High Impedance Fault Detection through a Machine Learning Algorithm in a recloser control

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***Abstract*— One of the most challenging protection problems in the distribution grid is to detect high impedance (HiZ) faults due to a live down conductor or a vegetation contact scenario. HiZ faults can produce low fault currents and are often not detected by traditional ground overcurrent protection. These faults if not cleared quickly may lead to arcing which can start a wildfire in presence of dry vegetation or grass. HiZ faults exhibit signatures with random erratic characteristics which slowly evolve with time. The signature detection becomes complex due to the low current amplitude and reduced measurement accuracy in traditional sensors in protection devices which are typically calibrated to measure and trip on high current. This paper presents hardware and software innovations in a recloser control to overcome these challenges. A sensitive ground channel is used to measure fault current changes as low as 1 Amp primary. An advanced signal processing technique is implemented in the recloser control to quantify harmonic energy change and randomness in current signature, distinguishing it from the background noise. A machine learning algorithm is then used to differentiate actual HiZ fault signatures from non-fault transient scenarios. These capabilities allow the recloser control to timely identify and clear HiZ faults in different ground surfaces limiting fault energy and reduce false alarms. The method shows high detection accuracy and low detection time in lab-emulated events in a medium voltage setup.**

***Index Terms*— Protection, High impedance faults, Machine learning, Wildfire**

I. Introduction

In recent years wildfires have become a huge economic risk affecting both infrastructure and human lives. Long, dry, and hot summers with high wind situations are more common due to impacts of climate change [1]. This situation is increasing the chance of starting large wildfires even with minimal ignition. Statistically, even though only 10% of wildfires are ignited due to electricity infrastructure, like arcing due to down conductor faults, insulation failure, tree contact etc. but the impact of the wildfires can be devastating [2]. Some recent examples include California's Camp Fire in 2018 [3] which resulted from a transmission line failure causing an estimated \$15B in capital losses and 85 fatalities. In 2021, Dixie fire [4] in Northern California was started when a Douglas Fir tree encountered a 12 kV distribution line, burning nearly one million acres over a span of 104 days. The Marshall fire in Boulder, Colorado in Dec 2021 was initiated when a live medium voltage conductor came unmoored from a crossarm and sagged low enough to contact support braces [5]. Utilities are looking for solutions to detect these events early and deenergize the circuit at low fault energy to avoid risking start of new wildfires.

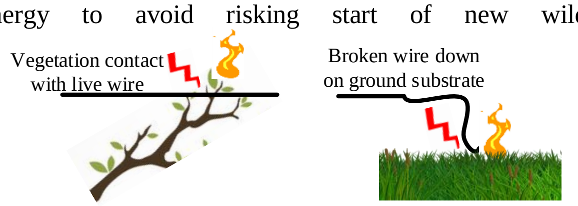

Figure 1. HiZ fault scenarios

Utilities are taking various steps to address this issue including grid hardening initiatives like vegetation management, covered conductor with weather-resistant materials, undergrounding and adding additional sensing and monitoring through innovative technologies [1] like lidars, drones etc. However, a major effort on behalf of the utilities is also to use sensitive protection settings in existing protection and control equipment such as reclosers, communication-assisted tripping in breakers and line sensors. According to recent research from the University of California, Berkley, powerline faults can be reduced upward of 72% through sensors already deployed at many utility feeders. However, the primary barrier would be the threshold-based overcurrent protection that is employed by utilities. Events such as HiZ faults exhibit a fault current magnitude that is typically small, often as low as 1-15A. For unbalanced 3-wire or 4-wire distribution power systems often the unbalance is in the same magnitude range [6]. Thus, typical ground overcurrent protection element in protective relays cannot be set at that low range to detect these faults.

However, in the field of system protection, detection of HiZ faults is a difficult challenge known for decades and several attempts have been made in the academia and the industry to tackle it. Academic research [7]-[16], [23] typically applies advanced signal processing, machine learning and deep learning models to address the issue. These works are often validated on simulated high impedance fault data and are not implemented

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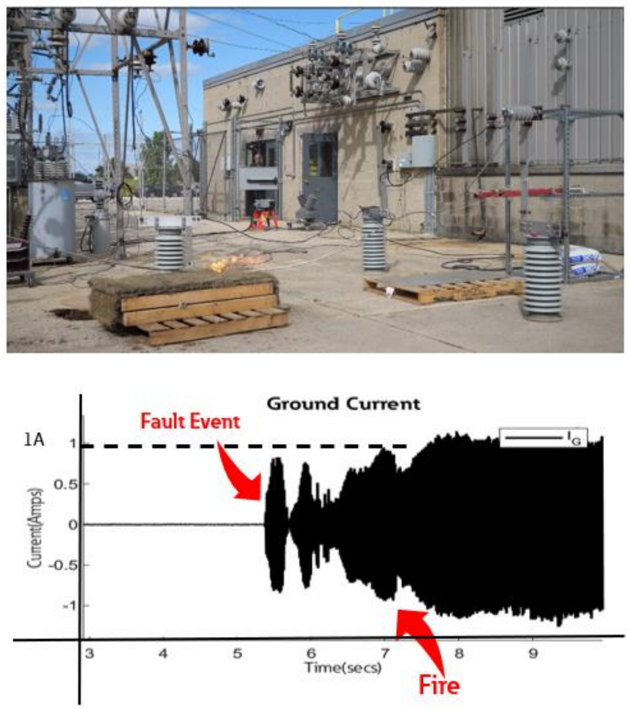

Figure 2 Down conductor on grass surface and fault current signature.

on actual edge intelligent devices like protection relays Additionally, they rarely consider the practical challenges of CT accuracy and noise in a real feeder which can affect detection time and the magnitude of fault current which defines the fault energy for starting wildfire [19].

Industrial applications, on the other hand, typically use simpler methods that are applicable to edge devices. Several protection relay vendors have made significant strides in providing solutions to this challenge. Various manufacturers offer solutions which provide diverse levels of accuracy [17], [18], [21], [24]. The fault detection rate for down conductor events reported in [20] is about 50% with fault amplitude range between 9 to 40A where the detection time is several minutes. Reference [23] on simulated data showed a detection rate of 80% for a current range more than 2A with an average detection time of 30 seconds. However, in experiments conducted by Eaton in a medium voltage test setup, it was observed that that fire can be ignited with even less than 1A fault current within 10 seconds of fault initiation.

