Forecasting Partial Discharges of Cable Joints using Weather data

[1]Raymon van Dinter
Sioux Technologies
Apeldoorn, The Netherlands
Information Technology Group
Wageningen University & Research
Wageningen, The Netherlands
raymon.vandinter@wur.nl

[2]Sander Rieken
Alliander
Arnhem, The Netherlands
sander.rieken@alliander.nl

[3]Philippe Leduc
Sioux Technologies
Singapore
philippe.leduc@sioux.asia

[4]Gerdtinus Netten
Sioux Technologies
Delft, The Netherlands
gerdtinus.netten@sioux.eu

[5]Bedir Tekinerdogan
Information Technology Group
Wageningen University & Research
Wageningen, The Netherlands
bedir.tekinerdogan@wur.nl

[6]Cagatay Catal
Computer Science and Engineering
College of Engineering, Qatar University
Doha, Qatar
ccatal@qu.edu.qa

Abstract— **Partial discharge (PD) is a symptom of a weak spot in an underground power cable. Additionally, environmental influences are an important factor in cable degradation. We show that PD in underground cable joints can be successfully forecasted using linear machine learning models leveraging historical PDs and weather data. This has potential applications in estimating the remaining life of cable joints, as we can extend the prediction horizon for predictive maintenance models, such as survival analysis models. Additionally, the model error can be monitored for anomaly detection. This study was conducted in collaboration with Alliander, an electricity and gas distribution system operator in the Netherlands.**

Keywords—Partial Discharges, Support Vector Machine, Lasso, time series, forecasting, electricity cables, predictive maintenance

I. INTRODUCTION

The Dutch Medium-Voltage (MV) electricity grid is rapidly changing from a centralized to a decentralized system due to increased wind turbine and solar panel adoption. As such, MV grids are experiencing increasing variations in load, and bidirectionality. Cable joints, the connections between two power cables, are critical components, as they are: (a) natural weak spots since they are constructed manually on-site, and (b) certain types are prone to faults due to varying currents. Unfortunately, historical usage data, such us currents, are not available. Partial discharge (PD) is a symptom of a weak spot that could lead to a fault. Diagnosing PD is a proven method to assess the condition of underground power cables. A PD induces a small pulse in the conductor(s) and earth screen that propagates through the cable in both directions [1]. The Smart Cable Guard (SCG) system [2] uses two inductive PD sensors placed in the cable network, one sensor at Ring Main Unit (RMU) A and the other at RMU B. The maximum distance between two inductive PD sensors is 8 or 15 km depending on cable types [1]. [3, 4] showed that SCG systems can effectively be used as a non-intrusive cable monitoring method. Alliander developed a system for automatically detecting PD in the data and forwarding warnings into their joint degradation monitoring system, which contains research documents on joints. When a warning is retrieved, one field expert and at least one data scientist analyze the PD data, provide documentation of the degradation state, and determine when another iteration of PD analysis must be conducted.

Temperature and moisture are two key environmental influences for fault rates of power cables due to the temperature pressure effect [5, 6] and water treeing phenomena [7]. As such, features based on these two environmental influences may be beneficial for forecasting PD of environmentally influenced joints. Previous work on predicting power outages due to PD and weather has been conducted by [8]. Forecasting PD is useful for extending the prediction horizon of predictive maintenance models like survival analysis. To our knowledge, no prior research was conducted on forecasting PD in MV cable joints, nor using weather data as exogenous variables. Thus, the PD forecasting model can be used as a component of a Digital Twin for predictive maintenance of cable joints.

II. METHODOLOGY

Our main goal is to forecast PD for determining the degradation of a cable joint. Seasonal patterns in PD may provide signals towards environmental influence on the joint's degradation. We hypothesize that if a model is trained on PD data, degradation information is included in the model, and the forecasting error will not increase towards the end-of-life of a joint. As such, we have the following research questions:

- RQ1: Can PD be forecasted based on historical PD data and weather features?
- RQ2: Is the model performance also satisfactory on joints with no seasonal PD trend?
- RQ3: Does the forecasting error increase towards the end-of-life of a joint?

