Reducing Cable Failure Risk through Online Condition Monitoring

Leonard S. Fifield[a*], Samuel W. Glass[a], Muthu Elen[a], Jonathan R. Tedeschi[a], Mohammad F.N. Taufique[a], Jacob A. Farber[b], and Alex Kaforey[b]
[a] Pacific Northwest National Laboratory, Richland, WA, USA
[b] Idaho National Laboratory, Idaho Falls, ID, USA
*leo.fifield@pnnl.gov

Abstract: Online monitoring of nuclear cables can provide ongoing confidence for reliable operation, trending information to inform operational considerations, and early signals of concern to enable efficient planned maintenance. Recent developments in instrumentation and advanced data analysis have demonstrated the feasibility of monitoring the condition of energized cables online using frequency-domain reflectometry (FDR) and spread-spectrum time-domain reflectometry (SSTDR). FDR and SSTDR tests have been applied directly to cable conductors for more than a decade to detect and locate cable damage. These measurements have mostly been performed off-line on de-energized circuits for reasons including that power line voltages can be damaging to diagnostic instruments and that reflectometry response spectra are complex and can require skilled experts for interpretation. These off-line-test limitations result in a cumbersome and costly sequence of testing events, including:

- Scheduling the cable system for offline testing
- De-energizing and uncoupling the cable from motors and terminals
- Bringing trained experts with specialized test equipment onsite to perform and analyze tests
- Re-connecting and returning the cable to service if it passes
- Repairing or replacing and re-testing the cable before returning to service if it does not pass.

This paper discusses three enabling technology advances funded by the U.S. Department of Energy Light Water Reactor Sustainability program that could enable a more cost-effective online cable monitoring program to increase confidence in the continued use of aging cables and reduce risks associated with unplanned cable or system failure. The technologies include (1) an inductive coupler that allows reflectometry of cables energized above 10 kV, (2) a field programmable gate array (FPGA) multiplexing instrument capable of performing FDR and SSTDR on a connected cable, and (3) a machine learning screening code to detect reflectometry responses well in advance of cable failure. These examples of technology to support online monitoring are timely as the industry evolves toward positive verification for continued confident use of cables with plant life extensions and for implementation in advanced reactors where manual inspections will be more difficult due to long refueling cycles and harsh environments.

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1. INTRODUCTION and BACKGROUND

Nuclear power plant cables are essential components that enable power distribution, control, instrumentation, and safety system functions across the facility. Although these cables were originally qualified for forty years of service, most operating plants have now received license extensions to sixty or even eighty years. Over such extended lifetimes, cables are subjected to a variety of environmental and mechanical stressors. Elevated temperatures, moisture intrusion, chemical exposure, radiation fields, bending and tensile loads, and inconsistencies in installation or termination quality all contribute to gradual changes in insulation and conductor properties. These stressors do not act suddenly; rather, they accumulate progressively as the cable remains in service. As a result, degradation may develop slowly and without obvious external signs, making continuous assessment increasingly important for long-term plant reliability.

Traditional cable condition assessments rely on offline testing during planned outages, when systems can be safely de-energized and disconnected. While effective in controlled settings, this approach is time-consuming and disruptive. It also introduces risk associated with repeated termination and reconnection activities, and it provides only a snapshot of cable health at widely spaced intervals.

Because cable routing often passes through conduits, underground ducts, or inaccessible compartments, visual inspection is rarely feasible. These realities highlight the need for nondestructive, data-driven methods capable of evaluating cable condition without interrupting plant operation [1].

Reflectometry has emerged as one of the most promising nondestructive techniques for cable monitoring. Both frequency domain reflectometry (FDR) and spread spectrum time domain reflectometry (SSTDR) detect impedance changes along a cable and convert them into spatially resolved signatures that can reveal damage or degradation. Historically, reflectometry has been used primarily on de-energized circuits because conventional instruments cannot tolerate high voltages and because the interpretation of reflectometry signals often requires expert judgment. This dependence on outage conditions and specialized expertise limits the frequency and accessibility of cable assessments. Recent advances have significantly expanded the potential of reflectometry for use in online environments. High-isolation inductive couplers now allow diagnostic signals to be injected onto energized cables without exposing sensitive instrumentation to power-frequency voltages. Modern field programmable gate array (FPGA)-based reflectometry instruments replicate the capabilities of laboratory-grade network analyzers in a compact, cost-effective form suitable for plant deployment. In parallel, machine learning techniques provide an analytical framework capable of interpreting even complex or noisy reflectometry signatures, enabling automated differentiation between normal conditions and emerging anomalies.

