Event Classification in Microgrids using Harmonic Synchrophasors

Dionatan A. G. Cieslak, * **Miguel Moreto,** * **Andre E. Lazaretti** **

* *PPGEEL - Graduate Program in Electrical Engineering, Federal University of Santa Catarina, UFSC*
** *CPGEI - Graduate Program in Electrical and Computer Engineering, Federal University of Technology - Paraná, UTFPR*

Abstract: The rapid advancements in monitoring technologies have opened up new possibilities for deploying Phasor Measurement Units (PMUs) in distribution networks. This development holds particular significance in active distribution networks, as it greatly enhances the availability of information to support network operations. However, the integration of renewable energy sources into existing distribution networks introduces a significant challenge in the form of increased harmonic content. These two factors, the abundance of complex data and the presence of harmonics, pose challenges for effectively managing modern systems. Hence, this research aims to propose a novel approach that utilizes PMU data, specifically harmonic synchrophasors, to improve event classification in distribution networks with distributed generation penetration. Simulations of typical scenarios in a 20kV and 11-bus benchmark model are conducted, resulting in a dataset comprising 2430 examples across four different event classes. The classification task is performed using optimized machine learning models, considering various feature scenarios. The robustness of the proposed method is assessed by evaluating the impact of factors such as measurement point distance, PMU location, and noise in the measured data on the overall accuracy. Preliminary results demonstrate the suitability of harmonic synchrophasors for enhancing state-of-the-art event classification methodologies in active distribution systems.

Keywords: Harmonic Synchrophasors; Active Distribution Systems; Event Classification; Machine Learning.

1. INTRODUCTION

Traditionally, PMUs have been widely used for event observation in transmission systems. However, there has been a substantial increase in the deployment of monitoring systems based on PMUs in distribution systems in recent years. The usage of these devices enables a wide range of potential applications, utilizing diagnostic methods that aid operators and planners in gaining a better understanding of the historical and current conditions of the systems (Sharma and Samantaray, 2019).

The monitoring of electrical systems faces a notable challenge due to the unprecedented technological evolution in the field. The introduction of new energy sources, the growing involvement of active consumers, the emergence of new devices and technologies, and the adoption of new business models have revolutionized electrical systems. Consequently, electrical networks now incorporate high-resolution data detection capabilities and acquisition rates that far surpass previous standards, leading to increased complexity and uncertainty in the information collected (Tu et al., 2017).

In the realm of distribution systems, PMUs are progressively gaining traction to enhance the characterization of events, as noted in Liu et al. (2020). Furthermore, the advancement in measuring systems plays a vital role in the development of emerging active distribution systems. The usage of PMUs for improving event detection and classification in power systems is exemplified in studies such as Farajollahi et al. (2018); Bhattarai et al. (2019); Hojabri et al. (2019); Miranda et al. (2019); Shaw and Jena (2020); Joshi and Verma (2021). Among the various disturbances encountered in distribution networks, High Impedance Faults (HIF) pose a significant challenge in terms of detection. These faults typically occur when power conductors break and come into contact with the ground or when objects like vegetation make contact with the conductors. The presence of high grounding impedance leads to low-level fault currents in such events (Gomes et al., 2019). While HIF may not exhibit significant variations in electrical quantities, effective signal processing techniques can identify noteworthy deviations. Over the past decade, researchers have introduced numerous algorithms for HIF identification that leverage a combination of computational intelligence methods and signal processing techniques. Many of these approaches rely on a blend of time and frequency analysis to differentiate between faulty and non-faulty events in the system (Samantaray, 2012; Ali et al., 2014; Sekar and Mohanty, 2017; Silva et al., 2018; Lima et al., 2019; Sarwar et al., 2020; Rai et al., 2021; Gao et al., 2022).

The usage of PMUs has been investigated in various studies. For instance, Ledesma et al. (2020) proposed an

⋆ Corresponding author: dcieslak@utfpr.edu.br

approach that demonstrated the capability of identifying, locating, and differentiating high and low-impedance faults in a distribution network. This was achieved by utilizing synchronized measurements of three-phase currents obtained from multiple points in the system. Soheili et al. (2018) presented a frequency domain approach that utilized the relative relationship between the third, fifth, and seventh current harmonics to classify events and distinguish HIF from non-faulty switching events, even in the presence of non-linear loads in the system. In the research conducted by Wang and Dehghanian (2020), phasor records were obtained, and features were extracted from current signals to distinguish events such as HIF, load changes, and normal operations.

