# Listening to your cable with Artificial Intelligence for Asset Monitoring

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## *ABSTRACT*

This paper describes a novel approach for detecting sub-sea power cable burial status using Distributed Acoustic Sensing (DAS) and machine learning — specifically artificial neural networks. Currently, DAS has been used predominantly to monitor power cables for faults and acoustic disturbances. With advancements in the quality of data captured by the AP Sensing DAS system, it is possible with feature processing to train a neural network to determine the burial status of a cable. This paper will explore such a case and the validity of the results from the experiment.

## *KEYWORDS*

DAS; Neural Networks; AI; Reburial; Subsea; Power Cable.

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## INTRODUCTION

Damage to subsea power cables creates significant impacts on revenue for the cable owner's business and for those affected by the loss of service. Repairs and cable monitoring for fault location can be a timely process causing further cost and loss of revenue. Typically, Remotely Operated underwater Vehicles (ROVs) are used to survey subsea cables. These have a high cost and cannot provide continuous monitoring of an entire cable. Distributed Acoustic Sensing (DAS) systems provide solutions for cable fault monitoring and has been successfully used to continuously monitor cables for faults and disturbances.

Developments in data processing and pattern recognition systems are happening at an ever-increasing rate. Consequently, sophisticated algorithms and artificial intelligence have become more accessible and less exclusive to the realm of academia and are being taken up and used successfully in industry for enhancing output, classification and predictive modelling. The DAS produces large amounts of valuable data which can be interpreted in many different ways, therefore it was logical to use advanced data analysis techniques and apply them to the DAS data to extract crucial patterns which could provide invaluable insight.

## DAS

Distributed Acoustic Sensors have been used for a large number of applications from intrusion detection to cable fault and leak detection, as they give measurement of acoustic signals without interference from electromagnetic radiation. In recent research it has also been shown that temperature changes can be measured in a phase-sensitive optical systems such as the AP Sensing Distributed Acoustic Sensor [1]. Current DAS Systems have been shown to be effective up to 70km making them viable for large scale deployment.

By exploiting this information, patterns relating to subsea cables can be explored in more depth than previously done before.

## ARTIFICIAL NEURAL NETWORKS

Neural networks are at the forefront of current machine learning technology. These are mathematical models designed to replicate the learning process of the human brain. They are heavily used in the process of identifying underlying patterns in data which can then be exploited and automated [2]. The basic structure of an Artificial Neural Network (ANN) is shown in **Fig. 1**. Models contain an input layer of nodes (shown on the left) that are features extracted from the data. Each adjacent layer in an ANN is fully inter-connected with the nodes in adjacent layers, and the strength of each connection is determined by the weight, $W_{xx}$. Each node has an activation function, *f*, which calculates the output from the node based on the weighted sum of the inputs from the connected nodes. The weights are calculated during the model's training via back propagation (minimising the error of the model). The direction of the data flow is shown by the directional arrows.

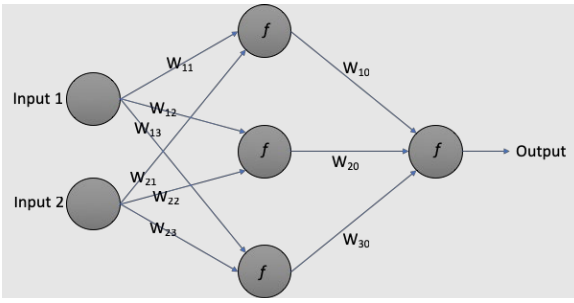


**Fig. 1: Structure and data flow of a basic ANN, demonstrating the weights ($W_{xx}$) and activation functions (*f*).**

The complex structure of these models makes them extremely efficient at identifying patterns in data, which can then be exploited and automated [4].

## CABLE REBURIAL

Subsea cable systems are susceptible to the environmental changes such as wave motion, natural disasters, and human activities such as anchoring and fishing [5]. Burying the cable not only gives stability to its physical location but also provides a safer environment from various threats. Therefore, it can be critical to know the cable burial status. Currently this inspection is carried out by ROVs with magnetic or visual sensors, making the evaluation of cable status costly in both time and resources, and does not continually monitor the cable [5,6].

The DAS measures the strain on the FO cable, a cable buried at a depth of >1 m in a subsea environment experiences different patterns of strain in comparison to an unburied cable lying on top of the seabed in the same location. Many different factors, such as the attenuation of acoustic signals in ground compared to a liquid (sea-water) medium, the suppression of motion of the cable, and differences in thermal changes due to the surrounding medium, can contribute to this effect. A subsea environment, however, is often very quiet, producing audio signals close to the noise floor of the system, resulting in small signal-to-noise ratios (SNR). Therefore, it is important to find methods of isolating these differing environmental signals from the system noise. With this, a DAS system can then serve as a cost efficient and continuous method of monitoring a cable asset.

