



The Journey to Cable System Remaining Useful Life and Predictive Maintenance

INTRODUCTION

Cable system components are highly engineered and are subject to significant quality control standards during manufacturing; however, after shipping and installation, about 40 percent of cable systems no longer meet those quality control standards.

The health of an underground cable system can often be traced back to its early life. In fact, over 90 percent of cable failures are associated with defects and anomalies that existed at the time of installation. Cable system components are highly engineered and are subject to significant quality control standards during manufacturing; however, after shipping and installation, about 40 percent of cable systems no longer meet those quality control standards. Properly commissioning a cable system in accordance with standardized partial discharge (PD) test specifications ensures that its components are free from significant factory defects and installation errors and will operate reliably for decades to come [1]. If defects and anomalies are addressed before a system is energized, grid operators realize increased system reliability, improved safety, and benefit financially; but not all cable systems have been properly commissioned, and proper commissioning does not guarantee that extreme transients, digging, or sabotage, for example, will not cause damage in the future.

Each year, millions of people and thousands of businesses are impacted by cable system failures, and the majority of these solid dielectric (SD) failures are associated with PD. All solid dielectric (i.e., plastic and rubber insulation) failures in underground cable systems are associated with PD, a phenomenon in which an electrical discharge does not completely bridge the insulating gap between two electrodes (conductors). But not every instance of PD poses an immediate threat to distribution systems, therefore the challenge to operators is to determine the severity of the PD, and to accurately estimate potential time to failure, or remaining useful life (RUL).

Detecting PD becomes more complicated once the cable is installed and then assembled with other cable system components. The only way to achieve a factory-comparable result in the field is to use a 50/60Hz excitation voltage, high-efficiency sensors, and advanced digital signal processing capable of achieving a measuring sensitivity of at least 5 picoCoulomb (pC) [1], as is the case with IMCORP's Factory-Grade® Technology. This allows identification of all potential PD signals for further determination regarding how far they deviate from the manufacturers' standards.



AUTOMATION AND DEEP LEARNING

With approximately 20% of today's transmission and distribution cables defined as significantly aged underground assets, as well as the tremendous expansion of underground cabling in recent years, determining an accurate condition of these assets is vitally important. Accurate assessment of PD performance and the automation of signal interpretation has never been more necessary. For almost a decade, IMCORP has been developing machine learning algorithms and deep learning models to automate the detection and characterization of PD signals originating from defects in cable systems. Automated PD location and classification provide a time savings over human analysis by up to 500 percent in the analysis and interpretation of complex datasets. The automated process serves as a quality assurance tool that makes diagnostic procedures more consistent, allowing critical performance metrics to be reliably tracked.

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The key to deep learning is the size and quality of the database used to "train" the computer. The more meaningful information you have, the greater the accuracy with which the machine can learn to make predictions. The database IMCORP is using to train its computer to diagnose the condition of underground cable is massive: it comprises the "labels" (or answers) assigned by human analysts to characterize tens of millions of instances of PD defects in hundreds of thousands of shielded underground cable systems tested by IMCORP over our more than 20-year cable diagnostic history. This immense data warehouse, containing over 150 million digital signal waveforms and associated user determinations, is used for data exploration and data science work.

IMCORP utilizes this extensive database as sample data, enabling deep learning networks to identify and characterize signals by "partial discharge" or "nonpartial discharge," determine the approximate location of PD defect in the cable, and identify PD defect type with ever greater precision and accuracy. Already, the deep learning networks are providing results that rival the accuracy of the human analysts in finding and diagnosing defects in underground cable systems – to date, an accuracy rate of 97 percent. And reciprocally, the deep learning results have revealed that the human accuracy is also not at 100 percent; so, as the DL learns from the human data, the human process improves from the DL results.

After applying the first AI tool to automate analysis, IMCORP set out to implement a proactive and predictive AI-based maintenance model for underground cable systems that provides visibility for future reliability and, ultimately, lower life cycle costs – a technology that costs less, takes less time, and is more accurate than training and using human analysts to analyze and interpret results from large data sets extracted from the field.

The new approach enables deep learning models to use the feature labels (features are numerical characteristics of PD signals) generated by analysts to autogenerate the best characteristics on which to base predictions. The model transforms PD signals originating from the same location within cable systems into images, called phase-resolved partial discharge (PRPD) plots. PRPD plots are composed of positively identified partial discharge events occurring from one specific defect location [2]. Figure 1 identifies a characteristic PRPD plot of the electrical-tree type. This second tool divides the PRPD plots into predetermined categories of risk ranging from higher-risk electrical tree types to very low risk, having no recognizable PRPD, and couples it with the defect's response to applied voltage level to create a condition-based triage for a cable system's health. Finally, operational environment data, such as loading, work history, overvoltage protection levels, and the statistical occurrence of transient overvoltage magnitudes, can be combined using a third AI tool into a risk factor that plays into the overall determination of RUL.