HIF pose a unique challenge in their detection due to their subtle manifestations in electrical quantities. Consequently, accurately observing and identifying these events becomes a complex task. Many existing approaches in the literature predominantly rely on current information to determine the presence or absence of HIFs. However, an emerging trend in HIF detection is the utilization of phasor measurements, particularly driven by the proposed integration of PMUs in medium and low-level voltage applications. It is worth noting that the exploration of PMU data from multiple points in the system is still relatively limited in recent works. Moreover, it is essential to consider the impact of distributed generation, a significant aspect of active networks, when effectively identifying HIFs. The inclusion of distributed generation sources contributes to increased harmonic content in the network, making the accurate identification of HIF events more challenging. While some recent studies have begun to address this issue, further research is needed to develop robust HIF detection algorithms that account for the presence of distributed generation in the network. An additional noteworthy aspect, particularly in studies utilizing synchrophasors, is the assessment of measurement quality and its impact on the results of event detection and classification. Referred to as error analysis, this evaluation is not consistently incorporated in all works.

The concern to enhance the generality and improve outcomes in HIF detection follows the scientific community up since at lest three decades. The continuous advancements in computer's performance have been allowed lots of improvements in plenty areas, like simulations, monitoring devices, signal processing and development of artificial intelligence tools. By taking a look in recent researches, it is possible to observe a trend in using data-based techniques through mining and featuring such information. Also, the increasing in available data results in challenges that adhere to big data concepts. Then, it is easily noted that to deal and solve some problems in current energy systems, more and more some knowledge are demanded. In this context, the proposed work intends to process and explore synchronized phasor measurements in order to engineer a group of suitable features that allows to discriminate HIFs from other possible events in the operation of distribution networks.

2. METHODOLOGY

2.1 Test System Modelling

In order to emulate an active distribution system reliably, a medium voltage distribution network benchmark, proposed by the Council on Large Electric Systems (in French, *Conseil International des Grands Réseaux Electriques* - CIGRE), is considered. A simplified system diagram is shown in Fig. 1, and consists of an 11-nodes system connected to the main grid through a power transformer. The network operates in 20 kV and 50 Hz. Switches S_1, S_2, and S_3 are liable to change the operational mode of the grid (it is considered that switch S_1 is closed, while switches S_2 and S_3 are opened). Other relevant details for modeling and reproducing the experiments are presented in the CIGRE technical brochure CIGRE (2014).

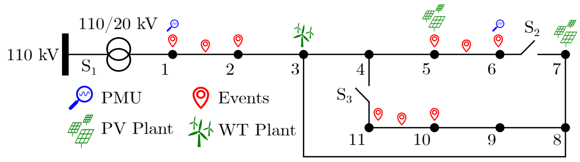

Figure 1. European MV distribution system.

In order to investigate the influence of harmonic content on the system, this study focuses specifically on the inclusion of photovoltaic (PV) and wind turbine (WT) units. These renewable energy sources are connected to the distribution system through inverter-based interfaces, which are known to introduce harmonic disturbances. The PV plant considered in the analysis has a capacity of 100 kW and is connected via a DC-DC boost converter and a three-phase three-level voltage source converter. Maximum power point tracking is implemented in the boost converter using the incremental conductance and integral regulator technique. The PV plant comprises an array of 66 parallel strings, delivering maximum power under a solar irradiance of $1000\,\mathrm{W}\cdot\mathrm{m}^{-2}$. Additionally, a 9 MW wind farm is included, consisting of six 1.5 MW units with a voltage output of 575 V each. The wind turbines are doubly-fed induction generators connected to the main network through 1.75 MVA coupling transformers. The wind speed is maintained at a constant $15\ \mathrm{m{\cdot}s^{-1}}$, and a torque controller is employed in the control system to maintain the turbine speed at 1.2 per unit while producing no reactive power. Three WT units are modeled and incorporated into the system, specifically located at buses 3, 5, and 7.

2.2 Generating Data

In order to extract meaningful information from harmonic synchrophasors, faulty and non-faulty events are considered in the simulations. The simulations focus on four major event classes: high impedance faults (HIF), low impedance faults (LIF - single, double and three-phase), capacitor bank switching (CPB), load variation (LDV - load increase and decrease). The parametric information used in the simulations is presented in Table 1, remembering that in each simulation the parameters are randomly selected among each interval of values, where V_P, V_N, R_P and R_N are the voltage sources and resistances used in the HIF model, R_f is the fault resistance, R_g is the ground

Table 1. Parameters of the simulations.