The internal Alliander research documents were filtered based on 'season', 'spring', 'autumn', 'summer', or 'winter' to describe the PD pattern. The retrieved set of 9 joints were considered our ground truth, as field experts rated them. We also selected a set faulty of joints due to PD – but without obvious environmental influences. Each joint's location was approximated to the primary SCG device location. We requested the location-specific hourly data from ERA5-Land from Copernicus' Climate Data Store (CDS) [9], provided by the Alliander Weather API [10]. Specifically, soil temperature and volumetric soil water at level 3 (28-100cm) are regarded as input features, as Alliander's cable depth policy is around 80 cm.

In order to align the datasets, we resample the PD data by summing the discharges per hour, which forms our response variable to be modeled. We combine the target and weather features and enrich the features by investigating the model's feature importance. Additionally, we transform the features to stationary features by calculating their element-wise

979-8-3503-3984-0/23/$31.00 ©2023 IEEE
DOI 10.1109/CAI54212.2023.00021

difference. We use the autoregression plot of the target for showing the seasonality.

At the start of our research, we compared multiple models and selected the following two traditional Machine Learning models due to their results: Lasso Regression and Support Vector Regression (SVR) [11]. The model hyperparameters were tuned using grid search with 80% of the timeseries of a single joint for training and 20% for validation. This single model was applied to all other joints for testing. We measure the model performance using the R^2 metric.

III. Results

The training set was taken from a joint with a seasonal PD pattern, and over 3 years of data. Figure 1 shows the autocorrelation plot of the training set. The plot shows peaks at around 150-, 360- and 700-days lag, indicating the seasonal pattern. The selected informative features were the moving average (MA), moving standard deviation, and moving minimum/maximum for lags 7, 14, and 21 days respectively, of weather and PD.

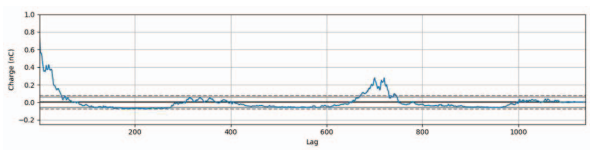

Figure 1 Autocorrelation plot for hourly partial discharges of the training set. Significant peaks can be seen at 150-, 360-, and 700-days lag, indicating the seasonal pattern.

Figure 2 shows the train and test set and model predictions. Test dataset 0 shows a seasonal, dampening pattern and is still intact at the last date. Test dataset 1 shows no significant seasonal pattern or correlation to weather data and has failed at the last date. As such, the joint for test dataset 1 could not be shown to be affected by the weather influences under investigation. We can see that the train R^2 for Lasso is slightly higher than SVR's, whilst the validation R^2 is rather similar. Lasso is especially correct at determining the up and downward motions of the charge. A higher R^2 for the Lasso model is shown for both test sets. The models show to be invariant to the amount of charge and can follow the trend of the partial discharges. As validation, we also used the most naïve approach: $X_t = X_{t-1}$, which showed less performance.

IV. Conclusion

Using feature engineering and linear machine learning, we were able to successfully model the highly stochastic nature of partial discharge (PD) in Medium-Voltage cable joints, as we correctly propagate the stochastic nature of the explanatory variables to the response. The models can forecast PD on datasets with and without significant seasonal PD patterns. As we have selected the correct features to forecast the future PD, the forecasting error does not increase at the end-of-life for the investigated joints. Alliander can leverage this model for extending the prediction power of their predictive maintenance models and anomaly detection for high prediction errors. This work is the first study towards forecasting PD to our knowledge. Future work should focus on increasing the forecasting horizon from one day to weeks or months, as joint degradation is a slow process. It should also work on testing with more joints. Additionally, forecasting PD on an hourly basis to determine intra-day trends.

