Condition Classification of Fibre Ropes during Cyclic Bend over Sheave testing Using Machine Learning

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ABSTRACT

Fibre ropes have been shown to be a viable alternative to steel wire rope for offshore lifting operations. Visual inspection remains a common method of fibre rope condition monitoring and has the potential to be further automated by machine learning. This would provide a valuable aid to current inspection frameworks to make more accurate decisions on recertification or retirement of fibre ropes in operational use. Three different machine learning algorithms: decision tree, random forest and support vector machine are compared to classical statistical approaches such as logistic regression, k-nearest neighbours and Naïve-Bayes for condition classification for fibre ropes under cyclic-bend-over-sheave (CBOS) testing. By measuring the rope global elongation throughout the CBOS tests, a binary classification system has been used to label recorded samples as healthy or close to rupture. Predictions are made on one rope through leave-one-out cross validation. The models are then assessed through calculating the accuracy, probability of detection, probability of false alarm and Matthew's Correlation Coefficient, and ranked based on the results. The results show that both machine learning and classical statistical methods are effective options for condition classification of fibre ropes under CBOS regimes. Typical values for Matthews Correlation Coefficient (MCC) were shown to exceed 0.8 for the best performing methods.

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1. INTRODUCTION

As offshore lifting operations move to deeper waters exceeding 3000 m, the possibility of implementing fibre ropes instead of steel wire ropes has shown to be a viable alternative. The benefits of fibre rope over steel ropes is well documented ((Foster, 2002), (Rebel, Verreet, & Ridge, 2006) and (Fronzaglia & Bosman, 2016)) but condition monitoring and determination of retirement criteria remain issues. Machine learning is rapidly gaining traction as a condition monitoring method across a number of industries ((Sutharssan, Stoyanov, Bailey, & Yin, 2015), (Nguyen et al., 2019) and (Chang, Lee, & Liu, 2018)). Due to improved monitoring methods and storage of historical data, there has been a shift in research towards “intelligent maintenance systems” focusing on automatically determining the condition and detecting faults of engineering components with less human intervention. Condition monitoring for fibre ropes used for subsea deployment also has potential for further advancement with machine learning. Manual inspection methods detailed in industrial standards are still mainly used in condition classification and are still largely based on experience from mooring application ((DNVGL, 2017), (DNVGL, 2018) and (ABS, 2011)). Machine learning adaptation would serve as a useful aid to these methods and allow inspectors and operators to make a more informed decision on rope retirement or re-certification.

Fibre rope degradation mechanisms related to mooring and offshore lifting have been summarised in previous studies ((Weller, Johanning, Davies, & Banfield, 2015), (Faria, Bosman, Crawford, Leite, & Boesten, 2017) and (McKenna, Hearle, & O'Hear, 2004)). These include but are not limited to: creep, temperature, abrasion, tension fatigue and compression fatigue. These damage mechanisms and potential failure modes add difficulty in developing an all-encompassing method of monitoring fibre ropes. Therefore a combination of machine vision cameras, IR camera and a distance measuring laser were proposed for this study.

Machine learning methods have previously been applied to condition classification of steel wire ropes for hoisting in the mining sector. The use of k-nearest neighbours and artificial neural networks was adapted to classify the condition of balancing tail ropes in (Zhou et al., 2018) and a type of support vector machine to classify rope faults based on vibration data in (Xue, Tan, Shi, & Deng, 2020). To the authors' knowledge there has been no publicly released research related to machine learning for condition classification of fibre ropes.

Condition monitoring for other engineering components benefits greatly form publicly available data sets, therefore allowing focus to be fully put on development for intelligent maintenance algorithms, rather than focusing on data recording. Fibre ropes for lifting operations do not benefit from this and major efforts are required to create these data sets. This article extends research on such condition monitoring methods performed at the University of Agder, Norway ((Falconer, Gromsrud, Oland, & Grasmo, 2017), (Falconer, Grasmo, & Nordgård-Hansen, 2019) and (Falconer, Nordgård-Hansen, & Grasmo, 2020)) that make use of cyclic-bend-over-sheave (CBOS) tests monitored by both computer vision and thermal monitoring. The changes in geometry and temperature of the rope recorded during CBOS testing are used to create features that form the machine learning models.

In this study decision trees, random forest and support vector machines are compared to classic statistical methods such as k-nearest neighbours, logistic regression and Naïve-Bayes for binary classification of fibre rope condition. The methods chosen for application reflect current practice in machine learning for diagnostics of engineering components. An introduction to these methods is outlined in Section 2 and the experimental set-up with associated data processing steps are summarised in Section 3. The results of the classification models are presented in Section 4, followed by discussion in Section 5. Subsequently, the potential for industrial application of machine learning for fibre rope offshore construction cranes is discussed in Section 6. Finally, conclusions are offered in Section 7.

2. METHODS

In this section, a brief overview of the methods that are applied in the present study is given.

2.1. Decision Tree (DT)

This study applies the decision tree algorithm as detailed in (Breiman, Friedman, Olshen, & Stone, 1984), using the implementation in scikit-learn (Pedregosa et al., 2011). It comprises a flowchart that assigns each sample to one of two classes based on a condition selected from the features available. The samples are split based on an attribute selection measure, in this case the Gini index, which measures the impurity of a data split with respect to the classes available ((Rokach & Maimon, 2005) and (Mingers, 1989)). This process is performed recursively until all samples are assigned to a class or there are no more features available to make splits. The depth of the trees can also be limited to change the complexity of the model. For example, a deeper tree can lead to a more accurate result but has the risk of creating an overfitted model due to unrealistic complexity. Since there is a random element involved in the algorithm each tree configuration is repeated 20 times to assess the spread and confidence in the classification predictions.