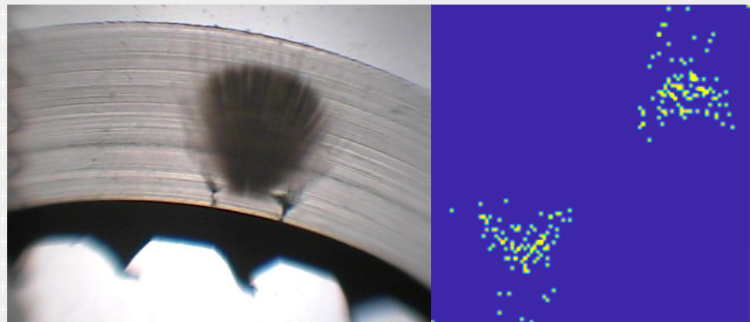


Figure 1.
Phase-Resolved Partial Discharge
Pattern (PRPD) of electrical tree-type
Defect.

REMAINING USEFUL LIFE (RUL) AND PREDICTIVE MAINTENANCE

To accommodate grid growth and modernization and the massive amount of asset and performance data while maintaining reliability, AI-based technology is necessary to effectively estimate RUL and drive optimized asset management and predictive maintenance decisions [2]. In the case of cable systems, RUL is the length of time a component is likely to operate reliably before it requires repair or replacement in order to avoid system failure. Knowing the RUL of cable system components provides the operator with the ability to accurately forecast when equipment will require repair or replacement, eliminating costly reactive O&M repairs, enabling the prioritization of critical repairs, and minimizing the probability of system failure and resulting impact to customers.

Multiple methods are used to calculate, or determine, RUL. The method used is determined by which types of data are available for input: lifetime data, run-to-failure histories, or known threshold values. Lifetime data involves comparison to similar machines or components over the course of their operating life and evaluating the length of time it took for them to reach failure. Run-to-failure data is derived from similar components, or those with similar behavior, and can be used to estimate RUL using similarity methods. In the case of run-to-failure using similarity methods, covariates such as load or operating temperature, or other variables that may affect RUL, are also considered. Run-to-failure models estimate RUL by predicting when a condition indicator will cross the threshold. Last, threshold values are helpful when run-to-failure or lifetime data is not available. Threshold data evaluates component condition based on certain factors known to cause failure, such as temperature or pressure values which fall outside of recommend use ranges [3].

