Study Committee B5

PROTECTION & AUTOMATION

Paper ID_1127

Using Machine Learning to Detect High Impedance Faults

Itani Phafula, Ken Nixon

Eskom Holdings, University of Witwatersrand

Motivation

- High Impedance Faults (HIFs): these are power system faults that occur when a conductor makes contact with a quasi-insulator such as the branch of a tree or where the conductor breaks and touches the ground surface.
- HIFs generate low fault currents in the region of 1A to 75A undetectable by overcurrent relays.
- Existing approaches analyse spectral components to determine the presence of HIFs.
- Emerging approaches analyse current and voltage waveforms by using Artificial Neural Networks (ANNs) to classify healthy and faulted states.
- However, classical ANNs are not designed for time-varying signals.
- Long Short-Term Memory (LSTM) has been designed to handle the classification and prediction of time-series data such as current and voltage signals.

Approach

- Figure 1 describes how:
  - HIF conditions were recreated in a high voltage laboratory on various surfaces including moist and dry soil, gravel, sand and a tree with leaves.
  - MATLAB/Simulink was used to generate more data that considered network loading.
  - LSTM was trained in MATLAB to detect HIF conditions using data generated in the laboratory and using MATLAB/Simulink.
  - the results of the LSTM method were compared with the results of a spectral energy variation method.

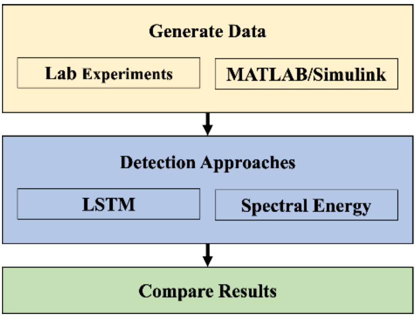

Figure 1: LSTM based HIF detection approach

Experiment Setup & Results

- Figure 2 describes the laboratory setup used to generate HIF conditions.
- Current and voltage signals in figure 3 were captured on the primary and secondary winding of the transformer during an experiment on a dry soil surface.
- The waveforms were sampled at 6.4 kHz using a high precision digital fault recorder.

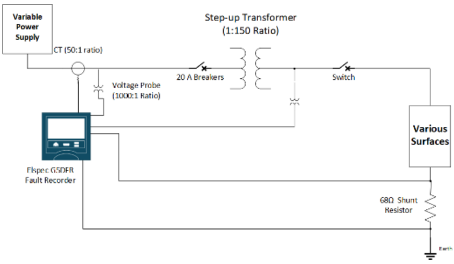

Figure 2: Laboratory experiment setup

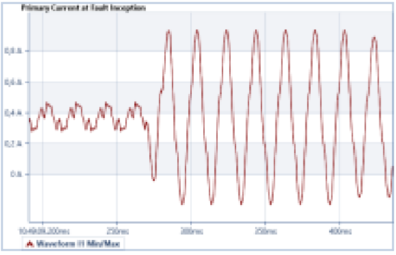

Figure 3a: Primary current waveform during an HIF condition

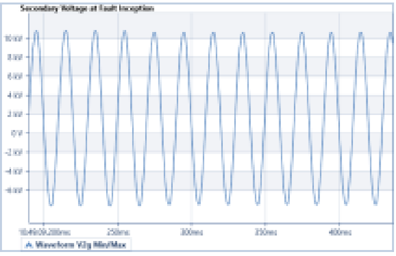

Figure 3b: Secondary voltage waveform during an HIF condition

Study Committee B5

PROTECTION & AUTOMATION

Paper ID_1127

Using Machine Learning to Detect High Impedance Faults continued

Simulation Setup & Results

- Figure 4 describes the MATLAB/Simulink setup used to generate HIF conditions.
- Other transient conditions such as transformer, capacitor bank and inductive load switching were also generated.
- Current and voltage signals in figure 5 were sampled at the fault location.