By combining improved coupling hardware, scalable instrumentation, and data-driven analytics, it is now feasible to transition from intermittent outage-based testing to continuous or periodic online cable monitoring. This shift supports more accurate trending of cable health, reduces reliance on manual inspections, and provides earlier detection of conditions that may precede failure. As nuclear plants continue to pursue long-term operations and as advanced reactor designs envision limited human access to many systems, such online monitoring capabilities will play an increasingly vital role in maintaining cable integrity and overall plant safety.

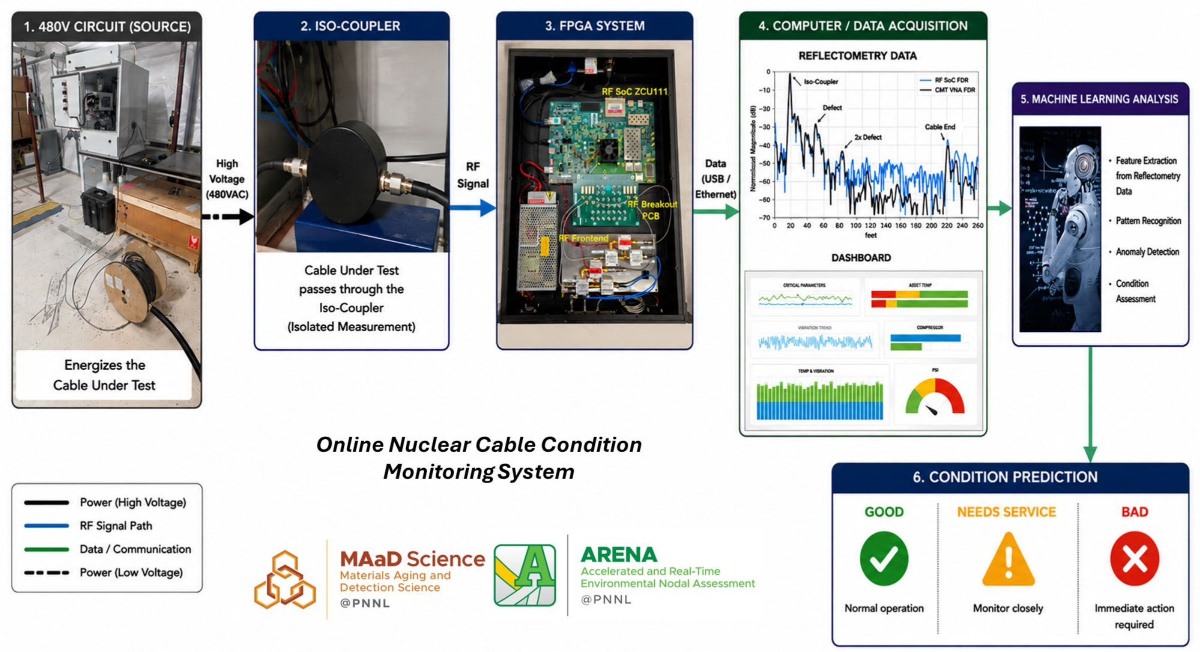


Figure 1: Online Condition Monitoring System for Nuclear Power Plant Cables. FPGA = field programmable gate array. RF = radio frequency.

2. METHODOLOGY

Reflectometry tests can employ both FDR and SSTDR to capture broadband diagnostic information.

2.1. FREQUENCY DOMAIN REFLECTOMETRY

FDR injects swept-frequency chirps across bandwidths typically ranging from 50 to 400 MHz. These signals travel along the conductor, reflect from impedance variations, and are captured for conversion into time- or distance-domain signatures

2.2. TIME DOMAIN REFLECTOMETRY

SSTDR uses broadband pseudo-random noise waveforms, correlating outgoing and incoming signals to identify reflections in a noise-tolerant and energy-efficient manner. Although FDR and SSTDR operate differently, both provide complementary insights into cable condition.