For example, in Figure 2, a 12.47 kV broken conductor was dropped on grass with topsoil underneath. It ignited within 10 seconds of the fault event with the substrate conducting around 1A to the ground. Another example in Figure 3, showed that a tree can be on fire touching an unbroken conductor while conducting less than 3A. The monitored fault current through the grounded substrate showed that in both scenarios a potential fire ignition was possible if it was not detected within a few seconds of fault initiation and at fault current magnitude as low as 1A. It is difficult for threshold- based ground current protection strategy to detect these events fast enough to avoid a

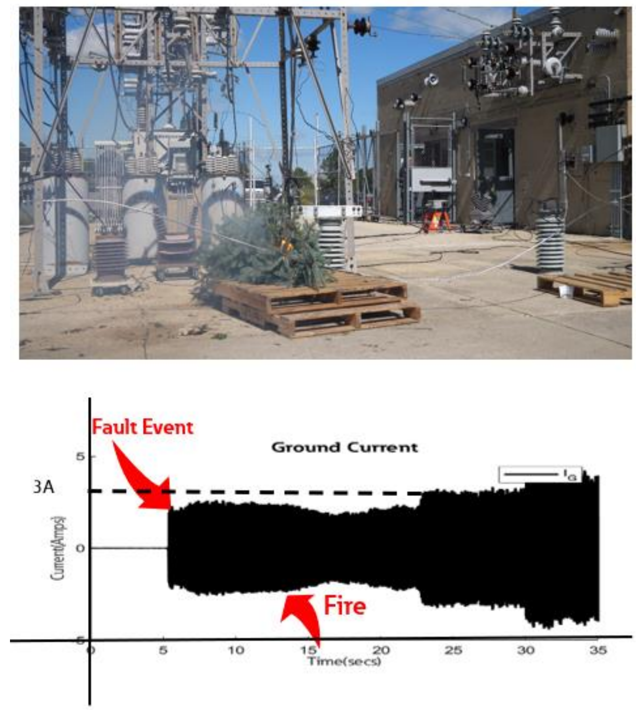

Figure 3. Unbroken conductor touching a tree and fault current signature.

fire particularly in dry, windy conditions. To address this problem, a sensitive event detection algorithm is developed leveraging machine learning which could learn from different current signatures and identify these scenarios in a timely manner.

The algorithm uses harmonic anomaly extraction, unique feature identification, and machine learning classification explained in the next two sections. For machine learning, both lab emulated and simulated data was used for fault and non-fault transient scenarios. Post training, the algorithm was tested against actual fault and non-fault data. The validation involves real-time testing injecting actual fault current signature through an amplifier to a recloser. The results are presented in terms of accuracy, detection time and false alarm rates. The algorithm could identify ground fault current change of 1A within 2 seconds of fault initiation in majority of tests, significantly reducing the fault energy and possibility of fire ignition.

II. HARMONIC ANOMALY IN FAULT CURRENT

The detection method proposed in this work is dependent on measurement of harmonic signature in ground current channel of a recloser. Typically, reclosers come with three CTs for three phases while the ground current measurement channel measures the sum of the three phase CTs. A sensitive ground current measurement channel is used which can accurately measure ground current signature as low as 1A in the recloser control using the three phase CTs. The measured ground current then undergoes discretization, low pass filtering and a Fast Fourier transform (FFT) to calculate the harmonics up to 15th order every quarter cycle (4 milliseconds).

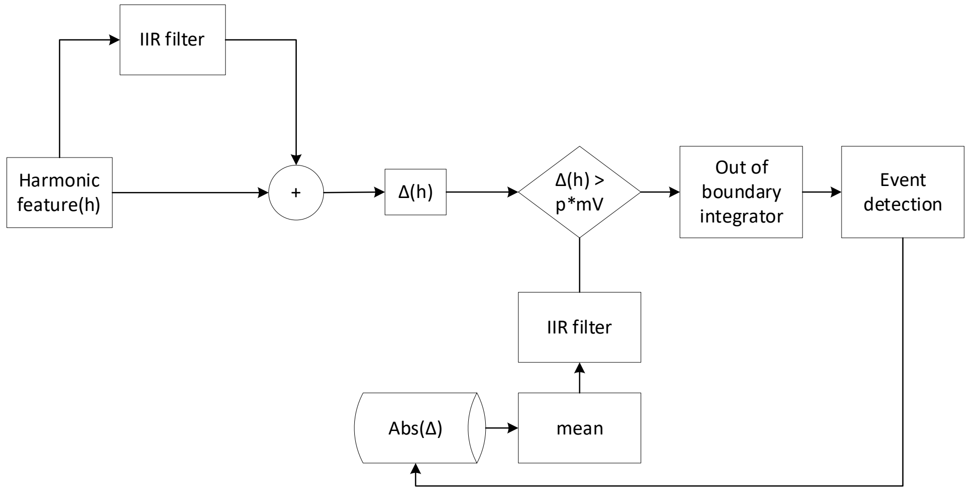

Figure 4. Anomaly event detection method

Thereby the harmonic energy signature is monitored every quarter cycle which is the computation cycle time of the microprocessor in the recloser controller.

In different distribution system feeders, ground channel characteristics, namely the unbalance, the background harmonic levels etc., are different and can change over time. Consequently, HiZ faults are difficult to detect using a fixed threshold on harmonic energy change across all locations. It can result in a lot of false alarms due to load changes and/or switching events. The proposed algorithm incorporates an anomaly event detection scheme as the first step of detection. As shown in Figure 4, the method employs an adaptive threshold on harmonic energy, which self-adapts based on the observed baseline characteristics of harmonics (within 10 seconds of load more than 1A on any phase). The detected anomaly in the harmonic energy do not necessarily point to a HiZ fault. Normal operation events such as transformer inrush and motor starts could potentially be identified as anomalies too as they would change the baseline profile as well. To further distinguish HiZ faults from those normal transients, unique features are used to quantify the random behavior in HiZ faults. In general, compared to the normal transients, the harmonic waveforms of the HiZ faults typically show irregular and chaotic patterns. No uniform pattern exists in all types of HiZ faults. However, the harmonic energies in normal transients usually follow predictive patterns that gradually decay after onset. The proposed method uses some unique features to quantify the randomly rising-and-decaying patterns shown in high impedance faults. These include cycle to cycle correlation, t-score and other features which are detailed later.

