Characterization of Underground Cable Incipient Behavior Using Time-Frequency Multi-Resolution Analysis and Artificial Neural Networks

Karen L. Butler-Purry, IEEE Senior Member, J. Cardoso

Abstract—This paper presents preliminary work of a research project with a long-term goal to develop an on-line, non-destructive underground cable monitoring system that can not only detect incipient faults but also predict the remaining life of the cable lateral. The results presented in this paper help identify and characterize possible incipient faults occurring in underground cable laterals being monitored on-line.

In this paper, two experimental setups designed and deployed for on-line monitoring of underground cable lateral to record data are presented. An analysis procedure of the recorded data implementing a time-frequency multi-resolution technique is presented. The results of using an artificial neural network for pattern identification of the recorded data are also presented.

Index Terms—Underground cable, incipient failure, wavelet packet analysis, distribution system, artificial neural network, self-organizing map

I. INTRODUCTION

D
ing distribution systems are primarily built with underground cables because of its long-life, safety and aesthetics. Though underground cables are preferred over over-head lines, the installation and maintenance cost of underground cable is more than that of over-head lines. Moreover, it is very difficult to detect and locate faults in underground cables.

Deregulation has forced the utility industry to be more cost conscious while the consumers are becoming more quality conscious. In the event of a cable failure, the cost of identifying the failed cable section and replacing it can be very expensive. Besides cost, an outage reflects poorly on the reliability index of the utility.

A number of cable diagnostic systems have been developed for incipient fault detection and location. Incipient faults are precursors to catastrophic failures. Thus by detecting incipient faults early, some unscheduled outages can be prevented.

Many of the present day underground cable incipient fault detection and location systems are based on partial discharge measurement and current injection methods [1]. Other systems use one or more of the following technologies: x-rays, infrared technologies, radar, time reflectometry, acoustic and pressure wave, and a variety of high frequency characteristics [2]-[6]. Most of the above mentioned techniques are off-line techniques. They require the cable section being tested to be de-energized, thus requiring the cable lateral to be disconnected from the distribution system. Some of the methods require the cable to be subjected to high-voltages for diagnostic tests, which can be destructive to the sample under test.

None of the present methods have the capability of predicting the remaining life of the cable being tested. A distribution level incipient fault detection system that can detect incipient behavior online and predict the remaining life of an underground cable would be of great benefit to the utility. The Power System Automation Laboratory (PSAL) at Texas A&M University is performing research to develop such a system.

In this paper, section II discusses the experimental setups developed and deployed for on-line cable monitoring. Section III discusses various types of abnormalities recorded. Section IV presents the wavelet packet analysis concept and its implementation for data analysis. Finally, section V discusses self-organizing map based artificial neural network and its implementation for pattern recognition.

II. EXPERIMENTAL SETUP

Two experimental setups were developed to monitor in-service single-phase underground cable laterals and record data in real-time. The first system developed was used for short-term monitoring and recording of data for numerous cable laterals feeding residential and commercial areas in Dallas, Texas [7]. Further, another experimental setup was developed to monitor and record data from an underground cable lateral in a residential area in Dallas, Texas for a long period of time.

A. Short-Term Monitoring Experimental Setup

Short-term monitoring experiments were performed on
residential and commercial underground distribution systems in loop configuration, while the cable was energized. Trained utility technicians connected the necessary equipment to the cable laterals being monitored. The cable was supplied at 7200V by a feeder in the system. The experimental setup developed for short-term monitoring experiments is shown in Fig. 1. The system monitored the single-phase underground cable lateral downstream of the measurement unit. Current transducers with a ratio of 0.1 V/A were used to measure the phase and neutral current in the cable. Voltage measurements were not monitored or recorded during these experiments.

For each input signal, the filter unit generated five outputs. Output 1 was the original input signal. Output 2 was the notched version of the original signal. The notch filter used in the signal-conditioning unit had 70 dB attenuation for the fundamental frequency (60 Hz). Output 3 was the amplified version of the notched signal. Outputs 4 and 5 were the notched high frequency component of the original signal with amplifications of 20dB and 40dB, respectively. Thus, for phase and neutral currents, the signal-conditioning unit generated ten output signals. The output signals were then input to the data acquisition system (DAQ) consisting of a laptop and a National Instruments 12-bit data acquisition card to record the output signals. The original and notched low frequency signals were sampled at 1920 samples/sec; whereas the notched high frequency signals were sampled at 15360 samples/sec.

