault signal, the ML algorithms are well capable of extracting and recognizing the fault signatures [98].

In [99], a combined Wavelet-SVM technique has been proposed for fault zone identification in a series compensated TL. The features extracted by the Wavelet transform are directed as inputs to the SVM classifier. The SVM is trained by a number of fault cases obtained from simulation studies. Similar approaches can be found in the literature employing different feature extraction tools and different ML algorithms. The most widely used signal processing tools used for the feature extraction are Discrete Wavelet Transform [100], S-transform [101], and Mathematical morphology [102]. Among the various techniques reported for fault classification, the most widely used techniques are ANN [103], Fuzzy Inference System (FIS) [104, 105], DT [106], and SVM [107].

4.2 Optimal adjustment of relay settings and coordination

Adaptive adjustment of the relay settings in response to the variation of TL power flow and the last configuration of the power system is another approach proposed to improve the protection system performance. The idea of modifying relay settings to correspond to changing system conditions was first proposed by Liacco in 1967 [108]. Adjusting the relay settings adaptively will ensure correct performance over a wide variety of operation conditions, which is an improvement compared to fixed settings for the relays.

Li et al. [109] developed an intelligent distance relay based on the ANN in which the relay operating region adapts to system-changing conditions. A similar approach has been proposed in [79] using Radial Basis Function Neural Network (RBFNN) and Back Propagation Neural Network (BPNN) algorithms. The BPNN has detection limitations when a case falls in a region with no training data, which is a serious deficiency in many practical applications. Bhalja et al. [79] reported that the RBFNN provides a more efficient approach compared to BPNN. The mentioned schemes are based on a batch learning type, which is usually a time-consuming affair. Furthermore, the learning parameters must be properly chosen to ensure convergence. To achieve better generalization performance and faster learning speed, the Extreme Learning Machine (ELM) has been employed in [110, 111] to adaptively adjust the distance relay tripping characteristics. The proposed method is validated for a two-terminal TL with complex mutual coupling and shunt capacitance [94] and a TL in the presence of a static synchronous series compensator [95].

In [112], the genetic algorithm is used to obtain the optimal quadrilateral characteristics of the distance relay, taking into account the uncertain parameters including fault resistance, measurement errors, pre-fault load flow, and remote infeed current with their corresponding probabilities.

Rather than modifying typical operating characteristics, a number of protection techniques have been proposed in the literature that employs the ML algorithms to either design adaptive schemes with implicit operating characteristics [113, 114] or to calculate adaptive correction factors to minimize fault distance estimation errors [115].

4.3 Adaptive decision-making logics

Adaptive decision-making logic can help achieve the optimal compromise between the security and dependability of the protection system. Incorporating the fault and the power system conditions into the relay final decision, adaptive logic schemes can prevent the relay maloperation during boundary faults and stressed system conditions, e.g., power swing, extreme loading condition, and voltage decline.

Bernabeu et al. [116] proposed a data-mining algorithm based on DT to classify the power system state and to predict the optimal security/dependability bias of a protection scheme. When the power system is in a “safe” state, not clearing a fault with primary protection has a greater impact on the system than a relay misoperation due to a lack of security. Therefore, a bias toward dependability is desired. However, when the power system is in a “stressed” state, unnecessary line trips can contribute to the propagation of the disturbance, and therefore, it is desirable to alter the reliability balance in favor of security. In [117], an adaptive neuro-fuzzy inference system (ANFIS)-based adaptive decision logic has been proposed for the first zone of distance relay to secure the relay operation for boundary faults. The proposed logic issues the trip command rapidly once the fault is detected with a high degree of certainty, whereas for boundary faults, the relay will extend its operation time adaptively to observe more impedance samples inside the zone.