A. Harmonic Anomaly Event detection

Energy of selected harmonics is passed through a lowpass infinite impulse response (IIR) filter to obtain a baseline harmonic energy profile. Difference between actual harmonic and the baseline harmonic energy profile, Delta Energy Δ(h) is monitored in real time to check if it exceeds an allowable threshold p*mV. This allowable threshold is adaptive and is estimated using a long-short variance estimator. The short variance is determined by taking the mean of the buffered absolute differences between harmonic magnitudes and the baseline reference, mean (Abs(Δ)). This calculated short variance is then integrated by another IIR filter with a long time constant in the absence of any detected anomalies. The threshold for the anomaly detector is set as a multiple(p) of the long-term variance(mV). If the instantaneous Delta energy exceeds this threshold, it is identified as an out of boundary event and fed into a leaky integrator. Should the output of the leaky integrator surpass this threshold, a delta energy anomaly event is detected for further pattern recognition.

An example anomaly event detection is shown in Figure 5. The left panel shows the normalized Delta energy waveform with the estimated threshold shown in dashed line. Note that the estimated threshold changes based on the change in Delta energy level as explained in Figure 4. The right panel is the leaky integrator that integrates the out of boundary events and provides an output in 0 to 1. When the leaky integrator output is greater than a given threshold, a Delta energy anomaly event is detected. Note that the value of the multiple p and the leaky integrator threshold are tools to increase or decrease sensitivity of the algorithm.

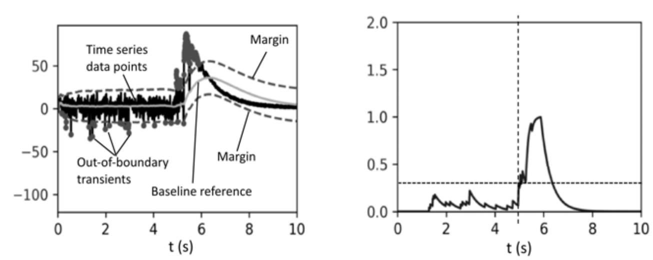

Figure 5. Delta Energy profile and leaky integrator

B. Unique Features distinguishing HiZ vs normal event

Once harmonic delta energy is detected, the algorithm looks at other features for distinction of HiZ with normal switching events. One such feature is the energy correlation which will check for cycle-to-cycle randomness by monitoring the temporal correlation between the energy of selected harmonic frequencies of adjacent time cycle windows of a current signal. However, it can be impacted by the background noise. When the harmonic energy has no significant changes over time, the energy correlation will compare two windows of energy with only noise, which also leads to small correlation. To avoid auto comparison of energy correlation over a low signal to noise ratio, we limit the energy correlation using T-score. The T-score module will check whether the two consecutive windowed energy waveforms are filling into the same distribution, as normally checked with a student's T distribution.

Features like delta harmonic energy, correlation with T-score etc. along with some hyperparameters learnt through machine learning are used to distinguish HiZ faults with high level of confidence. The next section covers data generation and the machine learning analysis for further classification.

III. Data Generation and Machine Learning Analysis

Traditional threshold-based protection can be setup through conduction of short circuit studies and is deterministic. However, this method tries to distinguish between pattern of harmonic energy changes between normal transients and HiZ fault events. HiZ faults are typically associated with intermittent arcing which exhibit changing current and voltage characteristics (time-variant, chaotic, and nonlinear). No uniform patterns exist in all kinds of HiZ fault scenarios. So, in this problem machine learning could potentially be useful to identify hyperparameters which can detect a wide range of events and reject false alarms. It is difficult to obtain a lot of HiZ fault data from utility feeders in the field. The research team tried to solve this issue by emulating HiZ faults in a medium voltage setup in Eaton's Edison Technical Center in Franksville, WI. The tests included diverse types of ground surfaces, species of trees under different moisture level and wind conditions. Beside the experimental HiZ fault events, the team also utilized electromagnetic transient (EMT) simulation in PSCAD platform to proliferate more fault and non-fault scenarios under different load and grid conditions. The experimental and simulated data was used in offline training process for the machine learning algorithm for distinguishing actual HiZ faults from non-fault events.

A. *Experimental Data Generation in Lab*

The Edison technical center in Franksville, WI is a medium voltage testing facility accredited for electrical testing. It utilizes two distinct facilities: the high-power lab and the high-voltage lab. The high-power lab operates on an isolated 8.13 kV generator, which is then stepped up to voltage levels up to 38 kV for the test cell. The high voltage lab receives power from a local utility's 25 kV distribution feeder which is stepped down to standard voltage levels like 12.47 kV as required. Given its specialized capabilities, the laboratory was an ideal match for the demanding requirements of HiZ data generation. Using source side impedance, the maximum fault current was limited to 100A. Broken down conductor tests as shown in signature in Figure 1Figure 2 were performed upon ground substrates like sand, gravel, concrete and grass. Vegetation touch tests as shown in Figure 3 were performed on distinct species of trees. The ground substrate or tree was connected via a ground rod to the facility ground through a high accuracy measuring CT.

In both types of scenarios, the laboratory meticulously replicated mechanical conditions using specialized test fixtures. This ensured that the state of the conductors, both before and after the fault events, accurately mirrored those in a real-world distribution system. The team designed custom fixtures for dropping or lowering the conductors so that they touched a grounded substrate or vegetation, as specified in the test requirements. The conductor movement was controlled using a pneumatic arrangement to mimic the motion of the conductor in HiZ fault events, ensuring precise and repeatable conditions.

To guarantee that the HiZ fault dataset is a true representation of actual HiZ faults in the field, a wide variety of surfaces and vegetation types was considered. Additionally, the tests accounted for various physical states of the substrates, like moisture condition, wind etc. to provide a comprehensive understanding of the fault behavior under different conditions. Table I and Table II detail the minimum current at which the ground substrates showed signs of ignition. This rigorous approach allowed for a detailed analysis of HiZ fault characteristics, contributing valuable insights of how varied factors influence the current magnitude and the likelihood of fire initiation. The analysis is crucial for the development of a more effective detection and protection strategies tailored to the unique challenges posed by HiZ faults.

TABLE I
VEGETATION TYPES AND IGNITION CURRENT

Vegetation Sample #	Vegetation Types	Fault Current for Ignition
1	Arborvitae	1.0A
2	Juniper	2.1A
3	White Pine	0.46A
4	Spruce	1.5A

TABLE II
DOWN CONDUCTOR TEST SURFACE TYPES AND CURRENT

Surface Sample #	Surface Types	Fault Current Observed
1	Sand	4.3A
2	Grass	9.1A
3	Concrete	9.0A
4	Gravel	1.4A

For down conductor events on dry grass varieties, freshly reinforced concrete, and sand, HiZ faults are capable of yielding currents within the 1-15A range while still having arcing. An example test case with dry grass is shown in Figure 2 The start of the fault event and fire are also noted in the figure which is within seconds of conductor drop.