## DATA COLLECTION

To show that machine learning techniques can be used to predict a subsea cable's burial status, data was collected from a reburial campaign on a subsea cable which reburied 5 sections of cables that were previously exposed. Details of this are shown in **Table 1**. An AP Sensing DAS system was connected to this cable for measurements, prior to the reburial campaign. The DAS system monitored and recorded data during and after the reburial, at all five locations. This helps to minimise the effects of changing environmental noise along the length of the cable and isolate the signal differences from the cable reburial.

Data was collected for an extended period before and after the reburial to also allow for averaging of the signal temporally. This helps to negate any spontaneous or anomalous signals which are not normally present. **Fig. 2** shows a frequency band energy plot of the reburial campaign over the course of approximately eight hours, data is discarded at a short time prior/post the reburial to factor out the ship transporting and controlling the ROV.

**Table 1: Reburial Details.**

| Site no. | Start location of the reburial site, relative to the fibre optic cable (m) | End location of the reburial site relative to the fibre optic cable (m) | Start time of reburial activity (UTC) | End time of reburial activity (UTC) | Max Depth Range (m) |
|---|---|---|---|---|---|
| 1 | 38185 | 38343 | 19:47:00 | 20:40:00 | 0.6 |
| 2 | 29872 | 29730 | 00:11:00 | 00:52:00 | 0.3 |
| 3 | 24066 | 24205 | 03:56:00 | 04:50:00 | 1.0 |
| 4 | 17465 | 17758 | 08:36:00 | 09:44:00 | 0.2 |
| 5 | 9917 | 10128 | 13:20:00 | 14:07:00 | 1.2 |

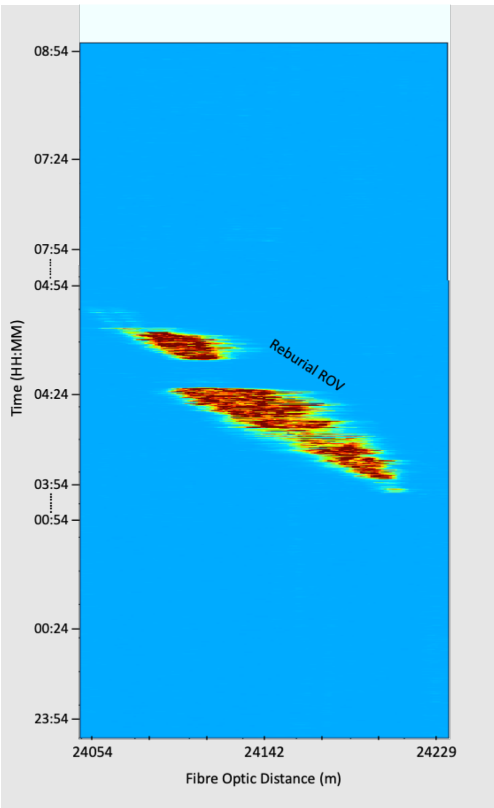


**Fig. 2: Frequency band energy plot (4-250 Hz) showing the reburial (site 3) process of a subsea cable using DAS.**

## THE MODEL

When training ANNs, the quality of the input data is one of the most critical parts. Due to this, it was imperative that the data used for training correctly represented the typical signals of both a buried and unburied cable. Therefore, from the data acquired during the reburial campaign, Reburial 3 and 5 were used as the other reburial processes did not fully rebury the cable or minimal reburial was carried out. Reburial Site 5 was used for training the data because of its closer position to the beginning of the fibre optic cable, thus giving it a better SNR. The data from Reburial Site 3 was used as a validation data set since the reburial was similar in depth, with a section going from totally unburied to >1 m buried. Reburial Site 3 was located approximately 15 km from the training data set (Reburial site 5), meaning it will have a slightly different environment, increasing robustness when testing the model.

The data before and after the reburial at site 5 was extracted and analysed in depth. This led to the development of a unique set of features that accentuate the differences between an unburied and buried cable. The features were extracted by splitting the DAS data into single channels of acoustic data for each 1.28 meters of the cable. Each of these channels were then split into multiple sections in time, with each section treated as an individual sample for feature extraction. Each sample then underwent processing that involved extracting specific frequency and time domain features; it was found that a mixture produced the best model. The feature set for each sample was then labelled according to the cable's burial status. All feature sets from site 5 were then fed into the ANN for training.

The training was carried out using a variety of different parameters such as the type of loss function used, the activation functions in the nodes, and variation in the number of nodes/layers to optimise the solution.