2.3. DATA ACQUISITION AND TEST CONFIGURATIONS

Reflectometry data were acquired at Pacific Northwest National Laboratory (PNNL) Accelerated Real-Time Environmental Nodal Assessment (ARENA) Test Bed [2]. The test bed consists of a 480-volt power source, a three-phase motor, and other features designed to monitor electrical cable status while controlling the environment around the cable to mimic nuclear power plant conditions. Electrical cables can be exposed to elevated temperatures using customized ovens, controlled moisture using submersion basins, or exposure to gamma radiation using cobalt-60 sealed sources. Test voltages, frequencies, and connection configurations can be easily explored using both physical tests and complementary digital twin simulation models. Data included a wide variety of cable types, lengths, end-conditions, and fault scenarios. Testing included both shielded and unshielded EPR cables, in lengths of 62, 150, and 200 feet, and included damaged, resistively faulted, thermally aged, and undamaged configurations. Measurements were taken under both energized and unenergized states, depending on the experiment. Data acquisition was complemented by systematic variation of measurement location, with instrumentation attached alternately to opposite ends of each cable to validate peak positions and confirm correct fault localization.

Post-processing of reflectometry data involved careful removal of the instrument lead section, subtraction of baseline signals, and transformation of raw complex data into magnitude-based composite waveforms. By combining multiple frequency bands into a unified signature, it became possible to reduce the influence of noise while amplifying genuine reflections arising from cable anomalies. These post-postprocessed signals formed the basis for machine-learning analysis.

2.4 MACHINE LEARNING FRAMEWORK

Machine learning methods were applied through both supervised and unsupervised approaches. Supervised learning required labeled datasets identifying normal and anomalous signals, while unsupervised methods learned the distribution of normal cable signatures and detected deviations automatically. Synthetic data were generated by shifting localized reflections to new positions, enabling the evaluation of model generalization beyond the specific fault locations used in experimental tests.

3. TECHNOLOGY DEVELOPMENTS

3.1. INDUCTIVE COUPLER FOR ONLINE MONITORING

The inductive clamshell coupler [3] represents a critical breakthrough for enabling reflectometry on energized cables. The device is based on a high-frequency injection current probe configured within a hinged clamshell structure that can be mounted around an individual conductor or the entire cable. It operates by inducing high-frequency diagnostic signals onto the conductor while providing strong attenuation at low frequencies, including the 60-Hz fundamental and associated harmonics present in energized power cables. The coupler achieves more than 60 dB of isolation at power frequencies while maintaining low insertion loss across the 1–500 MHz range used for FDR and SSTDR.

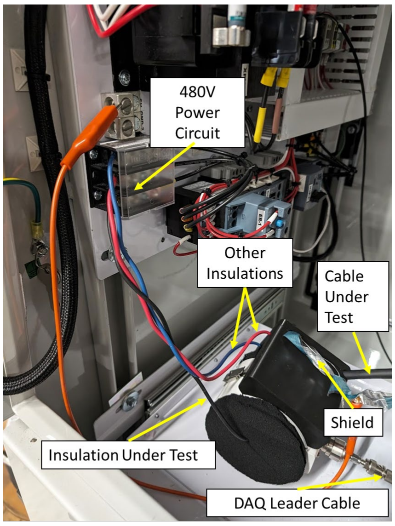


Figure 2: Clamshell coupler setup on cable for energized testing connected to 480-V source [4]. DAQ = data acquisition.

Testing confirmed that the coupler protects reflectometry instruments even when cables are energized to peak voltages of 6.7 kV, and analysis suggests that even higher voltages are feasible. Measurements collected through the clamshell coupler showed excellent agreement with those obtained through direct conductor connections, demonstrating minimal degradation of diagnostic quality. When reflectometry was performed under energized conditions, additional reflections from upstream circuit elements were observable, but these could be managed through baseline subtraction and appropriate test configuration strategy. To inspect each wire, a coupler must be installed at a location where the conductor can be accessed without its surrounding shield, which is typically possible near terminations or designated inspection points. To inspect the entire cable, the coupler can be installed on top of the jacket [4].