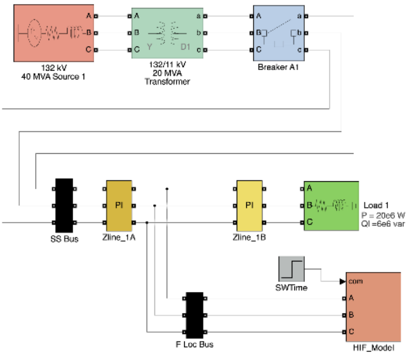

Figure 4: Simulink simulation setup

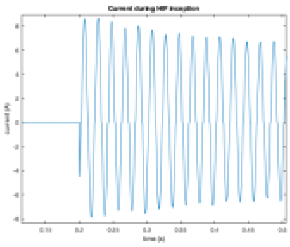

Figure 5a: Current waveform during an HIF condition

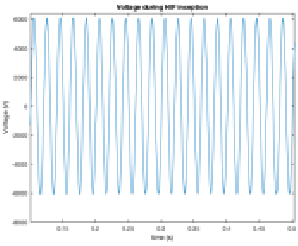

Figure 5b: Voltage waveform during an HIF condition

Spectral Energy Detection

- The voltage waveform was broken into smaller segments of a half cycle, one cycle and four cycles. They are referred to as detection windows.
- FFT was used to extract spectral energy information from the different detection windows. Analysis was done for frequencies between 100 Hz and 2.4 kHz. Figure 6 shows the spectral information of the voltage waveform during an HIF condition on dry soil.
- An increase of 25% above the cumulative average was considered a fault condition. This is described in figure 7.
- The performance of this method is described by the confusion matrix in Table 1.

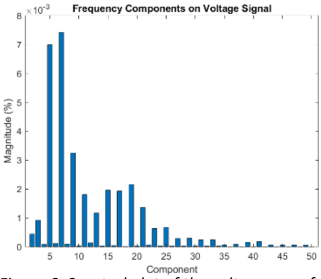

Figure 6: Spectral plot of the voltage waveform during an HIF condition

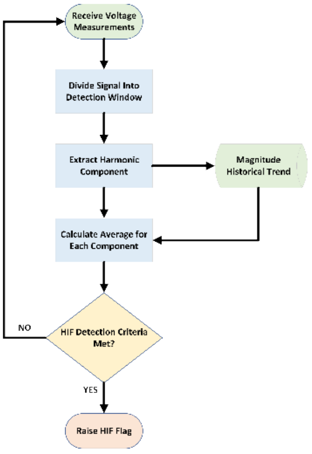

Figure 7: Spectral energy algorithm

Study Committee B5

PROTECTION & AUTOMATION

Paper ID_1127

Using Machine Learning to Detect High Impedance Faults continued

Table 1: Spectral energy detection performance

Detection Window	1/2 cycle	1 cycle	4 cycles
True Positive	0	89	98
True Negative	300	284	244
False Positive	0	16	56
False Negative	100	11	2

LSTM Detection

- The voltage waveform was broken into smaller detection windows of a half cycle, one cycle and four cycles.
- FFT was used to extract spectral energy information from the different detection windows. Analysis was done for frequencies between 100 Hz and 2.4 kHz.
- The extracted data was used to train an LSTM tool to classify HIF conditions under healthy and transient conditions. Figure 8 describes how the LSTM tool was trained.
- Figure 9 describes how the trained tool was tested using datasets extracted from the laboratory experiments and the Simulink data. Table 2 shows the performance of the trained tool.

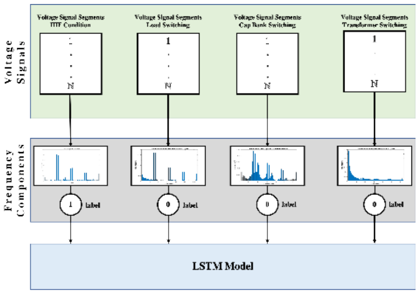

Figure 8: LSTM tool training process

Table 2: LSTM detection tool performance

Detection Window	1/2 cycle	1 cycle	4 cycles
True Positive	803	194	63
True Negative	1486	2737	723
False Positive	4111	31	0
False Negative	0	238	14

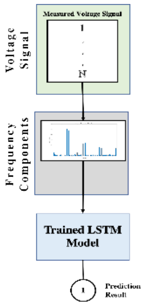

Figure 9: LSTM tool testing process

Results Discussion

- Accuracy and sensibility indices were used to evaluate the performance of the detection methods. Equations 1 and 2 describe how the accuracy and sensibility indices are derived.
- Table 3 compares the performance of the spectral energy method to the LSTM method on a 4 cycle detection window.

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FP}\% \quad (1)$$

$$Dependability = \frac{TP}{TP+FP}\% \quad (2)$$

Table 3: Detection methods performance

Detection Window	Spectral Energy	LSTM
Accuracy	85.5%	98.3%
Dependability	63.6%	100.0%

Conclusion

- Long Short-Term Memory architecture can be used to detect the presence of HIFs with high accuracy rates by using both low and high frequency components of the voltage signal on the faulted phase.
- LSTM architecture outperforms the spectral energy algorithm in terms of accuracy and sensitivity.
- Future studies should investigate the effectiveness of the proposed methods on a physical utility network.