Conventionally, distance protection schemes provide a delayed remote backup for TLs connected to the next substation busbar. Although it is desirable to cover the longest following line by zone-3 of distance relays, it is likely that under system stressed conditions, the measured impedance enters the relay operating characteristics. This could lead to spurious tripping of the distance relay, which may further lead to cascade tripping in the power system. An intelligent scheme has been proposed in [118] for supervising zone-3 of distance relays using vulnerability assessment and DT approach. The input features are collected from PMUs installed at specific buses. Once vulnerability assessment identifies the vulnerable relays, conventional zone-3 is blocked and the decision-making will be shifted to the DT approach to discriminate between fault and stressed situation. In [119], the online sequential ELM has been used to design an intelligent classifier for distinguishing fault events from power swing and voltage instability conditions. In [120], a fuzzy logic-based method combining different indices including angle, frequency, voltage, and damping information derived from wide-area monitoring, protection, and control (WAMPAC) data has been used to block the relay during power swing conditions. However, while the relay operation is blocked by a power swing blocking logic, the possibility of a fault occurring on the protected TL is not unlikely. Niyas et al. [121] proposed a supplemental logic based on DT to detect fault events during power swing condition and to unblock the relay under such a situation. In [122], the DT algorithm has been employed to design an intelligent logic for avoiding the distance relay trip on load encroachment.

4.4 Dealing with instrument transformers transient behavior

The distortion of the measured signals due to CT saturation and discharge oscillations of capacitive voltage transformer (CVT) can adversely affect the protective relay performance. To avoid the relay mal-operation or mis-operation due to the CT saturation, Yu et al. presented an ANN-based approach [123] to correct CT secondary waveform distortions. A similar approach has been presented in [124] training the ANN to achieve the inverse transfer function of iron-core toroidal CTs, which are widely used in protective systems. An alternative approach has been proposed in [125] using ANFIS to provide a simple solution with fast response time, no cumulative estimation error, and no dependency on CT parameters and its secondary burdens.

The CVT transient behavior due to its internal energy storage elements can cause the relay overreach under large voltage drops, particularly in high source-to-line impedance ratio applications. In this respect, the ML algorithms can be used to either compensate for the CVT transient errors [126] or design a CVT transient detection logic to delay the relay operation until the CVT generated transients die out.

4.5 Adaptive auto reclosing of TL

The auto-reclosing of TLs is a common practice in the transmission network to improve the power system transient stability as well as the TLs availability. According to statistics, the majority of short-circuit faults occurring on overhead lines are of transient nature, and a very high percentage of these transient faults are of the single-phase-to-ground type. Therefore, the auto-reclosing scheme could help prevent unnecessary outage of the line by interrupting the current feeding the arc channel by de-energizing the faulted phase for a short dead-time, thereby quenching the transient arc.

During the dead-time interval, the fault arc could be fed from the energized phases through the capacitive and magnetic mutual couplings. Accordingly, a secondary arc would follow the primary arc after isolating the faulted phase. This could prolong the extinction of the fault arc and consequently might result in the failure of a fast single-phase auto-reclosing scheme. In this respect, recognizing the arc extinction using ML approaches would be very helpful not only to minimize the auto-reclosing dead-time but also to prevent reclosing the TL circuit-breakers onto a non-extinguished or permanent fault [127].

4.6 Future trends

Based on the explanations provided in this section, some of the future trends of the ML applications that can be used for the TL protection schemes are as follows:

- Developing a ML-based protection scheme to enhance both dependability and security.
- Fault type classification.
- Discriminating permanent faults from temporary ones to prevent reclosing the TL circuit-breakers onto a non-extinguished fault.
- Enhancing performance of the protection schemes of TL during both CT and CVT transients.
- Accelerating trip time of the conventional TL protection schemes using ML applications.

5 System integrity protection schemes (SIPS)

5.1 Background and fundamentals

SIPS are designed and implemented to preserve the reliable system operation and protect the system integrity against extreme events such as cascading outages and blackouts. Unlike the conventional protection plans, which are designed for a specific power system element, in the SIPS, multiple elements with different detection and mitigation levels are utilized to stop or minimize the propagation of harmful