The short-term monitoring experimental setup monitored cable laterals at thirty-two residential areas and thirty-six commercial areas in the Dallas, Texas area over an eight-month period. All sites monitored by the short-term monitoring setup contained 15kV class cables that were installed in a time period ranging from late 1960s to early 1970s. The commercial sites contained cables insulated with XLPE. Cables at the residential sites contained either PE or HMWPE insulation. Most cables monitored were jacketed and all cables had a concentric neutral primary shield. Most of the sites monitored were close to cable sections that had been changed out due to catastrophic failure.

![Fig. 1. Short-Term Monitoring Experimental Setup](image)

**B. Long-Term Monitoring Experimental Setup**

The long-term monitoring system was functionally similar to the short-term monitoring system in the respect that it measured phase and neutral current, and had an analog signal conditioning unit and a data acquisition system. In addition, the long-term monitoring system monitored the secondary voltage signal. The signal-conditioning unit was revised for this experimental setup. Fig. 3 shows the experimental setup for the long-term monitoring experiments.

The functional block diagram of the filter module implemented in the analog signal-conditioning unit of the long-term monitoring experimental setup is given in Fig. 4.

![Fig. 2. Analog Signal Conditioning Unit 1 for Short-Term Monitoring](image)

For the phase and neutral current input signals, the filter unit generated four outputs. The LF output represented the low frequency component of the input signal. The NLF output represented the notched low frequency component of the input signal. The notch filter used in the signal-conditioning unit had 70 dB attenuation for the fundamental frequency (60 Hz). The NHF and NHFx10 represented the notched high frequency components with amplification of 1 and 10, respectively. In Fig. 4, I.A represents an instrumentation amplifier and F1 to F5 represent filters. The instrumentation amplifier acted as an electrical isolation device between the input signals and the filter unit. The current signals and secondary voltage signal were then input to the data acquisition system (DAQ) for recording. The data acquisition
The long-term monitoring system was deployed in August 2001 to monitor a residential area in the Dallas, Texas area. The system monitors a 100KVA cable lateral being fed by a 7200 V feeder. The cable lateral has XLPE insulation and is jacketed with concentric neutral primary shield. The cable was installed in the distribution system in early 1970s. The system monitored the cable for over five years.

III. ABNORMALITIES

The data recorded during the short-term monitoring experiments are referred to as the short-term (ST) data set, and the data from long-term monitoring are referred to as the long-term (LT) data set. Each of these data sets had neutral and phase current signals, their low frequency components, and their high frequency components.

Once the data was recorded and compiled, an analysis procedure was performed that had three stages. The first stage of analysis involved detection of an abnormal event in the data sets and their categorization. The second stage involved analyzing data using a time-frequency multi-resolution analysis technique to characterize the abnormalities detected. The third stage involved pattern identification using an artificial neural network to identify similar types of abnormalities at different monitoring locations (hence in different cable laterals). This section discusses the first stage of the analysis process.

For detection of abnormal conditions, notched signals (NLF, NHF, and NHFx10) were used to identify abnormal conditions in a signal because the dominant fundamental frequency component is attenuated in the notched signals. Abnormalities in the recorded notched signals manifested themselves in two forms: spikes and bursts (a series of spikes). An example of a spike and a burst seen in recorded notched signals (notched phase high frequency signal) is given in Fig. 5. In the figure, the top graph depicts occurrences of abnormal activities in the form of spikes, whereas, the bottom graph depicts an abnormal activity in the form of a burst.

Since the abnormalities or transients in the recorded signal are caused by a variety of reasons such as, load changes in the system, arcing fault, transformer in-rush current, single phase faults, incipient faults, etc., the first step of detection involved separating signals with load change transients from the rest of the abnormal conditions. The abnormal condition category was labeled as possible incipient faults.

![Fig. 4. Analog Signal Conditioning Unit 2 for Long-Term Monitoring](image)

![Fig. 5. Example of Abnormal Activity in a Signal](image)

An example of typical load change transients seen in a recording is depicted in Fig. 6. The figure depicts a family of phase current signals: phase low frequency, RMS phase current, notched phase low frequency, and notched phase high frequency signals. It can be seen from the figure that a burst is present in the notched low frequency signal and the time of occurrence of the burst coincides with the change in load depicted in the phase low frequency and RMS phase current signals. It can also be noted that the notched high frequency signal does not convey any changes during the changes in the other signals.

An example of a typical possible incipient fault seen in a recording is shown in Fig. 7. This figure depicts the same family of phase current signals as used in Fig. 6. From the figure, it can be seen that the load current (phase low frequency) signal remains constant for the time period and the change in RMS current is in the order of 0.05 A, which is negligible. A spike is present in the notched high frequency signal. As this transient is not associated with any load change, this is categorized as possible incipient fault. Signals categorized as possible incipient faults were further analyzed to characterize the abnormality using a time-frequency multi-resolution analysis technique. The next section discusses the
procedure and results of time-frequency multi-resolution analysis of possible incipient faults using the wavelet packet analysis technique.