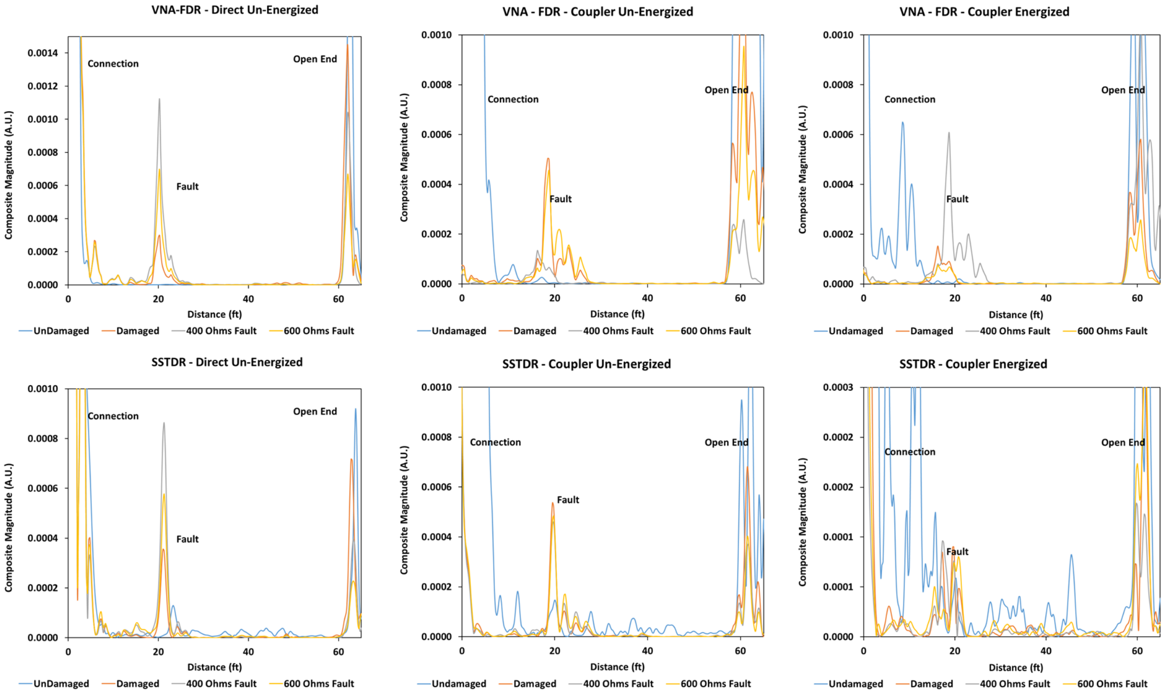


Figure 3: Different fault types compared to the Undamaged 62-ft Shielded Cable for frequency domain reflectometry (FDR) and spread spectrum time domain reflectometry (SSTDR) subtracted reflectometry responses in direct connect, coupler-un-energized, and coupler energized configurations [4].

Low-voltage and medium-voltage testing demonstrated that reflectometry could be performed reliably on cables energized to several kilovolts using the clamshell coupler. Measurements taken from energized and unenergized configurations showed nearly identical peak positions, and the primary difference was the presence of additional reflections from energized upstream circuitry. These additional features were manageable and did not obstruct the detection of cable faults. By applying the multi-band composite processing technique, subtle reflections became prominent even in the presence of energized background noise. Reflections observed from opposite ends of the cable aligned with expected distances, confirming accurate localization of faults.

3.2. FIELD PROGRAMMABLE ARRAY (FPGA) MULTIPLEXING INSTRUMENT

The FPGA-based reflectometry system employs a radio-frequency system-on-chip (RF SoC) platform capable of generating broadband excitation signals and digitizing return waveforms across multiple channels. The system integrates digital-to-analog and analog-to-digital converters with high-speed memory, programmable logic, and a configurable RF front end. It can synthesize precise FDR chirps or SSTDR sequences and can acquire synchronized return signals suitable for real-time or periodic monitoring [5].

