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Cable protection system monitoring using DAS and machine learning

Distributed Acoustic Sensing (DAS), which belongs to Distributed Fibre Optic Sensing (DFOS) monitoring methods, is currently deployed more and more on HV power cables. DAS is expected to recognize and localize quickly and accurately electrical faults, whilst providing fishing activity or anchoring information (offshore) and Third-Party Intrusion (TPI) information onshore. Unlike Distributed Temperature Sensing (DTS) that typically has a measurement time of a few minutes to a few tens of minutes on long export cable, a DAS is providing measurements every millisecond, resulting in as much as one to two Terabyte of data per single day. Most of the data has no meaningful content; in other words, it only features background noise such as traffic on a land section, or vessels and waves on an offshore section. Rarely, hidden within this vast amount of data, there is an intrusion, an anchor drop or an electrical fault to identify and to localize.

Given the amount of data and the speed at which it is made available, human review is not possible and simple algorithms are not sufficient. Artificial Intelligence (AI) is at least to be considered and is potentially the only viable and efficient solution for handle the vast amount of data produced by a DAS.

As an illustration, we report on a measurement campaign featuring a chirped-pulse DAS installed on an Offshore Substation in the North Sea, in view of investigating integrity of Cable Protection System (CPS). The Offshore Wind Farm (OWF) was in operation. Altogether, 6 different strings were monitored in 3 different measurement campaigns. The fibre section corresponding to the CPS position were isolated form the other data, stored and analyzed. Both supervised and unsupervised machine learning (ML) were tested on the data set. For the supervised approach, survey data from Remotely Operated Vehicles (ROVs) were used for labelling. As common practice in ML, part of the data was kept out of the training process for subsequent testing of the algorithms. Results were convincing and the agreement between survey data and processed data was good, despite some yet to be explained miss-classification.

Beyond a proof-of-concept experiment, it enlightened the fact that the availability of survey data is important in such an approach. This can be circumvented provided that DAS monitoring is installed at a very early stage in the OWF lifetime, namely when CPS are just installed and are therefore in good conditions. Then, unsupervised ML can be used to monitor trends in the CPS behaviour (anomaly detection) that will allow identifying failures.

From this test campaign, it is clear that ML can be deployed in the OFW industry to monitor HV systems and can be used to efficiently process the amount of data produced by a DAS. To do so efficiently, monitoring should begin at an early stage within the considered degradation process, or some survey data is available for training.