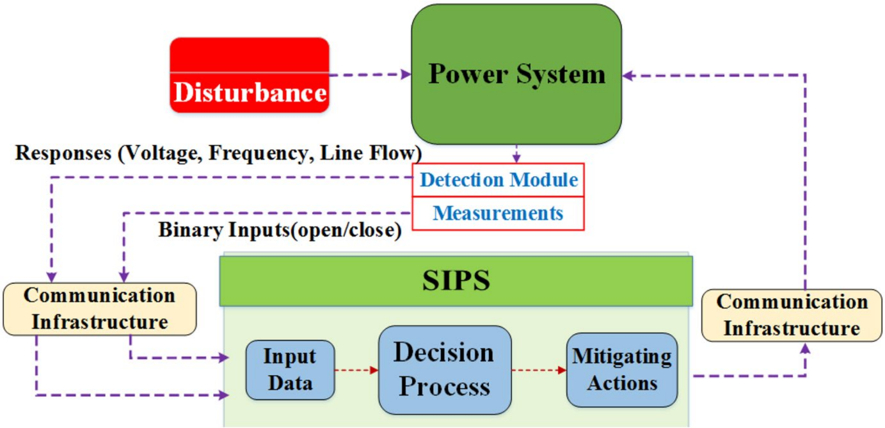
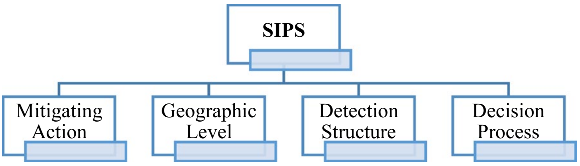


Fig. 7 Overall structure SIPS

Fig. 8 Classification of SIPS



disturbances [128, 129]. Special or system protection schemes (SPS) and remedial action systems (RAS) are the old acronyms for SIPS. The abnormal system conditions that a SIPS can mitigate include frequency instability, rotor angle transient stability, voltage instability, and thermal overloads. All these abnormal conditions can propagate through the power system, initiating a cascading failure or blackout. The overall structure of SIPS is illustrated in Fig. 7. According to Fig. 7, SIPS consists of different components, including detection and measurement module, communication infrastructure, mitigating actions, and decision process. In some parts of SIPS, consisting of outage detection, input data assessment, and decision process modules, the ML algorithms can be used to improve the SIPS performance.

According to Fig. 8, the SIPSs can be classified based on the type of mitigating actions (e.g. load shedding, generation rejection (GR), or controlled islanding (CI)), detection structure (event-based or response-based), geographic scale (local or system-wide), and decision process (model-based or model-free).

5.1.1 Mitigating actions

Based on the abnormal system conditions, different mitigating actions can be chosen. In Table 2, some of the common SIPSs and the abnormal system conditions that the SIPS is intended to mitigate are reported. GR, fast unit start-up (FUS), LR, under-frequency load shedding (UFLS), under-voltage load shedding (UVLS), CI or system separation, dynamic braking (DB), OOS tripping, turbine fast valving

Table 2 SIPS types based on mitigating actions and associated abnormal system conditions

SIPS	Abnormal System Conditions			
	Frequency Instability	Rotor-Angle Instability	Voltage Instability	Overload
GR	Applicable	Not-Applicable	Not-Applicable	Applicable
FUS	Applicable	Applicable	Applicable	Applicable
LR	Applicable	Not-Applicable	Not-Applicable	Applicable
UFLS	Applicable	Not-Applicable	Not-Applicable	Not-Applicable
UVLS	Not-Applicable	Not-Applicable	Applicable	Not-Applicable
CI	Applicable	Applicable	Not-Applicable	Applicable
DB	Not-Applicable	Applicable	Not-Applicable	Not-Applicable
OOS	Not-Applicable	Applicable	Not-Applicable	Not-Applicable
TFV	Applicable	Applicable	Not-Applicable	Not-Applicable
VS	Not-Applicable	Not-Applicable	Applicable	Not-Applicable
DCL	Not-Applicable	Applicable	Not-Applicable	Applicable

Not-Applicable: (yellow) Applicable: (green)

(TFV), var source switching (VS), and high-voltage Direct Current (HVDC) link control (DCL) are among practical SIPSs [113].