Fig. 6. Example of a Load Change Transient

Fig. 7. Example of Possible Incipient Abnormality

IV. TIME-FREQUENCY MULTI-RESOLUTION ANALYSIS

Though frequency domain analysis has proved to be a crucial tool in the past, it has significant drawbacks, especially when analyzing non-stationary, high-speed transients and incipient abnormalities. One of the modern techniques that overcome some of the problems of the Fourier Transform (FT) is the Short-Time Fourier Transform (STFT) technique. STFT breaks the signal into small parts (windows) and conducts Fourier Transform over the small window of data. This increases the time resolution of the method; however, STFT has the limitation of a fixed window width, which leads to a trade-off between frequency resolution and time resolution [8].

A. Wavelet Packet Analysis Theory

One of the methods to overcome this drawback is wavelet analysis technique. Wavelet is a transient signal, and methods that make use of wavelet functions would seemingly be suitable for transient and incipient analysis [9]. In simple terms, wavelets have a window that automatically adjusts its width to give the appropriate resolution. The wavelet analysis employs a prototype function called the mother wavelet as the windowing function [9]. Mathematically, a discrete wavelet transform (DWT) is defined by (1).

\[
DWT (m, k) = \frac{1}{\sqrt{a^m}} \sum_{n} x(n) g\left( \frac{k - nb}{a^m} \right)
\]

Where, \( g(.) \) is the mother wavelet, and the variables \( a \) and \( b \) are the scaling and translation parameters, respectively. Both the scaling and translation parameters are functions of an integer parameter \( m \), giving rise to a family of dilated mother wavelets called daughter wavelets. The integer variable, \( k \), refers to a particular sample number in an input signal. The scaling gives rise to geometric scaling providing the DWT logarithmic frequency coverage in contrast to the uniform frequency coverage of Fourier analysis methodologies. As the wavelet-based analysis provides time and frequency information besides providing varying resolution, this type of analysis tool is named time-frequency multi-resolution analysis.

Wavelet analysis can be employed in a digital computer using complementary high pass and low pass filters, which split the original signal into a low frequency component (approximation) and high frequency component (details). The model is called two-channel sub-band coding [9],[10].

Wavelet packet analysis is a generalization of wavelet decomposition that offers a richer range of possibilities for signal analysis. In wavelet packet analysis, the details as well
as the approximations are split at each level, giving rise to better frequency resolution to the approximations and better time resolution to the details as shown in Fig. 8. In the figure, $S$ is the original signal, $A$ represents the low frequency component – approximation, and $D$ represents the high frequency component – detail.

### B. Formulation of Wavelet Packet Analysis Framework

For the research study discussed in this paper, wavelet packet analysis was implemented to characterize possible incipient faults (abnormalities) for both the short-term monitoring data as well as the long-term monitoring data. As mentioned in section II, the sampling rates for low frequency and high frequency signals were 1920 samples/sec and 15360 samples/sec, respectively. For wavelet packet analysis, the low frequency signals were zero-padded symmetrically on both ends of the signal by 64 samples to make the signal length dyadic (power of 2). Thus, the modified low frequency signals had 2048 samples/sec. Similarly, the high frequency signals were also symmetrically zero padded on both ends of the signals by 512 samples. The modified high frequency signals had 16380 samples/sec.

**Fig. 8. Wavelet Packet Decomposition Tree**

The $4^{th}$ order Daubechies mother wavelet and fourth level decomposition was used. For a single input, the fourth level wavelet packet decomposition yields sixteen details numbered 1 to 16 represented as d1 – d16, henceforth. The frequency bands represented by each of the fourth level details (d1-d16) for notched low frequency signals are 64 Hz, and 0.512 kHz for notched high frequency signals.

### C. Wavelet Packet Analysis of Recorded Data

As mentioned in earlier sections, two monitoring systems were developed and deployed to monitor an underground cable lateral and record real-time data. The data recorded during short-term monitoring experiments will be henceforth referred to as ST data set, and the data recorded during the long-term monitoring experiment will be referred to as LT data set.

Wavelet packet analysis was conducted on both data sets to get the time-frequency information. The time-frequency information of each event was compiled to characterize the nature of the incipient faults. An example of possible incipient fault occurring in phase notched high frequency of LT data set is shown in Fig. 9.