Current magnitudes for vegetation contact depend on the impedance offered by the tree, which is typically several Megaohms. At 12.47 kV voltage level, this results in the tree conducting very low current. Generally, a green tree or bush with sap conducts less than 1 Amp to several Amps of current. If the trunk or path to ground is long and dry, the sap dries up

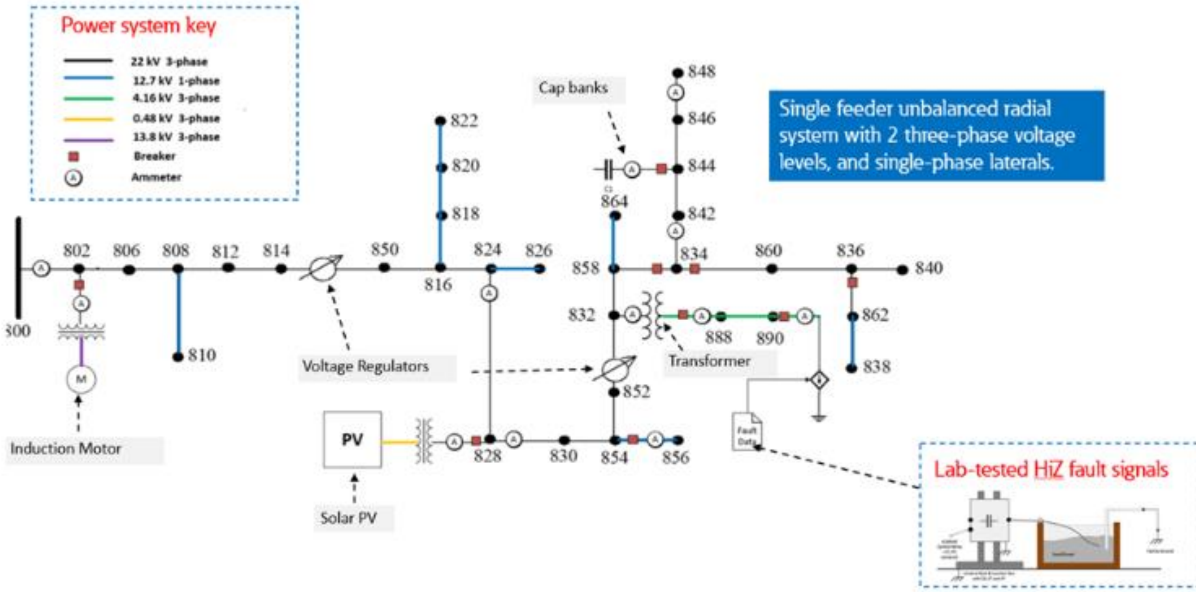

Figure 6. Diagram of Modified IEEE 34 Bus System with fault injected as controlled current sink in PSCAD.

quickly, causing the tree to cease conducting and thus not resulting in flames or fire. However, with a shorter trunk, the resistive loss is significant. The burnt wood quickly converts to charcoal, which conducts electricity exceptionally well, resulting in high current flow. Initial observations suggest that the detection algorithm must identify the fault within the first 20-30 seconds, even at low current levels close to 1 Amp to prevent fire. For instance, a test case involving a Pine tree is shown in Figure 3 which demonstrates the ignition at about 2.5A.

B. EMTP Simulations for Event Generation

Besides experimental data, a high-fidelity transient model of a distribution feeder has been developed to simulate HiZ faults and non-fault transients under various conditions. This study involved injecting field and laboratory generated HiZ fault data into Electro-Magnetic Transient (EMT) simulations of a modified IEEE 34 node feeder test system shown in Figure 6 using EMTDC/PSCAD. By varying the configuration, models, and conditions of the power system model, the study addresses considerations that could not be covered during laboratory testing. The system has the following characteristics to facilitate the HiZ simulation under different grid conditions:

- The original IEEE 34 Node Test Feeder, a 24.9 kV feeder system located in Arizona, is ideal for HiZ fault algorithm development and validation due to its unique features.
- The system is very long and lightly loaded, allowing for the fault location to be moved and single-phase loadings to be adjusted for algorithm development and validation.
- Two in-line regulators are required to maintain a good voltage profile under different load conditions.
- An in-line transformer reduces the voltage to 4.16 kV for a short section of the feeder, enabling HiZ fault injection at a different voltage level.
- Unbalanced loading with both 3-wire and 4-wire systems ensures the method works for different levels of unbalance.

The modified IEEE 34 Node feeder used in the simulations, as shown in Figure 6, has a nominal voltage of 22 kV. HiZ fault injection is simulated as a controlled current sink at multiple locations.

C. Machine Learning Analysis

To effectively train and validate machine learning models for detecting HiZ faults, high-quality data is essential. At Eaton's Franksville facility, 176 HiZ fault scenarios were emulated. Additionally, over 200 normal load change data scenarios were generated which included transformer inrush, recloser switching operations, capacitor bank switching, and motor soft starts, using the model in Figure 6. The comprehensive datasets, including HiZ fault experiments from Franksville and normal operations from simulation, are used for training and validation. The data is split into a 60:40 ratio for training and validation, respectively. The offline learning based on this data is used to find hyperparameters for the HiZ detection algorithm as mentioned in Section II.

HiZ fault identification solution involves four key steps: data preprocessing, anomaly event detection on harmonic waveforms of recorded neutral or grounding current, feature extraction, and the machine learning model for HiZ fault indication (Figure 7). The anomaly detector, detailed in Section II, learns the baseline variance of the monitored current harmonic features in real-time. It adapts to different grid systems, allowing for gradual noise level variations. When a potential HiZ fault event is detected, the anomaly detector's threshold is temporarily frozen for a few seconds until no significant harmonic changes are observed. Unique features of the captured signal are then calculated and fed into a physics-based model to generate a fault indicator. These features primarily quantify the time-varying up and down patterns in the harmonic waveforms. The final HiZ fault indicator model essentially counts these patterns within a predefined time window. The parameters within the indicator model are pretrained and optimized offline using a logistic regression model.

