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Machine Learning Approaches for Power System Fault Parameters Prediction: A Systematic Review

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Abstract: *Power system faults are a perennial issue that affects many industries due to the imperfection in the design and construction of power system components and the design and implementation of the interconnected system. This recurrent issue may be effectively mitigated by identifying the causal fault factors or parameters and more specifically the interaction of these factors in an interconnected power system. These parameters or feature factors are the subject of a large number of research studies in various aspects of power system faults including the diverse fields of power system network generation, transmission, and distribution in addition to other allied fields. The use of machine learning in the power field has shown to be very promising and effective and hence it is gaining more attention in the power industry. This review paper presents a systematic study of machine learning approaches that have been used for predictions of power system fault parameters. It captures firstly, the broad reviews from a chronological perspective and then presents the specific research studies that have adopted machine learning for the prediction of power system fault parameters, including that related to energy generation, transmission, and/or distribution of power networks. Reviews presented in this paper, observed that fault stability indices are frequently adopted as feature predictors in most of the research studies investigated. This is particularly true for most distribution and transmission networks. In addition, the use of artificial neural networks is somewhat more popular amongst power system researchers.*

Keywords: Fault parameters; Features; Machine learning; Power system network; Prediction

1. INTRODUCTION

Power systems are one of the most notable and comprehensively studied entity in the world. This may be largely attributed to the significant role it plays in the society as an energy provider for which no modern society can do without.

During a faulted power system condition, certain parameters need to be identified to determine the extent – magnitude and/or direction, of the faulted component. This identification is basically estimation or more correctly a prediction problem in which the aforementioned parameters are computed by using a suitable fitting model.

The estimation or prediction is typically determined by the manual provision of suitable fitting parameters, a training and test data in conjunction with a well-defined predictor model. In some special cases, the both the fault parameters and model may be determined automatically.

In the machine learning parlance, the fault parameters represent a set of features typically assigned a corresponding set of feature values – the values being numerical or symbolic depending on the nature of the fitting model predictor. In particular, the feature parameter values are presented in such a way and manner as a set of training and/or test data points where each point represent a particular power system physical phenomena occurrence in space. The occurrence of these physical phenomena is the result of the detection mechanisms put in place by power system operators in order to detect the presence of a faulted system component.

2. RELATED STUDIES

2.1 Broad Overview

In [1], an online voltage stability index is proposed using a Feed-Forward Back-Propagation Artificial Neural Network (FF-BPANN) configured sequentially and validated on the IEEE 14-bus and 30-bus power system networks. In [2], the PSO is used to predict the Maximum Power Stability Index (MPSI) including the optimization of the network size and placement in the presence of Distributed Energy Generator Systems (DEGS) for a 30-bus IEEE power network system.

Voltage collapse point prediction is conducted in [3] using the Eigenvalue Decomposition (ED) parameter theory and then comparing including an L-based voltage stability index for 9-bus and 14-bus IEEE power network systems.

In [4, 5], a set of power system energy parameters including the power generation, the electrical loading requirements, costs of operation and real-time shortage penalty factors were considered in the scheduling of power exchanges in a micro-grid utility connected power system.

Cao et al (2017) studied the forecast of power network lines and load-shedding under critical states and using a betweenness methodology [6]. Their approach was applied to the 39-bus and 118-bus IEEE power network systems. Game theoretic model is used to maximize the voltage stabilization point and hence predict the imminent voltage collapse in power system transmission network.

Shiddieqy et al [7] proposed the use of convolutional neural network (CNN) with feed-forward artificial neural network (FFANN) for the automatic determination of a combination of transmission line faults. The use of parameter model sweeps enabled the determination of a variety of faults for the generation of training and test data. Some of the considered parametric adjustments included fault locations, fault resistances, fault inception angles etc. Simulation results showed that the CNN-only model outperformed the rest models with 100% accuracy on test simulation data.

Rao and Vijayapriya [8] proposed two voltage stability indices – Composite Severity Index (CSI) and New Voltage Stability Index (NVSI) for the examination of several critical lines/buses in IEEE 30-bus and IEEE 118-bus based on the distance to collapse point. Their proposed method is compared to Line stability index (Lmn), the Line stability factor (LQP) and the Fast Voltage Stability Index (FVSI).