5.1.2 Geographic level

Based on the physical location of the measuring devices, decision process, and the control actions, the SIPS can be categorized as local, regional, or system-wide. In local SIPSs, the whole SIPS is limited to a specific substation, feeder, or TL. In regional SIPS, more substations are involved. In regional SIPSs, the decision process module is at a single location while the measurements can be received from remote locations, and control actions are executed at different substations. The system-wide SIPSs are more complex than regional SIPSs with great diversity in control actions, measurement infrastructure, and communication media. In another classification [112], there are two architecture options for SIPS, including the distributed and centralized structures. In centralized SIPSs, the decision-making and main computational tasks are performed at a central location. Input measurements and remote control commands are exchanged between the central unit and the remote substations and terminals. The centralized SIPS can be a function of an energy management system (EMS) utilizing SCADA and other measurement systems. In distributed structure, the decision-making module and control actions of SIPS are distributed at different locations. A communication system is required to coordinate the operation of controllers (i.e. combination of processing unit and control action) and data exchange. Distributed SIPSs are simpler than centralized SIPSs. Modern system-wide SIPSs can be implemented as a part of WAMPAC systems [130].

5.1.3 Detection structure

According to their detection and control strategies, the SIPSs are categorized as response-based, event-based, or combined schemes [112, 113]. Event-based SIPSs are designed to take predetermined discrete control actions upon detection of a contingency, such as the outage of a power plant, a major substation, or parallel TLs. In event-based SIPSs, the system response is not seen, and the outages are detected using binary inputs related to the open/close status of breakers. For more security in outage detection, in addition to the open/close status of breakers, zero current checking of TLs can be used. The event-based SIPSs are fast but not adaptive to the real system conditions. The old generation of SIPS or SPS was event-based, including GR, LR, CI, DB, TFV, and DCL. In response-based or condition-based SIPSs, the system responses such as voltage magnitudes, system frequency, and line flows are utilized and compared with predetermined thresholds to decide about the required mitigating control actions. UFLS and UVLS are the two most common types of response-based SIPSs.

5.1.4 Decision process

The core of SIPS is the decision process module. All the required calculations to select the proper mitigating actions are performed by the decision process module. The decision process unit uses the input data, including electric variables and binary topological information. The output of the decision process unit is sent to the mitigating devices to remove the abnormal system conditions. The decision process module can be model-based or model-free. In model-based SIPS, the power system model, including network topology, and specifications of power system elements should be available. Some parts of the model are known in prior, while other parts such as on/off status of breakers, actual generation, and load demand should be determined using the input measurements gathered by SCADA or WAMPAC infrastructure. The majority of model-based SIPSs are designed using offline model-based simulation studies. Model-based SIPSs are usually computationally cumbersome for large scale power systems. Additionally, the inaccuracy in model parameters may cause an unavoidable error in decision-making by model-based SIPSs. WAMPAC, enabled by the broad deployment of PMUs, has now become an established technology and implemented in many power systems across the world. The WAMPAC infrastructure provides a great opportunity to realize the model-free or data-driven SIPSs. In a typical model-free SIPS, the decisions about the proper mitigating actions are made based on the input measurements. In this regard, the ML algorithms are highly efficient to estimate the required parameters and construct a decision model. In most response-based SIPSs, such as UFLS, UVLS, OOS, and CI, accurate values of some system parameters, including the system inertia and load damping, are needed. The inertia time constant and load damping can be estimated using ML algorithms such as DT, SVM, and ANN. Also, for triggering the related mitigating actions by SIPS, the decision process module should assess the system operating conditions based on the input measurements. In the majority of SIPSs, the stability margin can be calculated or estimated by ML algorithms such as SVM, DT, ANN, and Deep Reinforcement Learning (DRL).