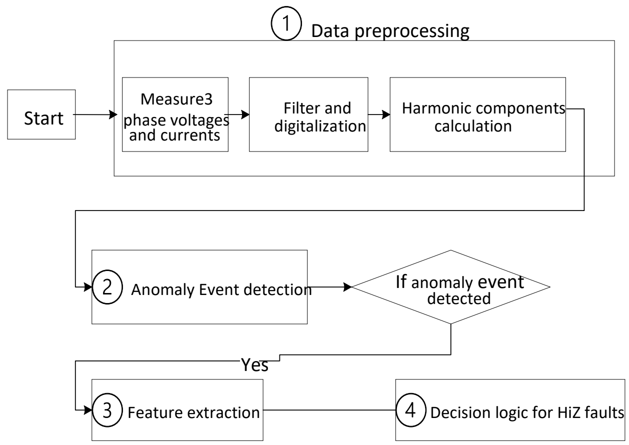

Figure 7. HiZ fault detection algorithm

IV. VALIDATION TEST RESULTS

HiZ fault detection algorithm was successfully implemented in Eaton's Form 7 recloser control platform with available 3 phase CTs. The team utilized an amplifier to inject recorded current data for HiZ events directly into the phase CTs of the recloser as shown in Figure 8. The Form 7 recloser collects measurements from the CTs and makes decisions based on the offline trained HiZ detection algorithm. The algorithm monitors a finite window of running mean of the change in the harmonic energy content of the sensitive ground channel current to detect if a predefined threshold of deviation from the mean is exceeded. To detect a HiZ fault, this detection is followed by monitoring the T-score of harmonic energy between two adjacent windows to identify the cycle-to-cycle differences. If both harmonic content change and T-score change is detected for a time period greater than a security delay a HiZ fault is detected.

Using the test setup shown in Figure 8 the HiZ fault detection algorithm was validated on the Form 7 recloser control platform with 175 HiZ fault cases staged in Franksville and 45 non-fault cases obtained from public data repositories for utility transients. Sample plots related to delta energy and energy, correlation T-score, recorded in COMTRADE files, were automatically saved by Form 7 upon HiZ fault detection, and are presented in the Appendix.

A. Downed Broken Conductor Case

This case illustrates a downed broken conductor that has fallen on grass. The performance of the proposed detection algorithm is shown in the results plotted on Figure 10. This incident occurs at phase A, where current changes from a pre-fault level of 20A rms to the fault current level of the HiZ fault path measured at 2.78 A rms. The process of the conductor falling and touching the grass can be observed through the phase A current signature. As the conductor descends, the load

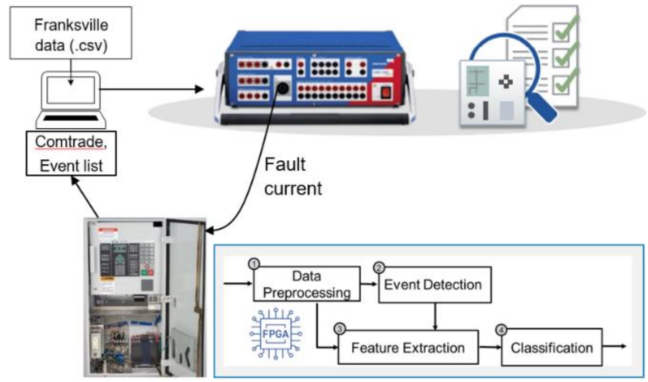

Figure 8. Validation test setup

break arc current exhibits a large proportion of harmonics, causing the delta energy of these harmonic contents to substantially exceed the threshold. The fault current begins to increase once the phase A conductor hits the grass. The delta energy of the harmonic contents continues to exceed the boundary, and the randomness of the harmonic signature shows higher t-score resulting from higher cycle to cycle variation as compared to normal operation. The correlation fault integrator integrates when the T-score is high and triggers the HiZ pickup.

The sequence of events (SOEs) recorded by the Form 7 controller is also shown in Figure 10. The delta energy fault is detected when the delta energy out of boundary integrator surpasses a pre-defined threshold Following this, the high t-score causes the correlation fault integrator to exceed another pre-defined threshold, triggering HiZ pickup. If the HiZ pickup persists for 1s, HiZ fault will be detected, and a trip signal will be issued. The trip time delays acts as a security against false trips for short transients. For the selected downed conductor case, it takes near 1.2s to trip after HiZ fault with 1s security delay, much before the fire ignition.

B. Vegetation Contact Case

The next case is that of an unbroken live conductor which contacted an arborvitae tree, resulting in a fault on phase A. The fault current in the HiZ path was measured at 1.78 Arms only which was reflected in the growth of A phase current. The vegetation contact introduced harmonics that caused the delta energy to exceed its boundary, triggering the delta energy fault detection. This was followed by a high T-score due to the randomness of the fault current, which further trigger HiZ energy correlation fault.

The sequence of events (SOEs) recorded by the Form 7 controller is illustrated in Figure 11. The delta energy fault is detected when the delta energy count surpasses the same pre-defined threshold. Subsequently, the high T-score causes the energy correlation integrator to exceed another pre-defined threshold. initiating the HiZ pickup. After a security delay of 1s, the HiZ fault is detected, and a trip signal is issued. The relay takes 1.6 seconds to trip the HiZ fault, effectively mitigating the fire risk way before the ignition can spread.

C. Capacitor Bank Switching Case

In this case, the performance of the algorithm is evaluated towards capacitor bank switching event. The capacitor bank switching is one of the typical events that brings dramatic change in harmonic content. The high frequency components in current are used to charge the capacitor and will last 1-2 cycles before the capacitor is fully charged. The tested data is from an event in Franksville lab on 300 kVA bank, with signature as shown in Figure. 12. The delta energy stays out of boundary for 2 cycles, and the maximum value of the delta energy count reaches 0.15, which is still below the set threshold. Since delta energy out of boundary integrator starts to decrease after 2 cycles, no SOE is recorded as shown in Figure 12.

D. Summary of Tests Results

The algorithm successfully detected 170 of the 175 fault cases. Figure 9 summarizes the detection times for the 170 detected HiZ fault events. In 80% of the cases, detection occurred in less than 2 seconds as shown in the histogram plot of Figure 9.. Out of 45 non-fault cases, the algorithm issued false alarms in 4 instances.