Class	Set of Inception Angle	Set of Parameters	Set of Values
HIF	$[0°, 180°]$	$\{V_P, V_N\}$	$[2, 5]$ kV
		$\{R_P, R_N\}$	$[150, 250]\,\Omega$
LIF	$[0°, 180°]$	$\{R_f, R_g\}$	$[0.01, 1]\,\Omega$
CPB	$[0°, 180°]$	Q_C	$[250, 500]$ kvar
LDV	$[0°, 180°]$	S	$\{15\%, 30\%, 45\%\}$ kVA

resistance, Q_C and S are reactive and apparent power, respectively.

HIF possess a distinctive characteristic, as electric arcs often accompany them. These arcs are formed when the voltage magnitude of the conductor in contact with a surface exceeds the break-down voltage of the surrounding medium. In addition to the presence of arcs and low-magnitude currents, HIFs exhibit several other physical characteristics. These include the intermittent nature of the arc, asymmetry in the current waveform, the presence of buildup and shoulder currents, non-stationary current behavior, randomness, non-linearity, and low-frequency components in the voltage waveform, as well as both low and high-frequency components in the current waveform Ghaderi et al. (2017). These aspects are accurately captured by the model proposed by Emanuel et al. Emanuel et al. (1990), which is widely accepted in the field. Furthermore, the adjusted model proposed Cui et al. (2019) is used in the simulations, as depicted in Fig. 2.

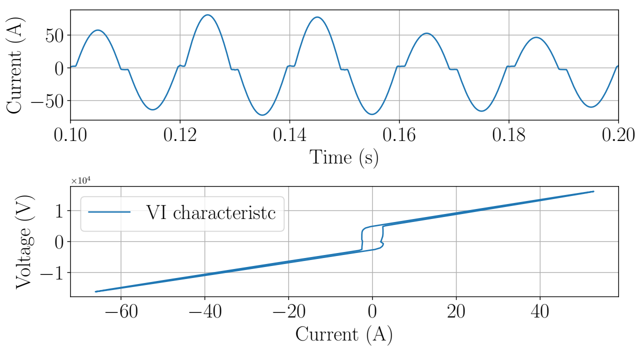

Figure 2. Typical behavior of a HIF.

The simulation involves generating events of interest at multiple locations within the system, specifically on and between (midpoint) buses. The monitoring of the system is conducted at buses 1 and 6, with a sampling frequency of 12.5 kHz, equivalent to 250 samples per cycle of the 50 Hz power system frequency. To ensure a consistent and uniform dataset, each class of event is simulated 30 times at each location, resulting in a total of 2430 examples. All simulations are carried out using the Matlab/Simulink environment. The entire simulation process takes approximately 1620 hours to complete and is performed on a system equipped with an Intel i5-3230M processor operating at 2.6 GHz and 8 GB of RAM.

2.3 Processing Data

The current and voltage waveforms previously obtained are processed in terms of harmonic phasor estimation, emulating the PMU. The estimation is performed by applying the recursive algorithm of the Discrete Fourier Transform—DFT, (Phadke and Thorp, 2008). It consists in applying the DFT over one cycle of the fundamental frequency, Eq. 1, and then correcting it, recursively, for every additional sample as in Eq. 2. This results in a rate of 250 phasors/second. The DFT converts the signal from the time domain to the frequency domain, revealing its constituent frequency components. This technique allows us to track the changes in the phasor over time, providing valuable insights into the behavior of the signal. The system is modeled considering that there is no frequency variation. In this way, DFT provides exact synchrophasors.

$$X_k^{(i)} = \frac{\sqrt{2}}{N} \sum_{n=k}^{k+N-1} x_n e^{-jni\theta}, \tag{1}$$

$$X_{k+1}^{(i)} = e^{-ji\theta} X_k^{(i)} + \frac{\sqrt{2}}{N} \left(x_{N+k} - x_k\right) e^{-jki\theta}. \tag{2}$$

In the equations above, x_k is the k_{th} sample of the signal, X_k is the k_{th} estimated phasor, N is the number of samples per cycle of fundamental frequency (250), $\theta = 2\pi/N$ is the sampling angle, k is the sample index and i is the harmonic index ($i = 1$ means fundamental frequency).