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CASE STUDY

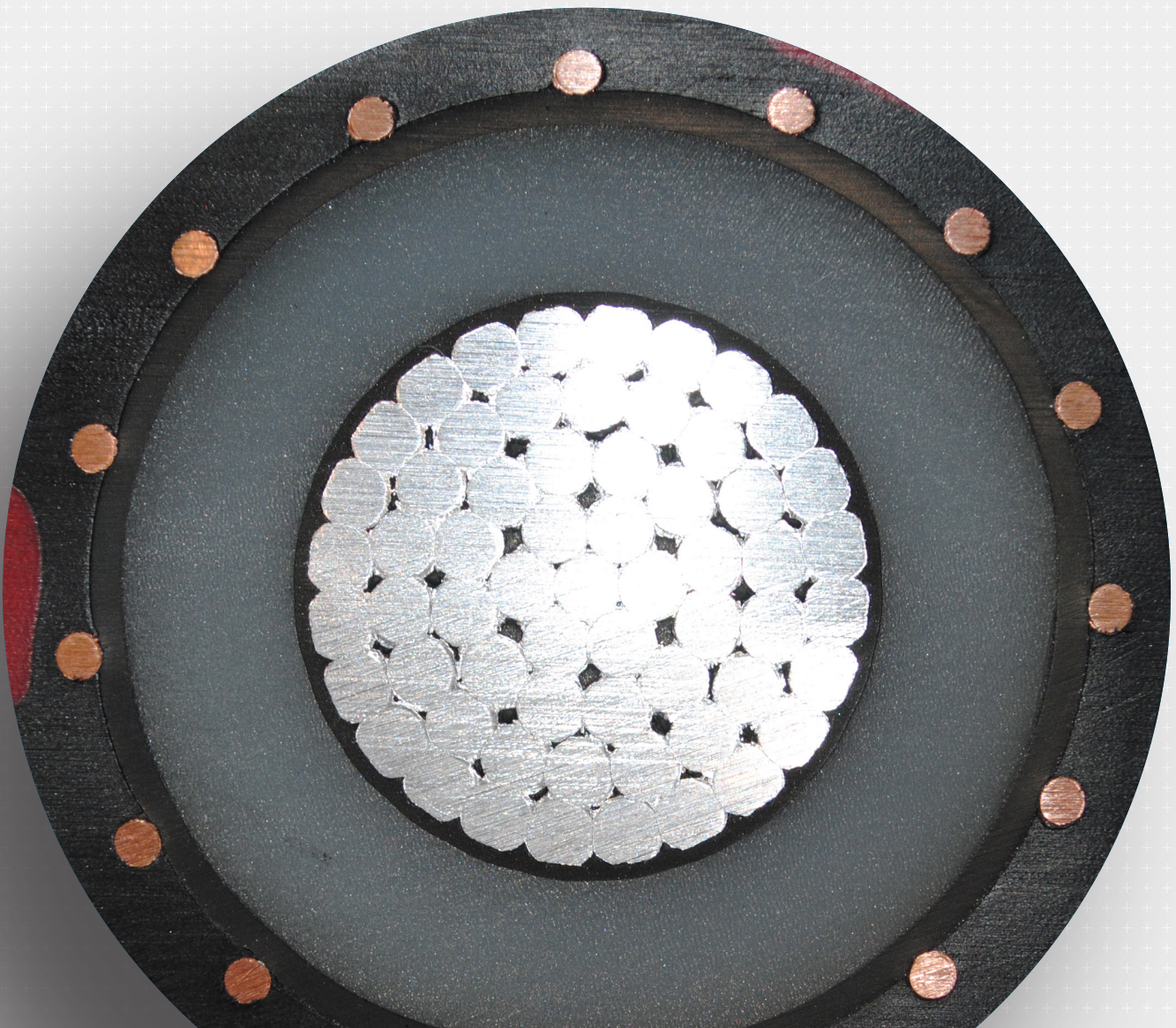
IMCORP employs similarity-based techniques in our predictive analytics, meaning a specific cable system defect with known severity will likely behave in a manner consistent with other, similar defects that have been historically detected and imaged [4]. In a recent utility case study, IMCORP was able to accurately reanalyze data from over 26,000 cable systems. The automated AI-based characterization and assignment of risk factors enabled the utility to reduce the number of repair actions by about 75% while maintaining a high level of reliability.

Predictive maintenance based on automated RUL calculations can decrease operating costs by reducing unnecessary maintenance, allowing maintenance to be scheduled when it is most needed, and minimizing the need for emergency repairs.

BENEFITS OF RUL CALCULATIONS AND PREDICTIVE MAINTENANCE

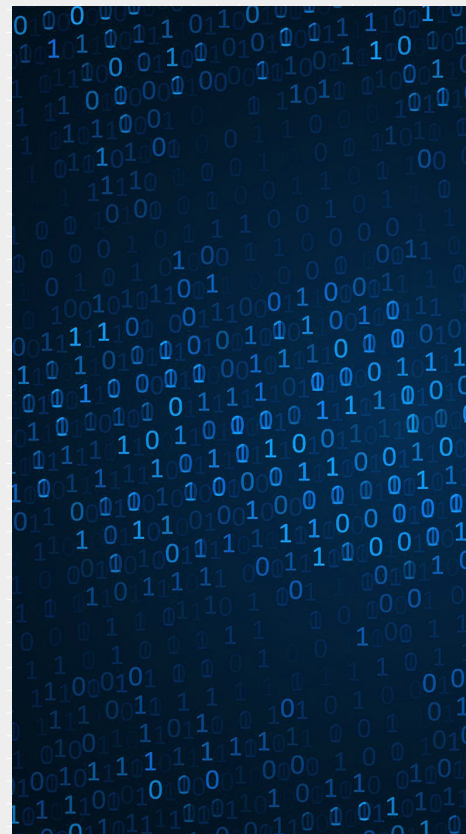
Predictive maintenance based on automated RUL calculations can decrease operating costs by reducing unnecessary maintenance, allowing maintenance to be scheduled when it is most needed, and minimizing the need for emergency repairs. This approach not only decimates capital expenditures (CAPEX), it also decimates future reactive operating expenses (OPEX) while improving reliability by over tenfold.

Additionally, minimizing unplanned downtime, or reactive work, by more than ten times, cable owners can greatly reduce accidents associated with site mobilizations, which often come with their own set of hazards, such as inclement weather, poor visibility, fatigue, rushing, and the potential of not having a proper Job Safety Assessment. As the OSHA Hierarchy of Hazard Control indicates, elimination of a hazard is the most effective method of risk reduction, and a planned outage is much safer than an emergency repair.