5.2 ML application in SIPS design

5.2.1 SIPS against voltage instability

The SIPSs designed against voltage instability or severe voltage abnormalities can benefit from ML algorithms in voltage stability assessment, determining the proper voltage instability mitigating actions and coordination between electric areas and local or regional controllers. In [131, 132], a decentralized adaptive emergency control scheme against power system voltage instability has been proposed. The entire network is divided into different control areas and intelligent agents are assigned to each area for monitoring the bus voltages and generator reactive powers to detect abnormal voltage conditions using shunt switching and load shedding. The coordination of different areas in SIPSs proposed in [115, 116], can be effectively promoted using a learning-based multi-agent system (MAS). UVLS plans are the most common SIPS against severe voltage abnormalities. Conventionally, UVLS plans are designed using offline and model-based simulation studies. However, modern UVLS schemes can be implemented using PMU data. In [133], a practical response-based SIPS for adaptive UVLS in large interconnected systems is proposed based on PMU data. In [134], a MAS-based emergency voltage control plan is proposed where bus agents are assumed as intelligent agents for monitoring the corresponding bus voltages and with the ability to exchange information with neighboring agents. Reactive agents including tap agent and cap agent are utilized as the mitigating actions. In [135], an innovative hierarchical SIPS against voltage collapse has been proposed for the Hydro-Québec system. The aim of SIPS proposed in [119] is to maintain voltage stability after severe voltage drop using local and wide-area PMU data.

Many modern SIPSs utilized in smart girds are centralized plans based on WAMPAC infrastructure. Since the wide-area SIPS are vulnerable to cyber-attacks, the detection of attacks and executing proper mitigating actions can be achieved using ML algorithms. In [136], a supervised learning algorithm, named as SVM embedded layered DT is proposed for anomaly detection and proper load rejection strategy. In [37], a dynamic UVLS plan is developed using DRL. Additionally, the estimation of voltage anomaly can be done using DT, SVM, and ANN algorithms.

5.2.2 SIPS against frequency instability

UFLS is the most common SIPS against frequency abnormal conditions such as frequency instability. UFLS plans are conventionally distributed response-based SIPS. However, modern centralized types of UFLS plans are proposed in the literature as a part of WAMPAC and can be realized in the future. UFLS plans are categorized as multi-stage, adaptive, and semi-adaptive. In multi-stage plans, the frequency set-points, time delay, and load shedding amount associated with different stages are to be specified so as to preserve the system frequency within the permissible range in the event of severe active power mismatches. Conventionally, these settings are determined using model-based and off-line dynamic simulations. In adaptive UFLS plans, the amount of load shedding is determined based on the

Rate-of-Change-of-Frequency (RoCoF) value. In semi-adaptive UFLS plans, the combination of RoCoF value and the multi-stage setting is utilized. In both adaptive and semi-adaptive UFLS plans, the whole frequency trajectories or the frequency nadir can be estimated using ML algorithms, such as SVM, and ANN [137–139]. Each UFLS relay can be seen as an agent and the MAS-based learning methods are used for the proper coordination of UFLS agents [140, 141]. More details about the application of intelligent computational methods such as ANN, Fuzzy, and ANFIS in power system stability plans can be found in [142]. Due to the rapid change of operational conditions in power systems, the learning-based algorithms can be utilized to promote the SIPS performance. In [143], a UFLS plan is developed using Reinforcement Learning (RL).

5.2.3 Controlled islanding (CI)

During severe contingencies such as cascading outages or undesired inter-area low-frequency oscillations, the interconnected operation of non-coherent groups of generators is no longer possible. In such conditions, the controlled or intentional islanding is utilized as the last resort to split the entire network into isolated stable islands by opening apt TLs. In each CI plan, two major questions of “when to island?” and “where to island?” are to be answered. To decide about “when to island?” the ML algorithms are used. In [144, 145], and [146], the time of CI is determined using DT technique. In [147], the wide-area power system islanding is detected using real-time PMU data based on an intelligent DT algorithm. The main part of each CI scheme is the identification of coherent generators. The coherency can be well determined using ML algorithms, such as Fuzzy C-Means clustering [148], and K-Mean clustering [149] approaches.

5.2.4 OOS tripping

Under a severe fault such as a delayed three-phase short circuit near a SG, the related generator may lose its synchronism. This condition is a local OOS condition that is detected and removed by conventional relays [150]. However, when a group of generators loses their synchronism with the rest of the network, the resulted oscillations appear on TLs. In such conditions, the OOS splitting SIPS is utilized. The OOS tripping is strongly related to the CI plans [151]. In [45], the DT algorithm is used to detect local OOS conditions. ANN can be used for predicting the transient instability and executing CI plan using PMU data [152]. Also SVM can be used for transient stability prediction in OOS-based SIPSs [153–156]. A major challenge in SIPS against transient instability is the online and adaptive detection or prediction of transient instability. In [157], a hierarchical deep learning machine is presented for online transient stability prediction.