From the figure it can be seen that a spike is present in the notched high frequency signal at a time range of 0.5 – 0.6 seconds. Fourth level wavelet packet decomposition was conducted on the signal and of the sixteen details only eight of them had spikes. The details were d5, d6, d9, d10, d11, d12, d15, and d16. It should be noted that for high frequency signals, each detail represents a frequency band of 0.5 kHz.

**Fig. 9. Example 1 - Spike in Notched Phase High Frequency Signal**

Fig. 10 shows the eight details with spikes. From the figure, it can be seen that the time of the spike in the details corresponds to the time of the spike in the original signal. In Fig. 10, though the spikes are present at the same time instant in all the details, the magnitude of the spikes compared to the normal level is different in each detail. For example, in detail d5, the magnitude of the spike is 166% greater than the normal level. Similarly for details d9, d10, d11 and d12, changes in the magnitude during abnormal activity are 233%, 340%, 500%, and 255%, respectively. After calculating percentage change in all the details, the most dominant details contributing to the abnormality were found to be d10 and d11.

Another example of possible incipient fault is given in Fig. 11. In the figure, the event is present in the notched neutral high frequency signal of the LT data set. From the figure it can be seen that the event occurs in the form of a burst rather than a spike.

The fourth level wavelet packet decomposition was performed on the notched neutral high frequency signal. Of the sixteen resulting details, abnormal activity was found in twelve of them; details d5 – d16. It should be noted that the frequency range represented by each detail for the high frequency signal is 0.5 kHz.
Fig. 10. Details with Spikes for Example 1

Fig. 11. Example 2 – Burst in Notched Neutral High Frequency Signal

Fig. 12 and Fig. 13 show the details with abnormal activity. It can be seen that the time instant of abnormality corresponds between the original signal and the details. From Figs. 12 and 13, we can see that details d5 – d12 have multiple spikes whereas, details d13 – d16 have single spikes. For details d5 – d16, the magnitude during abnormal activity is at least three times more than the normal activity. Among the twelve details, d6 had the largest change in magnitude during abnormal activity, approximately 800%.

The earlier examples conveyed the faults or abnormalities information in the notched high frequency component of the signal. An example of possible incipient fault conveyed in the notched low frequency signal is shown in Figs. 14 and 15. Only the details with significant changes are shown in the figures. The figures depict a spike in the notched phase low frequency signal of ST data set. It can also be noted that there is a significant increase in the amplitude of the signal after the spike.

This section presented the concepts of the wavelet based analysis technique and its implementation for time-frequency analysis of the recorded data. A few examples of abnormal signals and their wavelet packet decomposition results were presented. The following section presents the concept of artificial neural network and its implementation for identifying similar abnormalities in the data sets.
Fig. 12. Details $d_5$ - $d_{12}$ for Example 2

Fig. 13. Details $d_{13}$ – $d_{16}$ for Example 2

Fig. 14. Example 3 – Spike in Notch Low Frequency Signal
V. PATTERN IDENTIFICATION USING ARTIFICIAL NEURAL NETWORK

The self-organizing map (SOM) is one type of unsupervised artificial neural network [11]. The input data for the model is described in terms of vectors, each of which consists of components representing an elementary feature of the data item, expressed as a numeric value. The output is a similarity-based map of the data items, similarity being defined as proximity of items in the feature space. SOM has properties of both vector quantization [12] and vector projection algorithms. Complete details about SOM and the implementation used for this research is discussed in [13].

An example of a SOM is given in Fig. 16. The figure depicts a 6x8 SOM neural network, each neuron represented by the black dots. The variables \( l \) and \( m \) represent the topological position of a neuron in the grid. Each of these neurons is connected to the input vector \( (IP) \) or training set with some weights \( (w_i) \). The weights are adjusted with each training step and thus the outputs of the neurons change. The outputs of the neurons are computed as given by (2). The outputs of the neurons are the projection of the input vectors in weight space.

\[
OP_{N}(l, m) = f(< w_j(l, m), IP(k) >)
\]

After training the SOM, the neurons on the grid become ordered and the neighboring neurons have similar weight vectors, forming a cluster of closely held neurons. The neurons in a cluster get excited only to similar type of inputs, each cluster representing a group of similar inputs.

After performing wavelet packet analysis of the possible incipient faults, a detailed pattern identification procedure was conducted on the data sets to identify clusters or groups of similar types of abnormalities in each data set. As each cluster would be unique, the group of abnormalities represented by each cluster can be referred to as a separate category of abnormalities. The following sections discuss the procedure and results of the pattern identification work.
A distribution study was conducted to calculate the number of abnormalities associated with each cluster. It was observed that 37 instances were associated with cluster number 2, and 5 instances with cluster number 1.