The fault files which the algorithm could not detect typically had a ground current change of less than 1A. However still the high detection rate at low ground fault current level demonstrates effectiveness in minimizing fault energy, critical to reduce chances of wildfire. The low number of false alarms also indicates a high level of reliability, The comprehensive validation process underscores Eaton's commitment to enhancing grid safety and reliability in utilities while minimizing the risk of wildfires,

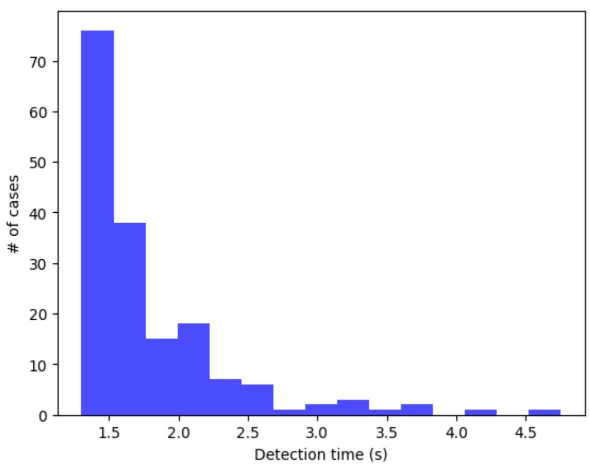

Figure 9 Summary of detection time for 170 HiZ events

V. Conclusion and discussion

The research team at Eaton has developed and demonstrated a machine learning based HiZ fault detection algorithm. The detection algorithm is 2 step- 1. Harmonic anomaly in current signature is used to detect an anomaly event such as a HiZ fault or a switching transient from normal operation; 2. Machine learning is used to distinguish between normal switching transients and HiZ faults through some unique features. The algorithm is implemented in Form 7 recloser control which uses traditional 3 phase CTs, can be used in both 3-wire and 4-wire systems. Extensive experiments were performed to emulate HiZ faults in lab environment. Experimental and simulated HiZ data was used to train machine learning algorithm which had 97% accuracy and less than 10% false alarm rate. The key achievement was that for majority of cases the algorithm could detect faults at just over 1A of ground current within 2 seconds of fault inception. This can significantly reduce the fault energy and reduce the risk of wildfire. However, the algorithm still needs to be tested in the field for more operational scenarios. At present Eaton is partnering with utilities to pilot the solution in the field to train the algorithm against false alarm scenarios.

VI. Acknowledgement

Disclaimer: The views, opinions, and/or findings in this paper are those of the author(s) and should not be construed as an official Department of Defense position or decision unless designated by other official documentation. Acknowledgement.

VII. References

[1] E. A. Udren, C. Bolton, D. Dietmeyer, T. Rahman and S. Flores-Castro, "Managing wildfire risks: Protection system technical developments combined with operational advances to improve public safety," *IEEE Power and Energy Magazine*, vol. 20, p. 64–77, 2022.

[2] "Wildfire and Wildfire Safety," California Public Utilities Commission, [Online]. Available: https://www.cpuc.ca.gov/industries-and-topics/wildfires. [Accessed 12 09 2024].

[3] "Camp Fire (2018)," Wikipedia, [Online]. Available: https://en.wikipedia.org/wiki/Camp_Fire_(2018). [Accessed 12 09 2024].

[4] "Dixie Fire," Wikipedia, [Online]. Available: https://en.wikipedia.org/wiki/Dixie_Fire. [Accessed 12 09 2024].

[5] S. Wilson, "Authorities: Marshall Fire caused by Xcel Energy power line, reignited junk burn," Boulder Beat, 10 6 2023. [Online]. Available: https://boulderbeat.news/2023/06/10/marshall-fire-cause/. [Accessed 12 09 2024].

[6] C. L. Benner and B. D. Russell., "Practical high-impedance fault detection on distribution feeders," *IEEE Transactions on Industry applications*, vol. 33, no. 3, pp. 635-640, 1997.

[7] A. C. Depew, J. M. Parsick, R. W. Dempsey, C. L. Benner, B. D. Russell and M. G. Adamiak, "Field experience with high-impedance fault detection relays," 2006.

[8] A. H. Etemadi and M. Sanaye-Pasand, "High-impedance fault detection using multi-resolution signal decomposition and adaptive neural fuzzy inference system.," *IET generation, transmission & distribution*, pp. 110-118, 2008.

[9] T. M. Lai, L. A. Snider, E. Lo and D. Sutanto, "High-impedance fault detection using discrete wavelet transform and frequency range and RMS conversion.,"

IEEE Transactions on Power Delivery, pp. 397-404, 2005.

[10] É. M. Lima, N. S. D. Brito and B. A. de Souza, "High impedance fault detection based on Stockwell transform and third harmonic current phase angle," *Electric Power Systems Research,* p. 105931, 2019.

[11] G. N. Lopes, T. S. Menezes, G. G. Santos, L. H. P. C. Trondoli and J. C. M. Vieira, "High impedance fault detection based on harmonic energy variation via S-transform," *International Journal of Electrical Power & Energy Systems,* p. 107681, 2022.

[12] S. R. Samantaray, B. K. Panigrahi and P. K. Dash, "High impedance fault detection in power distribution networks using time–frequency transform and probabilistic neural network," *IET generation, transmission & distribution,* pp. 261-270, 2008.

[13] A. R. Sedighi, M. R. Haghifam, O. P. Malik and M. H. Ghassemian, "High impedance fault detection based on wavelet transform and statistical pattern recognition.," *IEEE Transactions on Power Delivery,* pp. 2414-2421, 2005.

[14] V. Veerasamy, N. I. A. Wahab, M. L. Othman, S. Padmanaban, K. Sekar, R. Ramachandran and M. Z. Islam, "LSTM recurrent neural network classifier for high impedance fault detection in solar PV integrated power system.," *IEEE access,* pp. 32672-32687, 2021.

[15] A. Ghaderi, H. A. Mohammadpour, H. L. Ginn and Y.-J. Shin, "High-Impedance Fault Detection in the Distribution Network Using the Time-Frequency-Based Algorithm," *IEEE Transactions on Power Delivery,* vol. 30, no. 3, pp. 1260-1268, 2014.

[16] R. Bhandia, J. J. Chavez, M. Cvetkovic and P. Palensky, "High impedance fault detection in real-time and evaluation using hardware-in-loop testing.," in *IECON 2018-44th Annual Conference of the IEEE Industrial Electronics Society* , 2018.

[17] S. A. Kunsman, I. I. Jouny and S. Kaprielian., "High impedance fault detection". US Patent US7069116B2, 04 08 2005.

[18] E. O. Schweitzer III, M. V. Mynam and D. Hou, "Coordinated high-impedance fault detection systems and methods". US Patent US9160158B2, 13 10 2015.