CONCLUSION

With only wholesale replacement or recurrent testing available to cable system operators, how are risks prioritized, budgets and financial forecasts established, and the safety and reliability of underground systems maintained? The answer is AI-based tools that make it possible to locate and rank system defects by severity, then predict faults before they occur through RUL estimation. Deep learning algorithms applied to IMCORP's immense Factory-Grade® PD test database, including hundreds of thousands of cable systems, has enabled the development of three new AI tools. These new tools simplify complex PD analysis and integrate both enhanced condition assessment and operational environment data. The results are up to a 500% increase in analysis efficiency and approximately 75% reduction in priority rehabilitation actions, while achieving ten times higher reliability, decimating O&M costs and operational safety events, and enabling a lean, just-in-time repair asset management approach.





Cited Items / Works

[1] Standards:

- IEEE 48 – Standard for Terminations rated 2.5 kV through 500 kV
- IEEE 404 – Standard for Cable Joints rated 2.5 kV to 500 kV
- IEEE 386 – Standard for Separable Insulated Connector rated 2.5 kV through 35 kV
- ICEA S-97/94-682/649 – Standard for MV Extruded Shielded Power Cables rated 5 through 46 kV
- ICEA S-108-720 – Standard for Extruded Insulation Power Cables rated above 46 through 500 KV AC
- IEC 60502-4 – Standard for cable accessories rated from 6 kV ($U_m = 7,2$ kV) up to 30 kV ($U_m = 36$ kV)
- IEC 60502-2 – Standard for Power Cables rated from 6 kV ($U_m = 7,2$ kV) up to 30 kV ($U_m = 36$ kV)
- IEC 60840 – Standard for Power Cables with extruded insulation and their accessories for rated voltages above 30 kV ($U_m = 36$ kV) up to 150 kV ($U_m = 170$ kV)
- VDE 0278-629-1 – Standard for accessories on Power Cables with extruded insulation rated from 3,6/6(7,2) kV up to 20,8/36(42) kV
- VDE 0276-620 - Standard for MV Power Cables with extruded insulation rated from 3,6/6 (7,2) kV up to and including 20,8/36 (42) kV

[2] Ziegler, S., Shekhar, S. (2021). Using Machine Learning and Deep Learning for Characterizing Partial Discharge in Underground Utility Cables for Predictive Maintenance Application, CIGRE US National Committee 2021 Grid of the Future Symposium

[3] Baru, Aditya, Three Ways to Estimate Remaining Useful Life for Predictive Maintenance, Mathworks, 2018

[4] Soons, Y., Dijkman, R., Jilderda, M., Duivesteijn, W. (2020). Predicting Remaining Useful Life with Similarity-Based Priors. In: Berthold, M., Feelders, A., Krempf, G. (eds) Advances in Intelligent Data Analysis XVIII. IDA 2020. Lecture Notes in Computer Science, vol 12080. Springer, Cham. https://doi.org/10.1007/978-3-030-44584-3_38

[5] Ziegler, Steffen, Morello, Tim, Ferraro Parmalee, Lisa, Predictive Maintenance and Remaining Useful Life for Underground Cable Systems, Transformer Technology – Power Systems Technology, October 2022

[6] Ziegler, Steffen, Morello, Tim, Ferraro Parmalee, Lisa, Deep Learning Characterization of PD Defects, An Important Step Toward Predictive Maintenance of Underground Cable Systems, Transformer Technology - Power Systems Technology, January 2023



Steffen Ziegler holds a Master of Science degree in Electrical Engineering from the Karlsruhe Institute of Technology - Germany. Mr. Ziegler works for Eversource Energy as Lead Engineer in Advanced Forecasting and Modeling. His career began at IMCORP in 1999, where for over twenty years his positions included Director for Signal Analysis and Artificial Intelligence, and Manager for Research and Development. He has specialized in the field of digital signal processing applications and machine learning and deep learning applications for Underground Power Cable Systems.



Brenda Hite is a Strategic Communications Specialist for IMCORP. She is a technology evangelist who passionately supports industry electrification efforts through education about technical, financial, logistical, and societal benefits of using cutting edge diagnostics to increase power system resilience, reliability, and safety while lowering costs. Before joining IMCORP, Brenda was the Membership Engagement and Services Manager for EPRA (The Electric Power Reliability Alliance), where she supported a growing and collaborative community of commercial and industrial electric power safety and reliability practitioners. She began her career as a Project Manager in the environmental consulting industry.



Tim Morello is currently the Senior Vice President of Strategic Business Development at IMCORP where he is responsible for bringing IMCORP's Factory Grade technologies and services into various electric power generation and distribution markets. Specific focus is on services that support digital transformation initiatives that enable reduced operational costs, improved operating efficiency, underground power delivery reliability, and optimize revenue growth.