A sub-sample of the training data was used to test the performance of the model; this gives an indication of how the model is performing however although gives a limited scope in this instance due to the similarity of the data from the same reburial site (physical area). The result was an ANN binary classifier that could, for this data environment, accurately determine cable burial status.

## RESULTS

Once the model was trained and the parameters set, data acquired from Reburial site 3 was used to validate the performance of the model. The data from the reburial at site 3 was similar to site 5 in cable depth for both before and after either reburial however it was located approximately 15km further down the subsea power cable, meaning it had different environmental conditions.

The data from Reburial site 3 was processed and features extracted in the same way as for Reburial site 5. Data from several hours before and after the reburial were analysed due to the presence of a boat transporting the ROV impacting the predictions of the model. The model is not aware if the data correlates to a buried or unburied sample, it is up to the model to provide this classification. Figure 3 shows the section of the reburial (Reburial 3) temporally and spatially, with the reburial highlighted. Also highlighted is the burial depth of the cable before and after the reburial.

Once processing and feature extraction were complete, data was analysed by the trained ANN and a predication was given. Due to the spatial independence of the data an extra layer of analysis was then applied to give a spatial dependence on the surrounding classifications. The results of this can be seen in Figure 3.

The results highlight some flaws with the training process, such as the unburied data. The cable was truly unburied in some cases however at some other points it may have been around 0.1m buried. This leads to parts of buried cable being falsely classified as unburied. The accuracy of the model is demonstrated in Table 2. With an f1-score of approximately 88% this model shows strong promise.

**Table 2: Precision, Recall and F1-score on the validation data set (Reburial site 3).**

| | Precision | Recall | F1-Score |
|---|---|---|---|
| **Unburied** | 0.85 | 0.88 | 0.86 |
| **Buried** | 0.91 | 0.89 | 0.90 |
| **Avg** | 0.88 | 0.88 | 0.88 |

The model provides a strong basis for future work in this area, demonstrating that machine learning techniques can be used with DAS data to enable continuous monitoring of events. This also indicates that the methodologies used in the development of this model could be also be applied in other novel monitoring systems within the power cable industry.

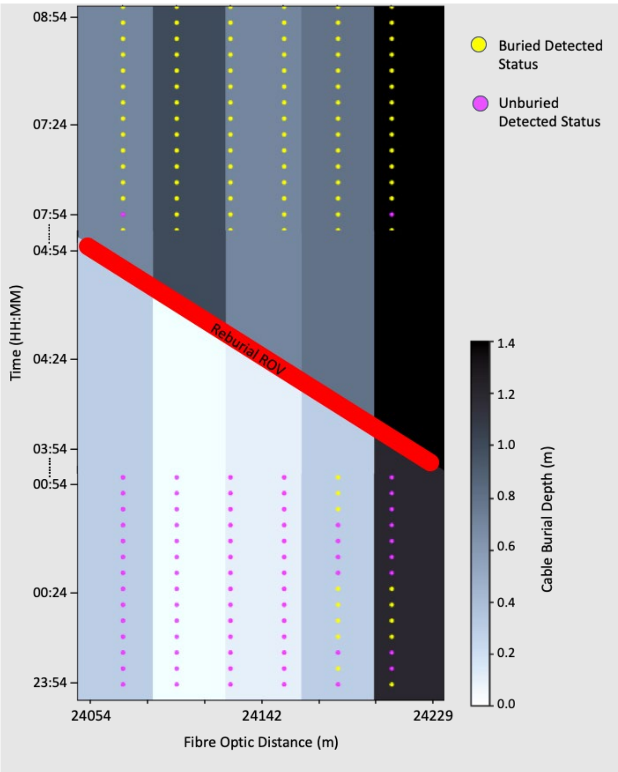


**Fig. 3: Diagram showing the results of the ANN in predicting the burial status before and after a reburial (site 3) along with associated seabed burial depths of the cable.**

## FUTURE WORK

The performance of the ANN shown in this paper could be improved with the addition of more training data. With more data from different sites, the model's performance would likely improve and be more generalisable. Additionally, more accurate data of the burial depth along the length of the cable could be used in a regression model to predict the actual depth of the cable, rather than just the burial status. This could provide an early warning system for cables that are shallow.

With recent improvements within the machine learning community, artificial intelligence has become more accessible and applicable to a wide variety of problems. These provide unique and powerful solutions to problems that were otherwise extremely difficult or impossible to solve. Using this technology for automatic detection will be a crucial factor in developing cutting edge systems in the sub-sea power market.

## ACKNOWLEDGMENTS

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## GLOSSARY

**DAS:** Distributed Acoustic Sensor
**ROV:** Remote Operated Vehicle
**ANN:** Artificial Neural Network
**FO:** Fibre Optic
**SNR**: Signal to Noise Ratio