The Bayesian networks and Markov models are widely used for fault diagnosis and reliability assessment of both conventional and special protection systems [158, 159]. The reliability assessment of SIPSs is more crucial since multiple power system elements are involved in SPS design and any mal-operation (i.e. fail to operate or undesired tripping) may push the power system toward a cascading failure. Modeling of SIPSs for reliability assessment is conventionally carried out using minimal cut-set, Bayesian networks and Markov models. In [160], a cognitive framework is developed to autonomously learn the model of the nominal state using hidden Markov models. In [161], the Markov model is used to assess the reliability of flow-constrained protection systems regarding the related communication infrastructure. Different states including in-service, limited operation, and outage are defined in [162], for reliability evaluation of SIPSs. The Bayesian networks are also used for reliability evaluation of protection systems. In [163], the defect of protection systems is identified using a combinatorial Bayesian network. In [144], the Bayesian network is utilized to incorporate the failures of protection systems in the large-scale power system reliability assessment.

Both Bayesian networks and Markov models can be used for fault diagnosis which is a major part of the SPS design. In [164], the comprehensive survey of recent Bayesian network models in fault diagnosis is presented. In [157], a new kind of protection scheme is proposed for the intertie zone between wind farm and grid line to overcome the undesired failure of available distance protection scheme. The protection scheme utilizes a Bayesian-based optimized SVM, as a supervised machine learning classifier approach to consider the dynamic behaviors of wind speed and the current measured by the current transformers.

5.3 Future trends

ML algorithms can effectively promote the efficacy of the SIPS plans. The research trends in applications of ML algorithms in SIPS design can be summarized as follows.

5.3.1 Abnormality detection

SIPSs are designed to detect and remove abnormal system conditions. In this regard, a major research field for ML applications in SIPS design is the creation of intelligent data-driven detection algorithms based on online measurements received from SCADA and WAMPAC infrastructures. Voltage magnitudes, line currents, line power flows, system frequency, and bus voltage angles can be used to develop efficient procedures for detecting abnormalities in system conditions. ML algorithms including DT, SVM, ANN, ANFIS, and DRL algorithms can be used for these purposes.

5.3.2 Abnormality prediction

Using dynamic measurements from the WAMPAC infrastructure, the prediction functions can be added to the SIPSs. Most of the available SIPSs act based on the current system state; however, the timing of mitigating actions can be optimized, and the consequences of severe contingencies are minimized by leveraging suitable ML-based prediction algorithms.

5.3.3 Cyber attack detection

Many centralized or system-wide SIPSs require enormous input data for decision-making via communication infrastructure. Bad data caused by modeling errors, data errors, transducer errors, and sampling errors may exist in input data. Conventionally, bad data are automatically detected by statistical methods during state estimation. However, cyber attacks are new threats for power systems that cannot be easily detected by available bad data detection algorithms. Cyber attacks may cause the maloperation of SIPSs, and the resulted consequences can be catastrophic. ML algorithms can be used to detect cyber attacks and deciding about disarming SIPS or taking alternative mitigating actions.

5.3.4 Model-Free decision process

The decision process is the core of SIPS and is conventionally implemented using model-based algorithms. Model-based SIPSs are usually computationally expensive, and the lack of a proper and accurate system model may cause an unavoidable error in decision-making. Using input–output data, the ML algorithms including ANN, DT, SVM, and DRL are able to give a black-box model that can be used as an alternative model for decision-making by SIPS.