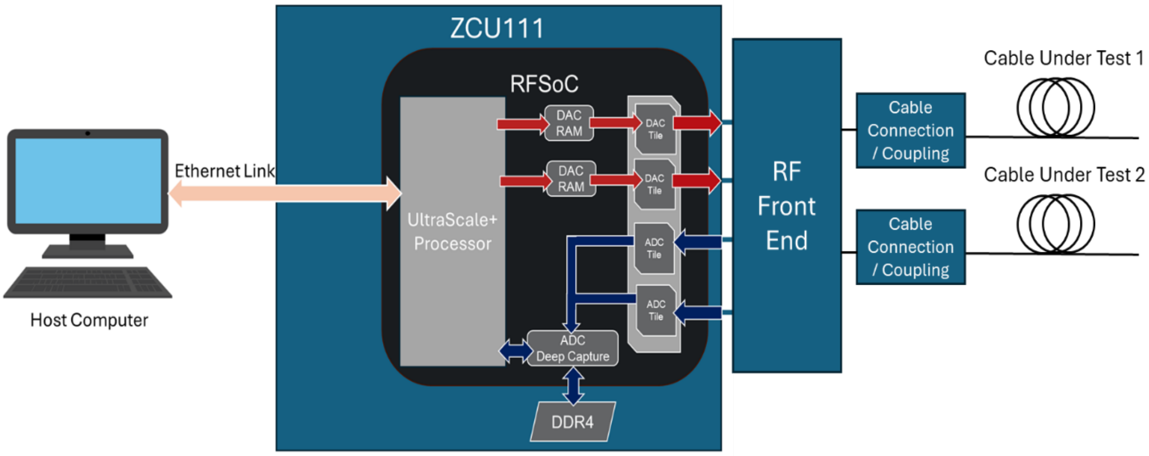


Figure 4: Radio-frequency system-on-chip (RF SoC) high level architecture shown with RF Front End and Cables Under Test [5]

Laboratory and field testing demonstrated excellent agreement between FPGA-based measurements and those acquired with a high-performance vector network analyzer. Even under energized conditions on 480-V circuits, the FPGA system captured the same fault-related peaks, cable-end reflections, and double-reflection patterns as the VNA. The platform also showed strong consistency across its channels, enabling simultaneous monitoring of multiple conductors or phases. Its compact form factor and potential for further integration make it well suited for deployment in plant environments where space and cost constraints would preclude the use of laboratory-scale instrumentation.

When monitoring two conductors simultaneously, the channels produced consistent and comparable results, demonstrating the feasibility of multi-conductor online monitoring. Testing on energized 200-ft cables confirmed that the FPGA instrument could operate safely and effectively in live circuits when paired with the inductive clamshell coupler.