2.4 Classifying Data

Each example is segmented according to the inception of each event. In this sense, this preset segmentation separated the example into three sections: pre, during and post-event. The mean value of each segment is calculated, resulting in a set of features $\mathbf{H}_k$ that contains the mean value of each segment of magnitude and angle of each harmonic synchrophasor of each PMU, for the current and voltage waveforms, where k indicates the desired harmonic content:

$$\mathbf{H}_k = [\mathbf{V}^k_{pre}, \mathbf{V}^k_{tra}, \mathbf{V}^k_{pos}, \mathbf{I}^k_{pre}, \mathbf{I}^k_{tra}, \mathbf{I}^k_{pos}] \tag{3}$$

The features are normalized between -1 and 1. Then, the dataset is split, with 80% of the data used for training and 20% for the test. In addition, all the machine learnign models are evaluated via a 5-fold cross-validation procedure. In the task of multiclass classification, several classic algorithms including Artificial Neural Network (ANN), Decision Tree (DT), k-Nearest Neighbors (kNN), Logistic Regression (LR), Random Forest (RF), and Support Vector Machine (SVM) are tested to explore the potential of the data. The machine learning models are further tuned using Bayesian Optimization Wu et al. (2019). All classification steps are implemented using Python-based open-source libraries, namely Scikit-Learn and Pandas.

3. RESULTS AND DISCUSSIONS

The method proposed by Soheili et al. (2018) is selected as the case study for several significant reasons: the authors utilize DFT to extract features from waveform signals. They also assess the discriminative potential of odd harmonic contents within the signals to classify various events in an electrical network. Since electrical networks naturally contain some level of harmonics, this evaluation also allows the analysis of the impact of harmonic contents generated by renewable energy sources on event classification tasks.

The selected method employs the relative relation between the third, fifth, and seventh current harmonic to distinguish high impedance faults from capacitors bank switching and non-linear loads switching. The approach is tested with data simulated from the radial distribution network, IEEE 13-bus. This method only considers a single point of measurements, located nearby the substation, and also, they do not consider the presence of distributed generation in the system, so the only sources of harmonics in the system are the considered classes of disturbances themselves. Based on this, some amendments are considered in the analysis, basically in order to adequate the author's methodology to the considered benchmark system: instead of non-linear loads, inverter-connected energy sources are considered in order to add natural harmonic levels to the microgrid, other classes of events are considered, once the non-linear loads switching is out of the simulations. Instead of a single measurement point, the measures are acquired from two points in the system (bus 1 and bus 6), and finally, the kernel of the detection task proposed by the authors is the comparison with some defined thresholds and considering that the major interests of our method is the extraction of valuable information from synchrophasor data and the usage of machine learning techniques to process and classify a large amount of such information, the concept of threshold comparison is substituted by a pre-processing step based on the segmentation and mean value calculation of the estimated synchrophasor data.

In addition, the investigation of promising features from synchrophasors data and the impact of using the angle information in the classification task is also evaluated. All the considered scenarios are presented in Table 1. When compared to the case study, the addition of information (features) increases the overall accuracy, as can be seen in Fig. 3.

Table 2. Scenarios of features - each PMU.

Scenario	Set of Features	Input	Information	Amount
(Soheili et al., 2018)	$\{H_5/H_3,\ H_7/H_3\}$	{I}	{M}	6
#1	$\{H_5/H_3,\ H_7/H_3\}$	{V, I}	{M}	12
#2	$\{H_5/H_3,\ H_7/H_3\}$	{V, I}	{M, A}	24
#3	$\{H_2,\ H_4,\ H_6\}$	{V, I}	{M}	18
#4	$\{H_2,\ H_4,\ H_6\}$	{V, I}	{M, A}	36
#5	$\{H_3,\ H_5,\ H_7\}$	{V, I}	{M}	18
#6	$\{H_3,\ H_5,\ H_7\}$	{V, I}	{M, A}	36
#7	$\{H_2,\ ...,\ H_7\}$	{V, I}	{M}	36
#8	$\{H_2,\ ...,\ H_7\}$	{V, I}	{M, A}	72

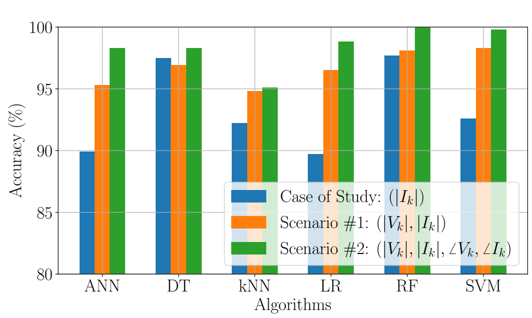

Figure 3. Effect of the number of features in the classification's accuracy.