6 Challenges and barriers

It is a common practice to signify the status of emerging technologies on the Gartner's hype cycle to characterize the maturity, adoption, and social application/adaptation of technologies. Specific to the ML, various evaluation reports have reached a consensus that ML has already surpassed the *technology trigger* phase and is more or less at the *peak of inflated expectations* stage, as depicted in Fig. 9. This phase is recognized by the mass media commentaries, technology publication blasts, proliferation of suppliers, and expansion of activities beyond those evident in the *technology trigger* phase. Many ML success stories and opportunities are

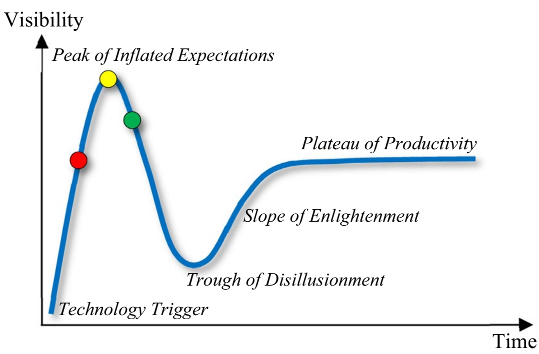


Fig. 9 Five-phase Gartner's hype cycle

broadcasted daily, also accompanied by scores of experiments failed due to unresolved challenges.

In Fig. 9, three status points are specified by red, yellow, or green dots. Although the application of ML techniques in some pioneering areas such as content discovery, recommender systems, voice and speech recognition, image processing, chatbot assistants, game production, toy manufacturing, transaction fraud detection, and healthcare industry has passed the yellow area and lies in the downhill toward the green dot, some other applications areas such as those pertaining to electric power engineering are still in need to hike up the hill from the red dot toward the apex. This section scrutinizes the crucial and common barriers and challenges associated with this hard battle that the power engineering community is going through right now. In addition to technical factors, it is endeavored to discuss non-technical issues as well.

Principally, any sort of ML algorithm requires extensive, rich, and inclusive datasets to be able to lead to a satisfactory performance. This requirement, commonly referred to as data availability, necessitates further and various data gathering sensors and platforms whose implementation takes time due to budgetary or even technology limitations. Wireless communication technologies and IoT platforms would play decisive roles in this arena, but the consistent concerns of power engineers/system managers over the data security and customers' privacy should be fairly elevated at first. Especially about the composite generation and transmission systems and TLs in which the system has spatial dispersion, the status data of grid-wide points/equipment need to be time-synchronized to be accurately informative. Otherwise, the ML technique might breed nothing or false outcomes. Accordingly, time-synchronized sensor technologies such as WAMPAC are urgently essential for the future measurement and monitoring infrastructures of power systems.

The other crucial aspect of the data availability is the dataset temporal granularity. We already knew that SCADA tackles the system as a quasi-stationary setting, and it is unable to make the system natural dynamics observable. The level of system dynamicity intensifies more and more in the wake of intermittent/variable renewable energy integrations along with the advent of customers' participation. Should we take a ML algorithm in use to tackle the time-series data for the system protection and control, a reasonable degree of temporal granularity is to be granted for the datasets. To do so, the communication systems dedicated to data transfer should essentially have sufficient bandwidth and speed. This challenge would be gradually getting vanished with the proliferation of wireless communication networks and internet accessibility and their high quality of service/security assurance.

Another concern around data availability is the diversity of datasets. Power systems operate most of the time in the normal condition, and the pertinent data would not be of great value in terms of the diversity needed for the learning process of a ML technique. A ML algorithm needs to observe various disturbance conditions, which are really scarce in comparison to the normal state datasets. In addition, disturbances come in different classes, and not all abnormal data would help in training a particular application. Power system protection obviously falls in this category as it normally operates during disturbances. The asset management also depends on abnormal condition data to be able to predict the maintenance schedules or remnant life. In this sense, power system simulations in either or both software and hardware platforms would be of significant assistance. Such a procedure calls for dependable models of the components/system and adds further efforts to the whole process.

Since a ML algorithm learns some conditions and interpolates/extrapolates the unobserved ones, they need inclusive test phase plans to be trusted as real-world players. In this way, it is a very sensitive matter to keep the ML algorithm away from over-training while it should not be under-trained at the same time. Followed by a fitting training process, the ML may still yield unsatisfactory outcomes in some rare conditions. This shortcoming is prominently addressed in RML techniques in which a penalty/reward mechanism retrains the algorithm based on its performance in the operating phase. Specifically talking about power system protection and asset management, any failure could be extremely costly or even bodily harmful. We need to be super cautious and prudent to prevent such a catastrophic happening. However, we should never let it block the entire path of ML applications in power systems since we already have a notable number of forensic accidents where the cause of a wide electricity interruption or a person's injury/death was directly attributable to the maloperation or misoperation of the conventional protection systems.