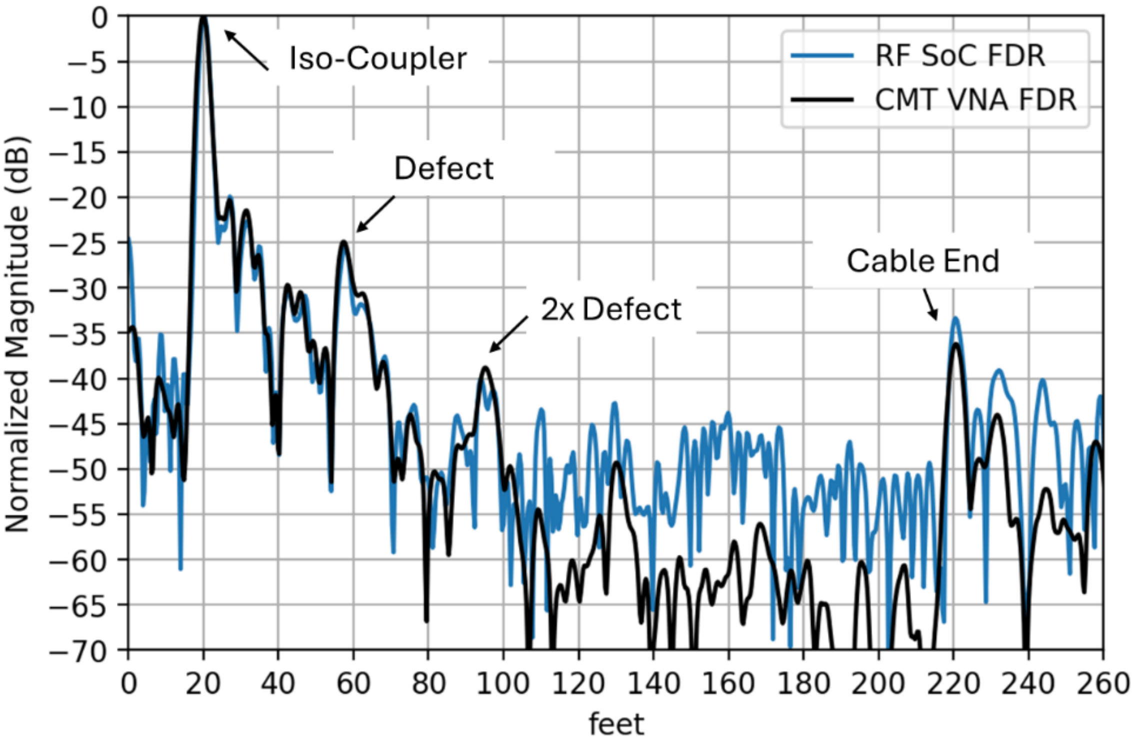
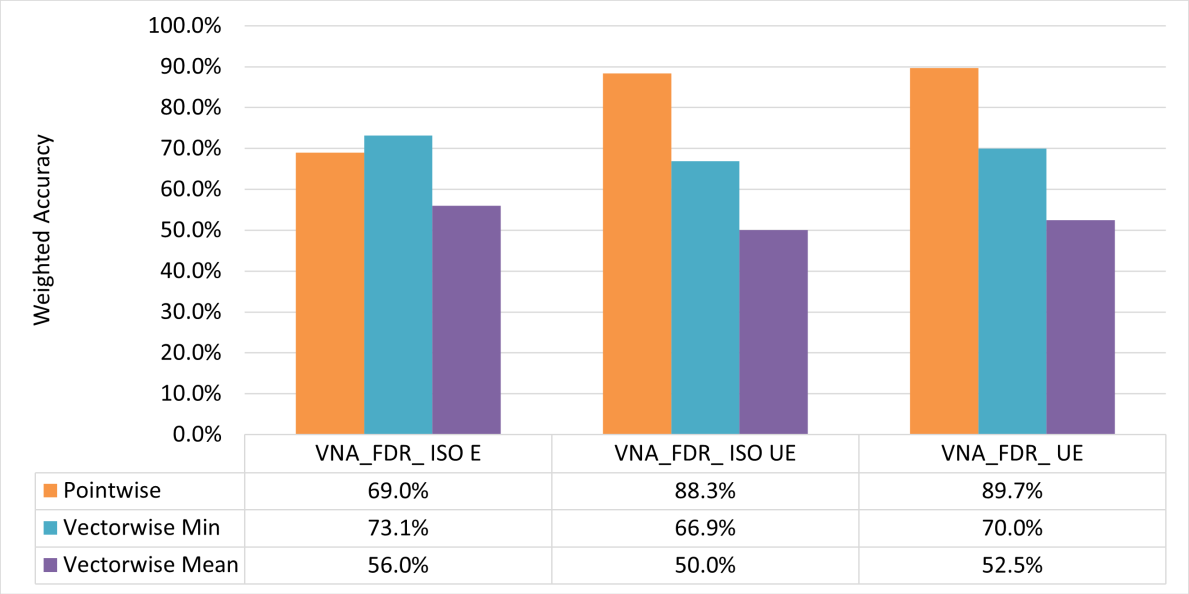


Figure 5: 480 VAC energized 200 ft low voltage cable frequency domain reflectometry (FDR) results for a Copper Mountain vector network analyser (VNA) vs. the radio-frequency system-on-chip (RF SoC) system [5]