The accuracy of the classification, considering all the proposed scenarios, can be seen in Figure 4. By looking at the results from the models that use only the magnitude information of voltage and current harmonic synchrophasors it is possible to see that the usage of odd harmonics instead of even ones results in more accurate predictions. This aspect, the usage of odd harmonics in power systems' event classification problems, is widely accepted and emphasized among the literature. By the point of view of number of features, by combining even and odds contents does not result in a significant improvement in the accuracy of the models, whereas the number of feature double up. With the addition of angle information into the classification task, the majority of the models naturally present a better performance when compared with the scenarios that only counts with the magnitude information. The improvement pattern when comparing the accuracy of the models that use, separately, even and odds harmonic contents is maintained, i.e, the accuracy of the classifications that use odd contents overcome the accuracy of the classifications that use even contents.

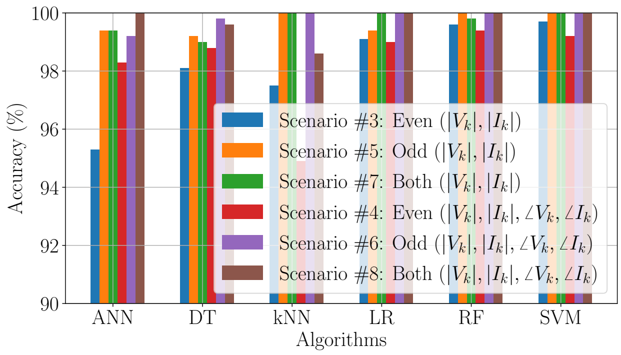

Figure 4. Effect of harmonic contents in the classification's accuracy.

In order to evaluate the robustness of both estimator and classifiers, a noise analysis is carried out considering regular noisy scenarios, around 70 dB of SNR, as well as critical ones, around 40 dB, and the overall accuracy is observed as a function of the SNR. For that, several SNRs are applied to the simulated waveform, then, the harmonic synchrophasors are estimated. The impact of a noisy environment is depicted in Fig.5 and shows how the accuracy is affected with different levels of noise in the raw signals.

The presence of the angle information tends to enhance the accuracy of the machine learning models. Furthermore, it is also possible to see that for severe levels of SNR (around 40 dB), the impact of the noise overcome any possible enhancement obtained by the addition of angle information in the machine learning models, i.e, conditions of strong noise (lower than 50 dB), degenerate the performance of the classification. Nevertheless, the classification accuracy is well-behaved for usual conditions of SNRs in distribution systems.

4. CONCLUSIONS

An analysis of combinations of features extracted from harmonic synchrophasors to perform event classification of the considered microgrid using machine learning approaches is

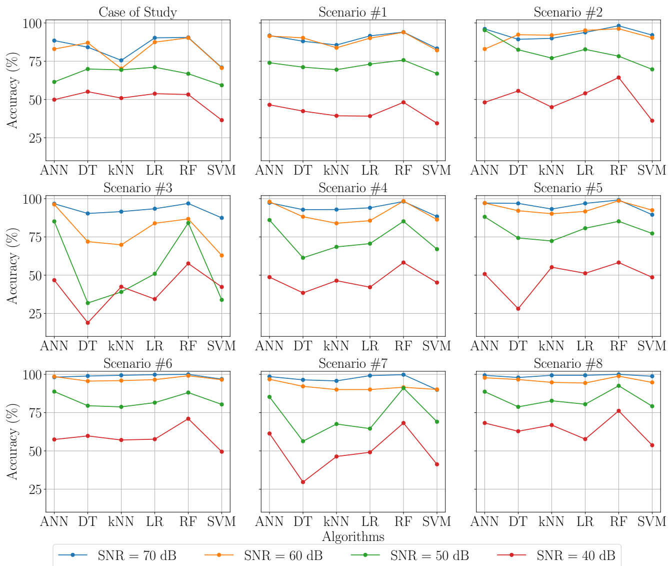

Figure 5. Impact of noise in the classification's accuracy.