2) **Notched Phase High Frequency Signal – LT data set**

Similar to ST data set, a 5x8 SOM was created and trained for the LT data set using the possible incipient abnormality instances occurring in notched phase high frequency signals. The resulting distance matrix was given to the K-means clustering algorithm to identify distinct clusters. Fig. 20 depicts the cluster identification results. From the figure, it can be observed that eleven clusters were identified for abnormalities occurring in notched phase high frequency signals of the LT data set.

Also distribution study was conducted for this case to calculate the instances of abnormalities associated with each of the clusters or categories. Out of 955 instances of possible incipient abnormalities recorded in notched phase high frequency signal, 345 instances of abnormalities were categorized to cluster number 8, 125 instances of abnormalities were categorized to cluster number 5, and approximately 50 instances were categorized to each of the remaining clusters.
neural high frequency signals of the ST and LT data sets. From that comparison study, it was found that 42 out of 54 abnormality instances of ST data sets were similar to the abnormality instances present in the LT data set, representing 77% of the total number of instances.

VI. SUMMARY

The first step in developing an on-line condition monitoring method for underground cable entailed characterizing incipient fault behavior in the monitored current signals. An analysis procedure was formulated to extract unique information that characterizes such behavior using wavelet packet analysis. This technique, demonstrated with three examples, showed great potential in extracting unique information from the current signals. Further a pattern identification neural network was developed to identify clusters of similar types of transients. Each cluster represents transients of different severity.

The data analysis procedure was divided into three stages. The first stage of analysis involved detection of transients in the data sets and their categorization. This stage was essentially performed by visually inspecting each recorded signal one by one and assigning it to the appropriate categories. The second stage involved analyzing data using a time-frequency multi-resolution analysis technique to characterize the transients detected. This stage was partially accomplished on the data sets. The results and the examples mentioned in the paper, showed the potential of detecting transients. The third stage involved pattern identification using an artificial neural network to identify similar types of transients. From the comparison study results, it was seen that the transients in monitored data at various utility sites were fairly similar.

VII. CONCLUSIONS

This paper presents on-going work to detect on-line an incipient transients in underground distribution cable laterals and predict the remaining life of the cable lateral.

Two experimental setups were developed and deployed to monitor and record real-time data for numerous residential and commercial underground cable laterals. The data was analyzed implementing a wavelet packet analysis technique. A few examples of the resulting time-frequency decomposition of different type of abnormalities seen in the data sets were presented.

Features were extracted from the wavelet packet analysis results and used as input to a SOM based artificial neural network for pattern identification among the data sets. Clusters or categories of abnormalities present in each data set were identified using SOM. A comparison study shows the similarities between the abnormalities identified in the short-term and long-term monitoring data sets.

Further data monitoring is required to record more possible incipient conditions in the underground cable lateral. More detailed data analysis using diverse analysis tools is required.
to completely characterize incipient behavior in an underground cable lateral. This characterization will seek to identify and categorize the stages of incipient behavior. Successful characterization of incipient behavior will facilitate the development of a technique that can not only detect incipient faults but also predict remaining life of the cable laterals being monitored on-line.

ACKNOWLEDGEMENT
The authors acknowledge the contribution of Tyesa Harvest and Mirrasoul J. Mousavi in the preparation of this paper.

REFERENCES

BIOGRAPHIES
Karen Butler-Purry (SM'01) received her B.S. (summa cum laude) in Electrical Engineering in 1985 from Southern University in Baton Rouge, LA. She was awarded her M.S. degree in 1987 from the University of Texas at Austin. She was awarded her Ph.D. in Electrical Engineering in 1994 from Howard University, Washington, D.C. She joined Texas A&M University in 1994, where she currently serves as a Professor in the Department of Electrical and Computer Engineering. Her research interests are in the areas of distribution automation and intelligent systems for power quality, equipment deterioration and fault diagnosis.

Jesus Cardoso was born and raised in Dallas, Texas. He graduated from Texas A&M University with a B.S. and M.S. in Electrical Engineering in 1996 and 1999, respectively. He has been working for Ford Motor Company since September of 1999. Presently he is part of the Electric Drive Department of the Hybrid Electric Escape Program as a High Voltage Wiring and Electrical Systems Engineer. He is presently pursuing an M.S. in Product Development at the University of Detroit-Mercy. His professional interests are in Electrical System Integration and Architecture in Hybrid Electric and Fuel Cell Vehicles.