3.3. ADVANCED DATA ANALYSIS AND PREDICTION USING MACHINE LEARNING

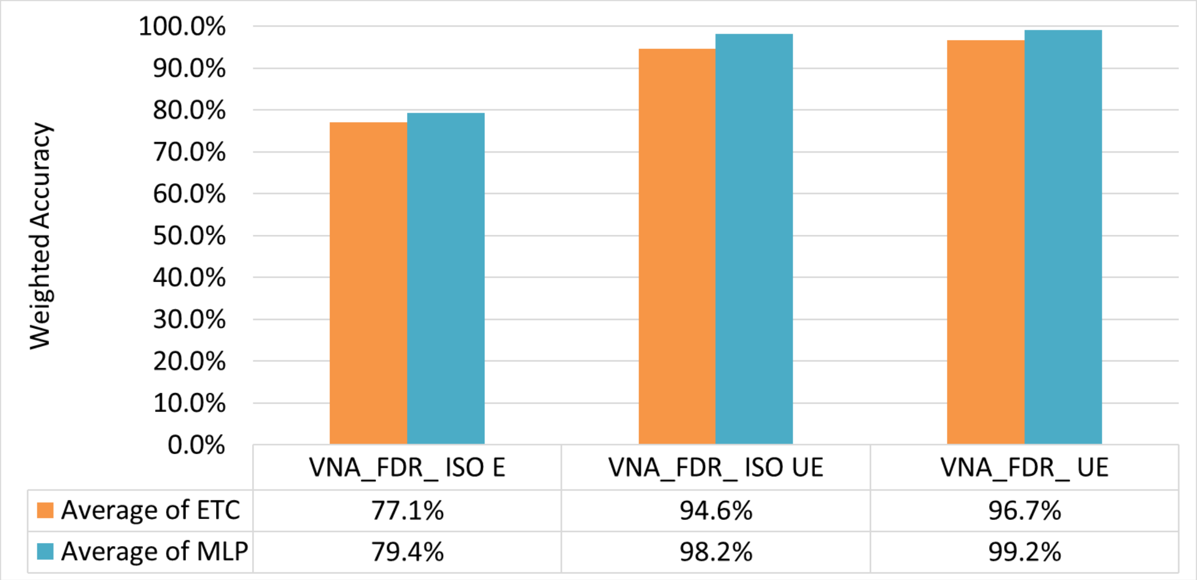
Machine learning was applied to processed reflectometry data to automate the interpretation of signatures associated with cable degradation. The complexity of reflectometry signals, especially under energized conditions, makes manual interpretation challenging. Machine learning offers a means to classify cable conditions more reliably and rapidly than human experts, particularly when deployed continuously.

Both supervised and unsupervised approaches were evaluated. Supervised classification models such as Extra Trees Classifier and Multi-Layer Perceptron Classifier achieved very high accuracy when trained and tested on similar datasets but displayed reduced ability to generalize when signals shifted or when faults occurred at previously unseen locations. Unsupervised models performed more consistently, particularly the Pointwise distance method, which analyzes the similarity between test signals and the distribution of normal conditions across all points along the cable. This method demonstrated strong generalization to synthetic damage scenarios and maintained robust performance even when energized data introduced additional background reflections, compared to the other vectorwise unsupervised model analyzed [6,7].



	VNA_FDR_ ISO E	VNA_FDR_ ISO UE	VNA_FDR_ UE
🟧 Pointwise	69.0%	88.3%	89.7%
🟦 Vectorwise Min	73.1%	66.9%	70.0%
🟪 Vectorwise Mean	56.0%	50.0%	52.5%

Figure 6: Comparison of unsupervised methods using "Mag" preprocessing and 200, 400 MHz [6].



	VNA_FDR_ ISO E	VNA_FDR_ ISO UE	VNA_FDR_ UE
🟧 Average of ETC	77.1%	94.6%	96.7%
🟦 Average of MLP	79.4%	98.2%	99.2%

Figure 7: Comparison of supervised methods using "Mag" preprocessing and 200, 400 MHz [6].

Machine learning was also applied to reflectometry signals collected during thermal aging experiments. Although the shielded cable used in the aging study exhibited limited aging effects in its insulation, the models were able to distinguish early-life signals from later-life signals with moderate accuracy. These results indicate that machine learning can support trend detection even when degradation progresses slowly or is partially masked by cable shielding [7].

Machine learning results indicated that unsupervised models provided the best combination of accuracy and generalizability. These models were able to classify cable conditions effectively even when trained on unenergized data and tested on energized data, or when evaluating synthetic signals with relocated damage positions. Supervised models offered excellent performance on experimental data but lacked the robustness needed for generalized deployment across unknown future damage states.

4. CONCLUSION

The collective findings of this research indicate that online cable monitoring in nuclear power plants is now technologically feasible. The inductive clamshell coupler provides the necessary electrical isolation and bandwidth to support high-quality reflectometry on energized cables, thereby removing one of the major barriers to continuous monitoring. The FPGA-based reflectometry system combines laboratory-grade performance with cost-effectiveness, scalability, and suitability for integration into plant monitoring infrastructure. Machine learning automation addresses the challenge of interpreting reflectometry signals, reducing reliance on human expertise, and enabling real-time or near-real-time anomaly detection.

These technologies complement one another. The coupler allows safe signal injection and measurement on live circuits; the FPGA hardware provides the multi-channel architecture needed to monitor multiple circuits simultaneously; and machine learning offers an analytical engine capable of screening vast amounts of reflectometry data. Together, they create a path toward condition-based qualification for aging cables, minimizing the need for outage-based testing and reducing the operational and financial impact of cable maintenance activities.

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