conducted. Faulty and non-faulty events were taken into account and, when comparing the proposed scenarios of features with a state-of-art method, the improvement in the overall perform was accomplished. The main observed advantages were acquired by virtue of the usage of both magnitude and angle of the synchrophasors, this approach is quite innovative when looking at the related methods available. The usage of all the synchrophasor information tends to increase the dimensionality of the machine learning models, however, it was possible to observe that the increase in the number of features not necessarily improves the results in a classification task. So it is evident that there is a trade-off that must be taken into account when modelling such tasks: what are the features that actually affect the accuracy of the models? The promising results obtained have been encouraged a further investigation that aims to explore the most suitable selection of features from the harmonic synchrophasors information.

When conducting tests of noise insertion, the models proved to be robust for common scenarios of noise in low and medium voltage electrical networks. Moreover, when evaluating the effect of the measuring point in the classification task it was observed that for some particular scenarios, the overall accuracy of the models was improved. This characteristic motivates the idea of creating a multi-measuring approach of event classification in microgrids by using PMUs installed all over the network. Such results corroborate that by using more than one measurement point, the classification accuracy can be enhanced by combining the information of each PMU. In addition, the presence of multi-sensors in the network can allow the development of features that are based on a comparison between the nodes of the considered network, for example, it would be possible to observe how a specific event causes the angular opening between specific nodes of the system. The idea of using relationships of specific electrical quantities from different points of the system is also an innovative approach, especially when dealing with harmonic synchrophasors.

REFERENCES

Ali, M.S., Abu Bakar, A.H., Mokhlis, H., Arof, H., and Azil Illias, H. (2014). High-impedance fault location using matching technique and wavelet transform for underground cable distribution network. *IEEJ Transactions on Electrical and Electronic Engineering*, 9(2), 176–182. doi:10.1002/tee.21953.

Bhattarai, B.P., Paudyal, S., Luo, Y., Mohanpurkar, M., Cheung, K., Hovsapian, R., Myers, K.S., Zhang, R., Zhao, P., Manic, M., Zhang, S., and Zhang, X. (2019). Big data analytics in smart grids: state-of-the- art, challenges, opportunities, and future directions. *IET Smart Grid*, 2(2), 141–154. doi:10.1049/iet-stg.2018.0261.

CIGRE (2014). Task Force C6.04.02 - Benchmark Systems for Network Integration of Renewable and Distributed Energy Resources.

Cui, Q., El-Arroudi, K., and Weng, Y. (2019). A Feature Selection Method for High Impedance Fault Detection. *IEEE Transactions on Power Delivery*, 34(3), 1203–1215. doi:10.1109/TPWRD.2019.2901634.

Emanuel, A.E., Cyganski, D., Orr, J.A., Shiller, S., and Gulachenski, E.M. (1990). High impedance fault arcing on sandy soil in 15kV distribution feeders: Contributions to the evaluation of the low frequency spectrum. *IEEE Transactions on Power Delivery*, 5(2), 676–686. doi:10.1109/61.53070.

Farajollahi, M., Shahsavari, A., Stewart, E.M., and Mohsenian-Rad, H. (2018). Locating the source of events in power distribution systems using micro-PMU data. *IEEE Transactions on Power Systems*, 33(6), 6343–6354. doi:10.1109/TPWRS.2018.2832126.

Gao, J., Wang, X., Wang, X., Yang, A., Yuan, H., and Wei, X. (2022). A high-impedance fault detection method for distribution systems based on empirical wavelet transform and differential faulty energy. *IEEE Transactions on Smart Grid*, 13(2), 900–912. doi:10.1109/TSG.2021.3129315.

Ghaderi, A., Ginn, H.L., and Mohammadpour, H.A. (2017). High impedance fault detection: A review. *Electric power systems research*, 143, 376–388. doi:10.1016/j.epsr.2016.10.021.

Gomes, D.P., Ozansoy, C., Ulhaq, A., and de Melo Vieira Júnior, J.C. (2019). The effectiveness of different sampling rates in vegetation high-impedance fault classification. *Electric Power Systems Research*, 174. doi:10.1016/j.epsr.2019.105872.

Hojabri, M., Dersch, U., Papaemmanouil, A., and Bosshart, P. (2019). A comprehensive survey on phasor measurement unit applications in distribution systems. *Energies*, 12(23), 1–23. doi:10.3390/en12234552.