In [9], imminent catastrophic failure prediction in power system based on Catastrophic Failure Index (CFI) parameter and considering the IEEE 30-bus power system is presented.

The Adaptive Neuro-Fuzzy Inference System (ANFIS) technique and the Moth Flame Optimizer (MFO) is proposed in [10] for the prediction of line voltage stability index (Lmn) during power system faults. Their technique was applied to the applied to the IEEE 30-bus and 118-bus power systems then compared to conventional neural network techniques such as the Multi-Layer-Perceptron Neural Networks (MLPNNs) and the Radial-Basis Function Neural Networks (RBFNNs) techniques.

In Kiel and Kjolle [11], a 3-mode parameter predictor solution based on a Bayesian machine learning systems network is applied to the detection of downtimes due to failure of power transmission lines.

Idris [12] studied combined effects of remotely captured in-feed currents comprising resistance faults with a localized and basic impedance-oriented Fault Localization Algorithm (FLA). They discovered the situation that the in-feed currents may result in accumulated errors which was most likely due to the FLA at local substation at zero fault resistance.

Luo et al. [13], presented an approach based on a basic artificial neural learning technique comprising a set of Stacked Denoising Autoencoder (SDA) for fault localization in High Voltage DC (HVDC) systems. Their approach aimed at dealing with time-signal domain data directly and equally providing a continual solver for fault localization.

Haq et al. [14] presented a dual-channel Extreme Learning Machine (ELM) hybridized with a Rectifier Linear Unit (ReLU) and based on a set of hyperbolic tangent activation functions for detecting and classifying transmission line faults. In addition, they employed a Discrete Wavelet Transform (DWT) to automatically detect features in transmission line data. However, these are conventional approaches which do not capture the essence of real time predictive monitoring.

In Rosenlund et al. [15], several approaches based on clustering were proposed for the prediction of the redundant/critical events in the power system of Norway. They employ unbalanced raw data and applied the Principal Component Analysis (PCA) for dimensionality reduction and prior to clustering operation. In particular the t-NSE and k-means approaches were employed in the clustering solution process.

Paul & Debnath [16] presented a fault localization approach based on impedance-methods and employing DWT voltage and current featurization during transmission line faults. The features represented an approximation to the line impedance with base coefficients presented to an Adaptive Neuro-Fuzzy Inference System (ANFIS) to determine precise fault locations. Considering only the single line to ground (SLG) faults, they identified the stability of both the Fault Resistance (FR) and Fault Inception Angle (FIA) to abrupt or sudden changes.

In Aker et al. [17], Bayesian Neural Network (BNN) is applied to the prediction of the faulted locations in power transmission lines. This was achieved by compensating the power transmission lines with STATCOM device.

The use of Associative Rule Mining (ARM) feature extraction and classification procedure was applied to the diagnosis and prediction of electric grid faults [18]. They applied the Supervisory control and Data Acquisition (SCADA) approach for data provisioning with respect to the criticality of the interrupted service hours.

In [19], the third version of Non-dominated Sorting Genetic Algorithm (NSGA-III) was employed in the optimal fitting of the active power and energy losses, voltage-profile deviations, in addition to the voltage-stability index in the presence of Wind Turbine and PV (WT-PV) and under constant loading. The sizing and placement considerations were also accounted for.

In Tiwari et al [20], the Teaching Learning Based Optimizer (TLBO) is employed for allocating optimally

Distributed Energy Resources (DERs) in a distribution power systems network. In their research, the optimal size and location of Distributed Generator (DG) system units in a Radial Distribution System (RDS) is sought using the TLBO and considering the minimization of the real power loss in order to enhance the voltage profile of the distribution power system. Their results show that voltage-profile improvements from minimum levels of RDS without DG units are possible and also increasing the DGs led to some reasonable improvements in minimum voltage levels.

In Sperstad et al. [21], a data-driven technique employing probabilistic-graphs for the prediction of transmission line faults is proposed which facilitated power system event sequence exploration and vulnerability understanding. Parameters such as interruption costs, costs of non-supplied energy, interrupted power and duration were all investigated.

In Gumus et al [22], a method based on the Thevenin impedance stability index with mixed integer Genetic Algorithms (MIXGA) was proposed for the optimal allocation and sizing of DG in two IEEE benchmark power networks during power system faults; verifications of the MIXGA approach were equally performed using a Grey Wolf Optimizer (GWO) technique. The results should improvements in voltage profile, reduction in power losses and enhancement in stability of power system network.