[19] M. Mishra and R. R. Panigrahi., "Taxonomy of high impedance fault detection algorithm," *Measurement,* vol. 148, p. 106955, 2019.

[20] M. Kistler, F. Heleniak and T. Varshney, "Practical Experience With High-Impedance Fault Detection in Distribution Systems," in *In proceedings of the 46th Annual Western Protective Relay Conference, Spokane*, WA, 2019.

[21] J. J. Theron, A. Pal and A. Varghese., "Tutorial on high impedance fault detection," in *In 2018 71st Annual Conference for Protective Relay Engineers (CPRE)*, 2018.

[22] J.-C. Gu, Z.-J. Huang, J.-M. Wang, L.-C. Hsu and M.-T. Yang, "High impedance fault detection in overhead distribution feeders using a DSP-based feeder terminal unit," *IEEE Transactions on Industry Applications,* vol. 57, p. 179–186, 2020.

[23] M. Afshar, M. Majidi, O. A. Gashteroodkhani and M. E. Amoli, "High impedance fault detection in a practical platform using a real-time-digital simulator," 2022.

[24] M. Adamiak, C. Wester, M. Thakur and C. Jensen, "High impedance fault detection on distribution feeders," *GE Industrial solutions,* 2006.

I. APPENDIX

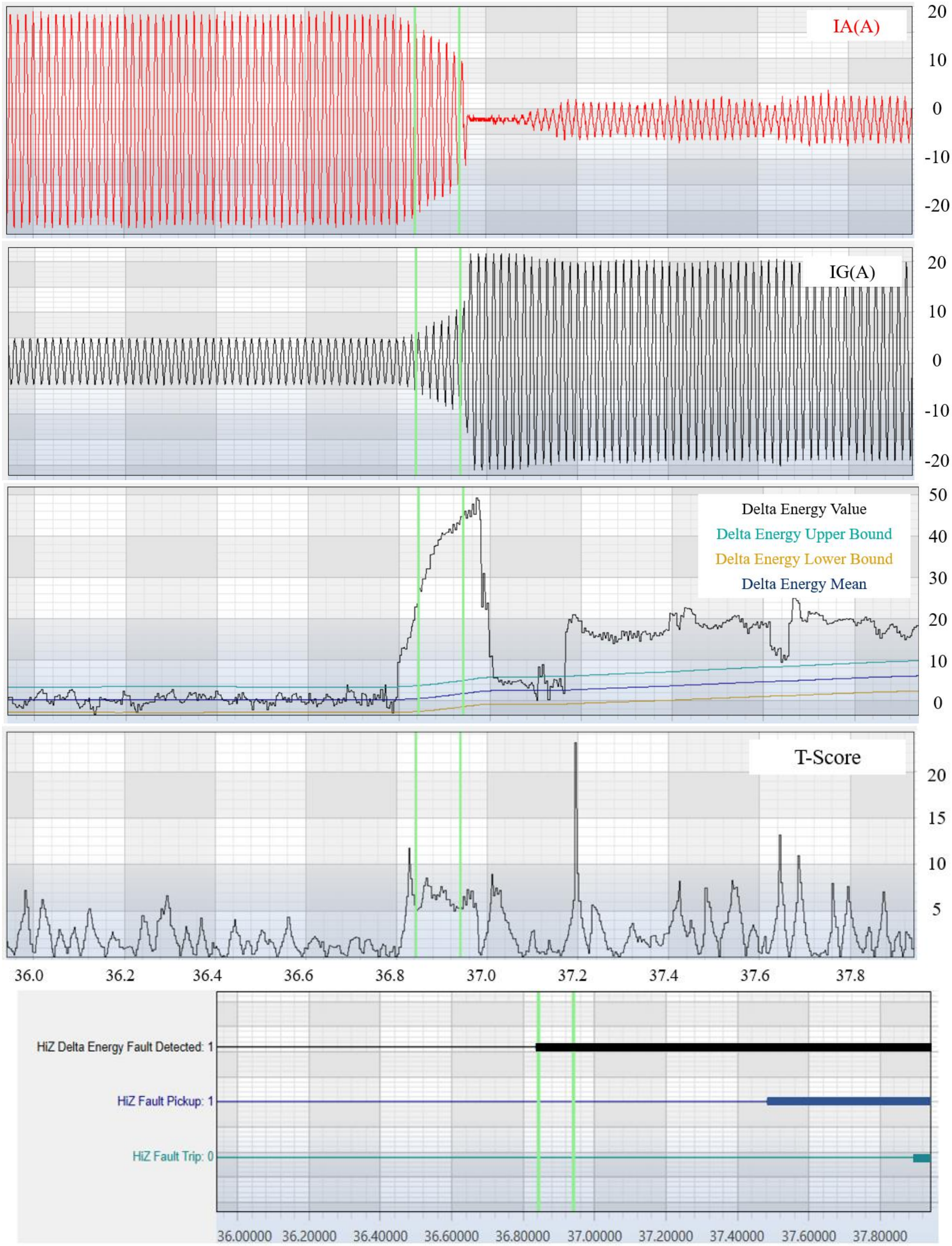

Figure 10. Event captured with down broken conductor on dry grass.

