Optimizing energy efficiency in underwater acoustic networks through machine learning classifiers.

STEWART, C., FOUGH, F., FOUGH, N. and PRABHU, R.

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Optimizing Energy Efficiency in Underwater Acoustic Networks Through Machine Learning Classifiers

Craig Stewart, Faranak Fough, Nazila Fough, Radhakrishna Prabhu
School of Computing, Engineering and Technology
Robert Gordon University, Aberdeen, UK

***Abstract* –Among many challenges in establishing an Underwater Wireless Sensor Network, is the challenge of resource constraints, battery and bandwidth being limited which renders acoustic networks limited in life and application. One identified application of TinyML is the potential of cutting the demand for network resources on the Internet of Things. Based on this hypothesis, this paper attempts to quantify the potential in using machine learning algorithms at the edge of the underwater network to reduce the burden on the battery powered acoustic node through an example automated of pipeline corrosion detection by transmitting only extracted conclusions from data.**

Keywords—ML, Underwater Acoustics, Underwater Internet of Things, Underwater Wireless Sensor Networks, Pipeline Monitoring

I. INTRODUCTION

Machine Learning (ML) has been embraced across a plethora of fields such as healthcare [1], energy [2], and marine [3] etc. and has now begun to become pervasive in regular tasks. One application of ML is in the field of communications where it is being anticipated that it will have significant benefits in managing traffic [4], Enhancing Quality of Service (QoS) [5] and Network Design itself [6].Underwater Wireless Acoustic Communication (UWAC) has many characteristics that render it disadvantageous when trying to obtain low-energy and high data-rate communications that render it a channel quite unlike a terrestrial radio frequency channel. The bandwidth is limited to lower frequencies in the spectrum as the physics tend to attenuate these frequencies less whilst requiring significant transmission powers to carry signals over vast distances of ocean wirelessly. ML classification at the edge of the Underwater Wireless Acoustic Networks (UWAN) shows promise as it can take complex multi-dimensional data such as that from submerged sensor arrays and draw "meaningful data" from them through classification or regression that is useful for specific applications that would usually involve a layer of human interpretation. Thus, this work proposes taking a potential scenario in subsea pipeline corrosion and failure classification for energy efficient transmission using Machine Learning Classifiers.

II. METHODOLOGY

On a terrestrial network, according to the OSI model, compression takes place on the Presentation Layer, traditionally, UWSN neglect this layer for energy efficiency reasons, however, computational resources are smaller and more efficient now that could enable for data to be reformatted before transmission for new energy savings to be found, compression mechanisms also use far more data than the single bit that is the aim of this investigation. For the purposes of quantifying the risk of leak or burst through pipeline corrosion, standards exist, one of these being DNV-RP-F101, [7] this quantitative mechanism inputs several metrics about the nature of a pipe's structure such as dimensions, the nature of the corrosion to outputs a value that corresponds with the risk of a burst or leak event. Based on this, a large synthetic dataset was developed. Figure 1 shows a block diagram of the process.

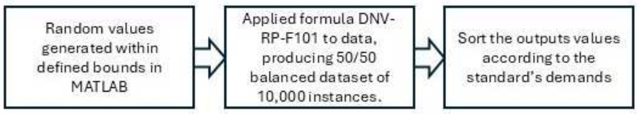

Figure 1 Block diagram of dataset generation process

Beyond this phase, the newly generated synthetic dataset was then used to train and evaluate common ML algorithms using MATLAB's Classifier application [8]. Formula 1 shows how to calculate burst pressure, P_b, according to DNV-RP-F101.

$$P_b = \left[\frac{1-\frac{d}{w}}{1-(\frac{d}{Mw})}\right]\left(\frac{2w}{D-w}\right) \quad (1)$$

$$M = \sqrt{1+0.31\left(\frac{l}{\sqrt{\sqrt{Dw}}}\right)} \quad (2)$$

Where, d, is the depth of the corrosion defect, w, is the pipe wall thickness, D, is pipe outer diameter and, M, is the Folias Factor given by formula 2. Where, l, is the length of the defect. For the purposes of this investigation, it was assumed that leak, $g1$, and burst, $g2$, are independent events and can be conveyed as limit state equations formulae 3 and 4.

$$g1 = \Lambda - d_{max} \quad (3)$$

$$g2 = P_b - P_{op} \quad (4)$$

Where, Λ, is the corrosion allowance (defined as 80% of wall thickness) and P_{op} is the operating pressure. Compliance with these rules was classified as 0 whereas non-compliance signifying a leak, or a burst was given by 1 for training and testing purposes with the ML algorithms. Table 1 shows the parameters used in the simulation for both the variables in the dataset and the pipeline. The ML algorithms selected were based on those that are known strong performers in classification from a brief literature review [9] and based on prior knowledge in the field of general performance [1].

TABLE I THE PARAMETERS USED IN THE DATASET FORMING FOR MACHINE LEARNING BASED COMPRESSION VIA CLASSIFICATION.

Parameter	Values
Pipe Wall Thickness	10mm
Diameter	150mm
Yield Strength	250 MPa
Operating Pressure	25 MPa
Defect Depth	0.1-10mm
Defect Length	0.5-100mm

This methodology produced a series of results that showed the potential of the concept.

III. RESULTS AND DISCUSSION

Table 2 presents the accuracies and prediction speeds achieved by the classifier on the synthetic dataset.

TABLE II THE RESULTS OF THE CLASSIFICATION ALGORITHM ACCURACY AND CORRESPONDING OBSERVATION SPEED.

Algorithm	Test Accuracy	Prediction Speed (Obs/sec)
Fine Tree	99.3%	58,000
Bagged Trees	99.5%	20,000
Linear SVM	97.0%	61,000
Quadratic SVM	97.6%	55,000
Neural Network	99.9%	48,000

As can be seen, the classifiers are adept at making the judgement whether the pipeline is at risk of leak or bursting for a given pipeline, particularly the Neural Network. The SVM was reduced in ability to effectively due to being to granularly separate the finer points at the interface between 1 and 0 classes upon observing the scatter plot. It is also key to mention that if we are to use prediction speed as a gauge for practical computational complexity then the NN was not the fastest, the SVM and Fine Tree being faster, however these were less accurate and, thus, less conductive to the application, the NN striking a better balance. Thus, if the observed link is assumed to be data linked by an Evologics 7/17 [10] device which operates at 6.9kb/s and transmits at 45W at a range of 8000m, with a constant frame size of 50 bytes for use in a simple ALOHA based system and the assumed flaw sensor output is 8-bits (1 byte) each for corrosion flaw depth and length in millimetres it can be shown that there has been significant energy savings. Given that the 16 bits of sensor data has successfully been reduced to 1-bit via the ML classifier, meaningful data can be drawn from 400 of such sensors to be transmitted in a single constant size ALOHA frame whereas before, it would have only been 25 with the full 2-byte sensor data. For the work done per sensor, post ML classification, it now takes 6.53mJ to transmit that meaningful data whereas, without the post ML processing, 90mJ would be needed per sensor, a significant energy saving merely by displacing the conclusion drawing process to the edge of the network rather than onshore where an operator or computer draws it.

IV. CONCLUSION

In conclusion, this paper has demonstrated how energy can be saved in a UWSN by displacing the conclusion drawing process using ML to the network edge. This will result in more work done per joule and more information to be carried in a single frame as well as a given period. This will be useful pro-active subsea maintenance regimes etc. Our current works are focussing on developing cognitive optics and Software Defined Radio [11] as well as multimodal underwater communications [12] technology for future autonomous networks.

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