In [23, 24], the prediction of faults in a section of the Nigerian 330Kv 34-bus, 11-machine power system was conducted employing hierarchical and sequence machine learning models based on the Hierarchical Temporal Memory (HTM). The goal was to estimate the faulted type based on measured impedances along the transmission lines.

In [25], a powerline fault mitigation technique based on a continual learning technique/algorithm inspired by intelligent processing and functional re-organization in the mammalian auditory cortex called the AMI, is employed for the prediction of the likelihood of a fault occurring. The approach exploited the resonant property of transmission line based on the fault inductance, capacitance of line. The AMI was subsequently compared with a conventional approach called the Group Method of Data Handling (GMDH) with competitive results.

In several very recent research studies, for instance in [26, 27], the resonance principle of the Nigerian 330kV power transmission lines are exploited to predict the likelihood that a fault will occur. The Power Spectral Density (PSD) is specifically estimated using continual learning neural networks based on auditory machine intelligence.

In related studies the use of machine learning based on decision trees [28, 29], and/or bagged trees [30], random forests [31, 32] and Deep Neural Networks (DNNs) [33 - 35], are employed as power system predictors for dc based microgrids.

3. Discussions

3.1. Chronological Presentation of Selected Studies

In order to carefully examine the trend of power systems fault parameters and correlate it to the Machine Learning (ML) approaches adopted, a trend analyzer using the MATLAB R2022b software tool is conducted and the plot as shown in Figure 1.

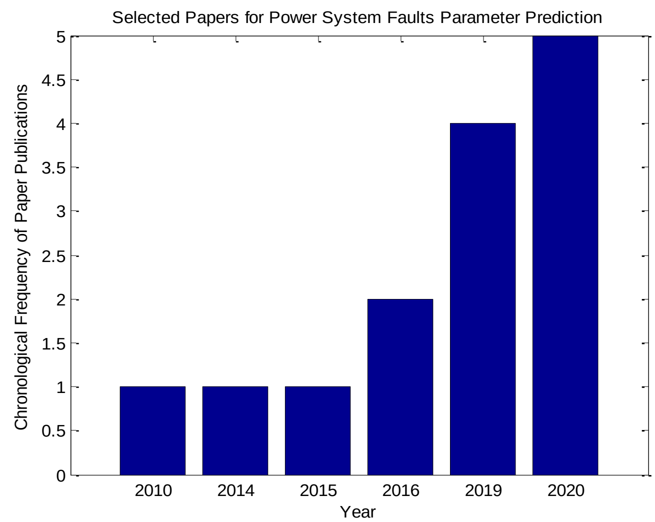

Fig 1. *Trend Analysis of Selected Studies on ML Approaches for Prediction of Power System Fault Parameters – 2010 to 2020*

As can be seen, the number or ML approaches increases as the year goes by from 2010 to 2021. This goes to show that the interest on the use of ML incorporating power system network fault parameter studies is generally on the rise.

3.2. ML Approaches and Power System Fault Parameter Types

When considering the reviewed studies conducted so far, the power system fault parameters that have been used in relation to the adopted ML approaches and with more emphasis on certain indices of voltage stability are as presented in Table 1.

From the Table 1, it can be clearly observed the increasing trend towards the use of ML techniques. Also noticeable is the increase in the variety of the ML approaches adopted as per the years 2019, and 2020.

Table 1. Some ML Approaches for Prediction of Power System Fault Parameters

Publication Year	ML Approaches	Type Count - Reviews
2010	ANN	1
2014	PSO	1
2015	Eigenvalue Decomposition (ED)	1
2016	CFBPANN, RBFANN	2
2019	CNN, FFANN, ANFIS	4

2020	SAE, ANFIS, NSGA-2, ANT-LION	5

4 Conclusions

In this paper, a systematic review, starting from a broad overview, to a chronological and then specific review of the ML approaches for prediction of power system fault parameters.

The research had shown that there is indeed an increase in the use of ML approaches for power system fault parameter prediction.

In particular, the research revealed that the neural network-based ML techniques are more adopted when compared to other approaches like the PSO.

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