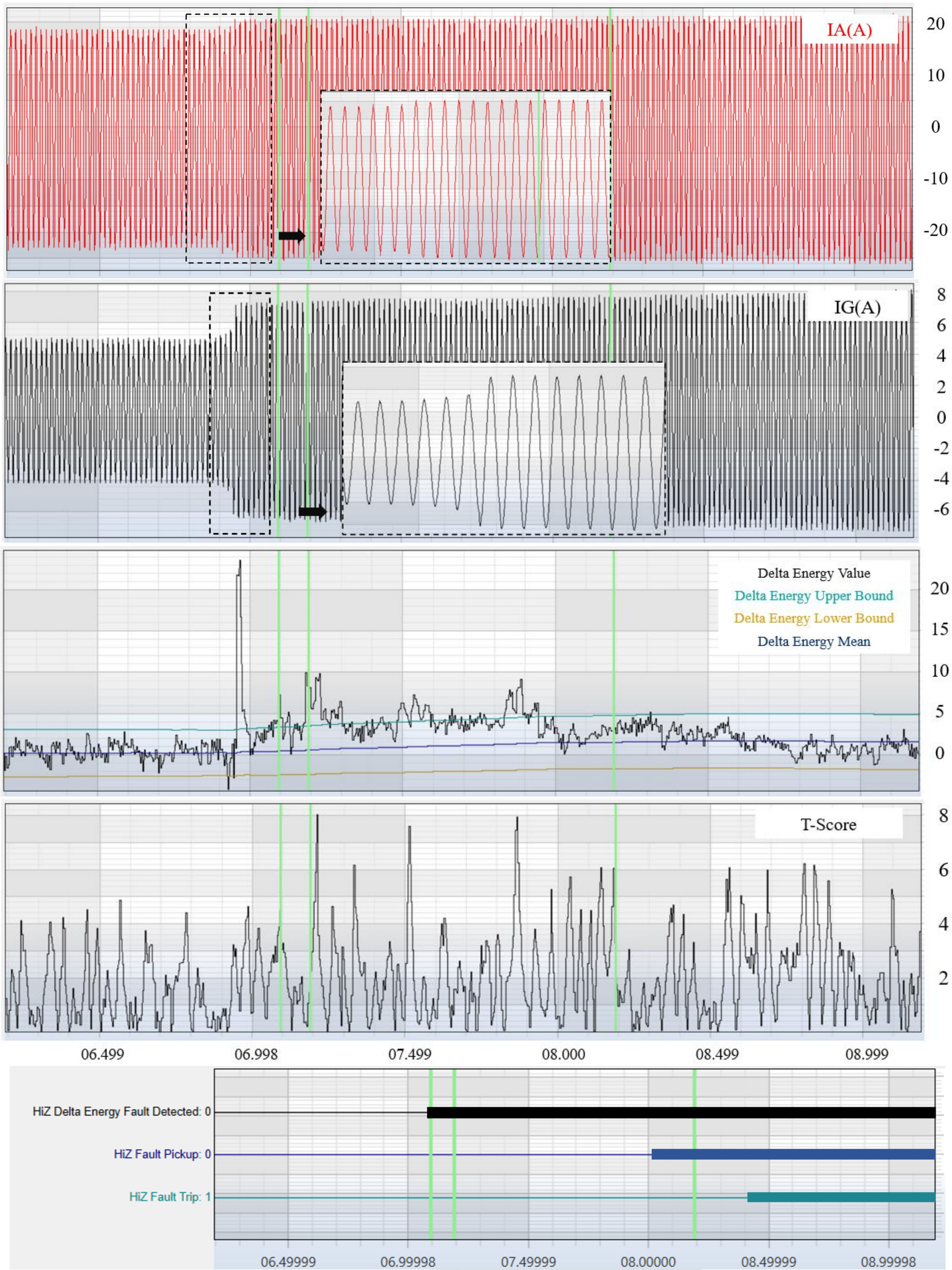

Figure 11. Event captured with live unbroken conductor touches a tree.

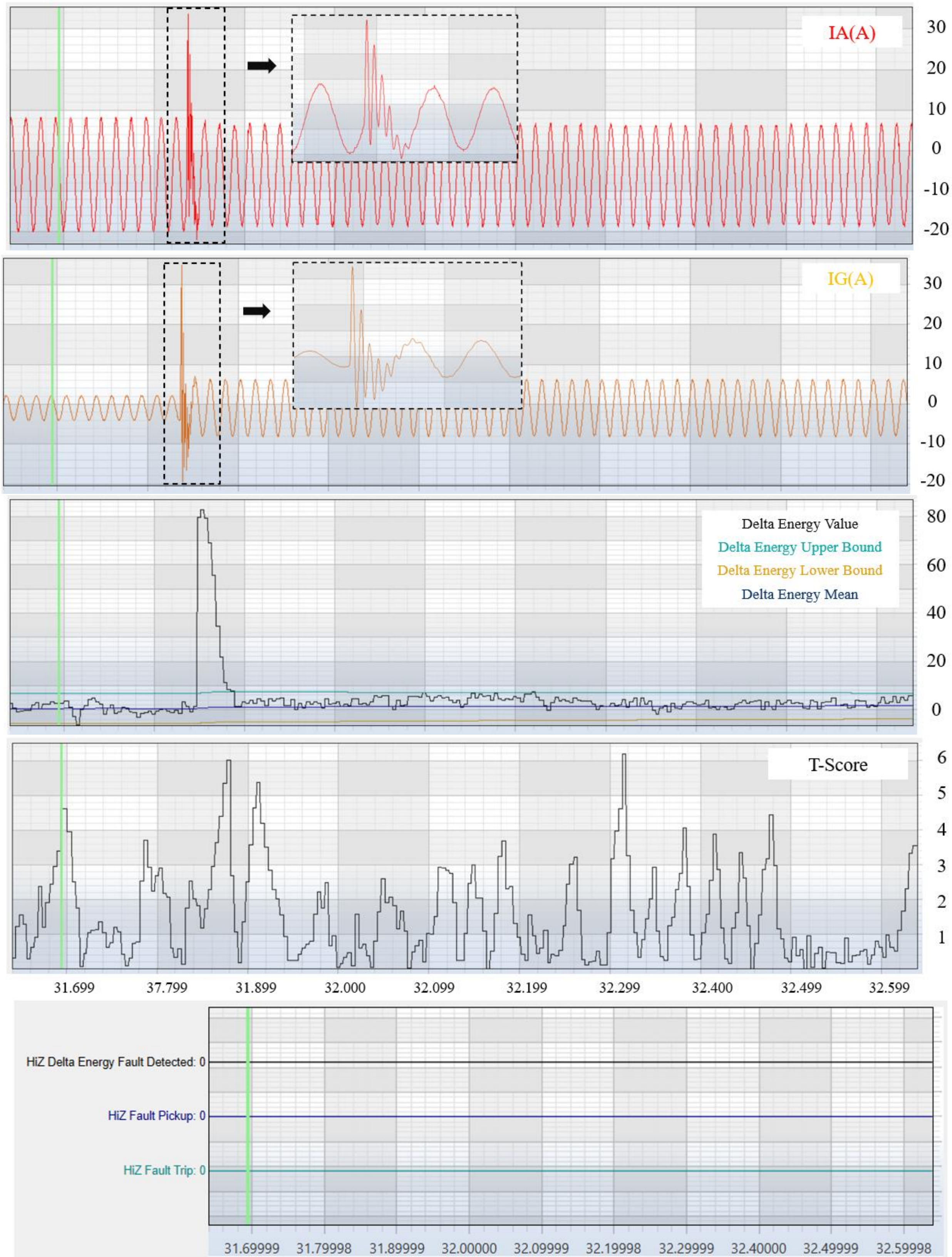

Figure 12. Event captured with a capacitor bank switching.