Joshi, P.M. and Verma, H.K. (2021). Synchrophasor measurement applications and optimal PMU placement: A review. *Electric Power Systems Research*, 199, 107428. doi:10.1016/j.epsr.2021.107428.

Ledesma, J.J.G., do Nascimento, K.B., de Araujo, L.R., and Penido, D.R.R. (2020). A two-level ANN-based method using synchronized measurements to locate high-impedance fault in distribution systems. *Electric Power Systems Research*, 188, 106576. doi:10.1016/j.epsr.2020.106576.

Lima, É.M., Brito, N.S.D., and de Souza, B.A. (2019). High impedance fault detection based on Stockwell transform and third harmonic current phase angle. *Electric Power Systems Research*, 175, 105931. doi:10.1016/j.epsr.2019.105931.

Liu, Y., Wu, L., and Li, J. (2020). D-PMU based applications for emerging active distribution systems: A review. *Electric Power Systems Research*, 179, 106063. doi:10.1016/j.epsr.2019.106063.

Miranda, V., Cardoso, P., Bessa, R., and Decker, I. (2019). Through the looking glass: Seeing events in power systems dynamics. *International Journal of Electrical Power and Energy Systems*, 106, 411–419. doi:10.1016/j.ijepes.2018.10.024.

Phadke, A. and Thorp, J. (2008). *Synchronized Phasor Measurements and their Applications*.

Rai, K., Hojatpanah, F., Badrkhani Ajaei, F., and Grolinger, K. (2021). Deep learning for high-impedance fault detection: Convolutional autoencoders. *Energies*, 14(12), 3623. doi:10.3390/en14123623.

Samantaray, S.R. (2012). Ensemble decision trees for high impedance fault detection in power distribution network. *International Journal of Electrical Power & Energy Systems*, 43(1), 1048–1055. doi:10.1016/j.ijepes.2012.06.006.

Sarwar, M., Mehmood, F., Abid, M., Khan, A.Q., Gul, S.T., and Khan, A.S. (2020). High impedance fault detection and isolation in power distribution networks using support vector machines. *Journal of King Saud University - Engineering Sciences*, 32(8), 524–535. doi:10.1016/j.jksues.2019.07.001.

Sekar, K. and Mohanty, N.K. (2017). Combined Mathematical Morphology and Data Mining Based High Impedance Fault Detection. *Energy Procedia*, 117, 417–423. doi:10.1016/j.egypro.2017.05.161.

Sharma, N. and Samantaray, S. (2019). Assessment of PMU-based wide-area angle criterion for fault detection in microgrid. *IET Generation, Transmission and Distribution*, 13(19), 4301–4310. doi:10.1049/iet-gtd.2019.0027.

Shaw, P. and Jena, M.K. (2020). A Novel Event Detection and Classification Scheme Using Wide Area Frequency Measurements. *IEEE Transactions on Smart Grid*, 3053, 1–11. doi:10.1109/TSG.2020.3039274.

Silva, S., Costa, P., Gouvea, M., Lacerda, A., Alves, F., and Leite, D. (2018). High impedance fault detection in power distribution systems using wavelet transform and evolving neural network. *Electric Power Systems Research*, 154, 474–483. doi:10.1016/j.epsr.2017.08.039.

Soheili, A., Sadeh, J., and Bakhshi, R. (2018). Modified fft based high impedance fault detection technique considering distribution non-linear loads: Simulation and experimental data analysis. *International Journal of Electrical Power & Energy Systems*, 94, 124–140. doi:10.1016/j.ijepes.2017.06.035.

Tu, C., He, X., Shuai, Z., and Jiang, F. (2017). Big data issues in smart grid – A review. *Renewable and Sustainable Energy Reviews*, 79, 1099–1107. doi:10.1016/j.rser.2017.05.134.

Wang, S. and Dehghanian, P. (2020). On the use of artificial intelligence for high impedance fault detection and electrical safety. *IEEE Transactions on Industry Applications*, 56(6), 7208–7216. doi:10.1109/TIA.2020.3017698.

Wu, J., Chen, X.Y., Zhang, H., Xiong, L.D., Lei, H., and Deng, S.H. (2019). Hyperparameter optimization for machine learning models based on Bayesian optimization. *Journal of Electronic Science and Technology*, 17(1), 26–40. doi:10.11989/JEST.1674-862X.80904120.