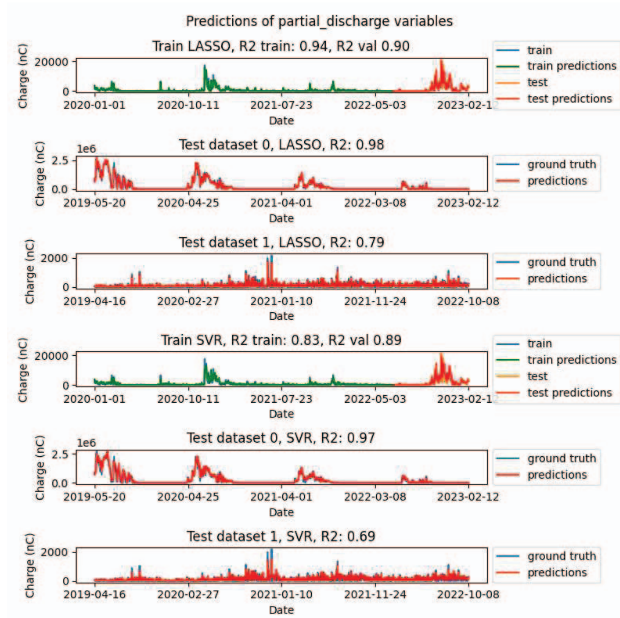

Figure 2 Train and test set and their predictions for hourly partial discharges. R2 is shown in the title. Datasets 0 and 1 are joints with and without a significant seasonal pattern, respectively.

References

[1] P. Wagenaars, "Integration of online partial discharge monitoring and defect location in medium-voltage cable networks," 2010.

[2] DNV. "Smart Cable Guard." https://www.dnv.com/power-renewables/services/scg/index.html (accessed 9 March, 2023).

[3] F. Steennis, P. Buys, R. Mehairjan, P. Mehairjan, and P. Van der Wielen, "Smart Cable Guard for PD-online monitoring of MV underground power cables in Stedin's network," in *International Conference on Condition Monitoring & Diagnosis*, 2014.

[4] F. v. Minnen, D. Harmsen, and P. Wagenaars. "On-line Fault Detection to Prevent Network Failure." (accessed 7 March, 2023).

[5] A. Ghaderi, A. Mingotti, L. Peretto, and R. Tinarelli, "Effects of mechanical pressure on the tangent delta of MV cable joints," *IEEE Transactions on Instrumentation and Measurement,* vol. 68, no. 7, pp. 2656-2658, 2019.

[6] A. Sturchio, G. Fioriti, M. Pompili, and B. Cauzillo, "Failure rates reduction in SmartGrid MV underground distribution cables: Influence of temperature," in *2014 AEIT Annual Conference-From Research to Industry: The Need for a More Effective Technology Transfer (AEIT)*, 2014: IEEE, pp. 1-6.

[7] E. Steennis and F. Kreuger, "Water treeing in polyethylene cables," *IEEE Transactions on Electrical Insulation,* vol. 25, no. 5, pp. 989-1028, 1990.

[8] M. v. Osch, "Analyzing Data of the Medium Voltage Grid and the Weather to Predict Power Outages," MSc. Mathematics, Radboud University, 2021. [Online]. Available: https://www.math.ru.nl/~bosma/Students/MeesvanOschMSc.pdf

[9] J. Muñoz Sabater, "ERA5-Land hourly data from 1950 to 1980," *Copernicus Climate Change Service (C3S) Climate Data Store (CDS),* pp. 1181-1194, 2021.

[10] Alliander. "Weather API." https://weather.appx.cloud/api/v2/docs# (accessed 7 March, 2023).

[11] F. Pedregosa *et al.*, "Scikit-learn: Machine learning in Python," *the Journal of machine Learning research,* vol. 12, pp. 2825-2830, 2011.