There are wrong perceptions, mostly by nonprofessionals or those with individual business objectives, regarding ML capabilities and features. ML will never offer perfect solutions for unmanned power system operation and planning, but rather, it should be designated as a decision support system to makes the jobs easier and offer solutions where and when analytical model-based techniques fail to run. Similar challenges were raised once computers came into control rooms decades ago; but we have not yet released the whole operation routines to computers and operators still play the major role. Last but not least, we may examine the applicability of ML techniques just on occasions at which conventional systems fail to operate perfectly rather than a universal tendency to switch everything.

Successful implementation of a ML project should be conducted by a team constituted of ML experts having a deep understanding of the current technologies in addition to the experts of any specific application area. With the spotlight on the ML applications in almost all fields of science and technology, the shortage of data science and analytics talent is pretty evident. Many job boards/portals, as well as recruitment firms, consistently publish reports of high salaries and strong job growth for ML developers. So, the lack of skilled and developed ML experts remains one of the biggest challenges, at least at present. On the other hand, the high salary of ML professionals and project managers, along with the data gathering, handling, and storage facilities, make ML implementation projects unaffordable for most businesses. Training qualified and skilled ML experts by universities and institutions is greatly demanded.

Advanced technologies such as ML needs a seamless relationship between industry and academia. The industry leaders should be open to discuss the ongoing challenges and concerns with talented research teams in the academia. This win–win collaboration effectively addresses the industry challenges while turns the academia research efforts to be innovative and applied. In this way, one barrier is the data privacy issue. The industry side usually does not tend to share real data with any third-party entity, and the academia needs them to examine the products. Relabeling datasets is a way to go, but it needs a reverse path too for interpreting the outcomes. The other issue to be tackled with extra care to make industry academia relation sustainable is the intellectual property of the products. Clear and flexible alternatives such as take over, royalty payment, joint venture, etc. of the intellectual property of products are to be defined and agreed upon first. Cost-sharing, as a successful and effective policy adopted by the governmental funding agencies for grant admission, can accelerate the establishment of this relation.

On a worldwide scale, ML is often exploited by startups and small companies into the fabric of their software/hardware products for automation, biology, and energy. These sorts of companies do not have notable markets/customers at the beginning; they hence take higher risks and are more agile in adopting new technologies. On the opposite side, large and established companies who make power grid components do not have such privilege and treat more risk-averse regarding substituting their products. For these companies, deployment of any technology will only proceed if a value proposition can be found. Creating simple instances of ML applications in power systems but with tangible outputs can evoke the attention of these companies to invest in pertinent new businesses. They might also show some tendency to take over the products of successful startups or even buy themselves. As the protection and asset management tasks usually have very limited boundaries encompassing a single or at most a few components and they are free of large-scale systems complexities and dynamics, it is highly recommended to first adopt ML techniques on these occasions. System-level applications might be touched thereafter.

7 Summary and conclusion

With increased development and interest in various ML applications, electric power systems are among the industries standing to benefit from ML technology. This paper gave a high-level overview of the wide range of de facto and potential applications of ML techniques in power system protection and asset management. In this regard, SGs, power transformers, TLs, and SIPSs were exclusively focused, their pertinent challenges were thoroughly acquired, and how ML can address these challenges was unreservedly discoursed. As discussed, ML can offer a significant paradigm shift in situations where model-based/analytical techniques fail to effectively run beside an immense amount of data with sufficient spatial and temporal diversities is available. In these situations, ML wisdom might be able to make data-driven recommendations and decisions only based on the input data. Further opportunities are those having unknown phenomena whose modeling is not feasible, at least currently. However, technical and non-technical challenges have slowed ML deployment. Data availability, low confidence and reliance on ML persistent performance, overestimated expectations, lack of ML experts, weak industry-academia relation, and risk-averse strategies of large companies are foremost barriers and challenges to the wide-spread deployment of ML techniques in power system protection and asset management.

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