2.2. Random Forest (RF)

Random forest is an example of an ensemble learning method comprised of many decision trees. The method is described in detail in (Breiman, 2001) and also implemented using scikit-learn (Pedregosa et al., 2011). A random forest is formed with a defined number of decision trees, where each individual tree is formed on a subset of samples and features created through random sampling with replacement. These multiple predictions are combined in the bagging phase (Breiman, 1996), where the a class is assigned based on a majority vote by the individual trees in the random forest. Similar to the decision tree algorithm, the depth of the individual tree can also be controlled. The number of trees that make up the forest can also be adjusted. Each configuration is repeated 20 times to assess the variation in the predictions made by the model.

2.3. Support vector machine (SVM)

Support vector machine has also found use for classification problems as defined in (Cortes & Vapnik, 1995) and are implemented through scikit-learn (Pedregosa et al., 2011). The algorithm works by fitting a hyperplane that divides a set of instances into classes. The optimal solution is separated is where the margin that separates the instances has been maximised, with the instances used referred to as "support vectors" (Shmilovici, 2005). The generalisation to the nonlinear case is achieved by applying the so-called kernel trick, using nonlinear kernel functions for transforming the task into a higher-dimensional space, in which the number of possible linearly separating hyperplanes is larger than in the original space. In this study linear (SVM-linear), Sigmoid (SVM-Sigmoid) and radial basis function (SVM-RBF) models are applied to alter the hyperplane shape applied to the data. Each configuration is performed once and the performance of the kernels is compared.

2.4. Classical Statistical Methods

The machine learning models detailed previously are also compared and assessed along with classical statistical approaches such as k-nearest neighbours (Altman, 1992), Naïve-Bayes (Rish, 2014) and logistic regression (Cramer, 2002). These methods are also commonly used for classification problems as an alternative to machine learning. As this research is new use for machine learning, classical statistical methods are also investigated to assess if they are sufficient enough to achieve good classification results.

3. EXPERIMENTAL STUDY

3.1. CBOS Testing and Data Acquisition

Two different types of 28 mm diameter, 12-strand HMPE fibre rope (denoted “A” and “B”) were tested in a CBOS test machine installed by DEP Engineering at the Mechatronics Innovation Lab (MIL) in Grimstad, Norway. The machine has two sheaves: a driving sheave and a test sheave. The test sheave is designed to be smaller than the driving sheave so that the rope break would occur there. The driving sheave is controlled via a motor which instigates rope movement during testing. The test sheave is 800 mm diameter and made of 42CrNiMo4 steel with a U-groove profile, which equates to a D/d ratio of 28.6:1. It is attached to a portion of the machine which moves with the extension of a hydraulic cylinder. Tension in the rope is applied and maintained via this hydraulic cylinder, which will extend as the test progresses. Each rope is tested until failure, which can occur through rupture or accelerated extension of the rope detected by sensors in the cylinder. An overview of the machine is shown in Figure 1. The safety factor (SF) of the each test is defined by expression 1:

$$SF = \frac{MBL_{rope}}{T_{test}} \tag{1}$$

where MBL_{rope} is the rope minimum break load as specified by the manufacturer and T_{test} is the test tension exerted by the cylinder in the CBOS machine. The safety factors used in testing for data sets A and B are 11 and 8, respectively. Data set A contains five ropes and data set B contains four ropes.

Data is acquired from a set-up that includes: four machine vision cameras, a thermal camera and a distance measuring laser. The features used in model training are derived from the data acquired through the monitoring system. Algorithms developed in OpenCV (Bradski, 2000) are used to extract local length and width data from the machine vision cameras. The change in these parameters as result of fatigue and abrasion during CBOS testing can be monitored. FLIR software

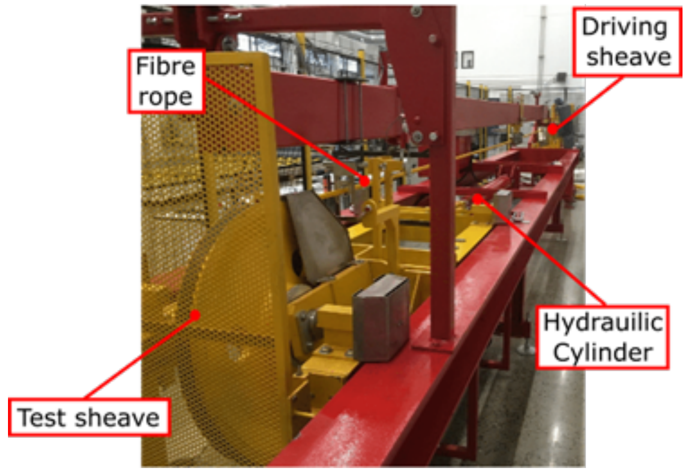

Figure 1. Overview of CBOS machine at Mechatronics Innovation Lab, Grimstad, Norway.

with built-in features is used for thermal data (FLIR, 2015) recorded with the IR cameras. This allows the temperature in each distinct bending zone to be monitored throughout testing. The distance measuring laser allows the global length to be continuously monitored and the effect of creep on elongation to be monitored. Further specific details related to data acquisition are available from previous work (Falconer et al., 2020).

Figure 2 shows a schematic of different bending zones measured throughout each experiment: the straight zone (SZ), single bend zone (SBZ) and double bend zone (DBZ). For each of the eight sections defined in Figure 2, one length measurement and four width measurements are used as features. Each separate local length measurement equates to half a lay length. Computer vision data is recorded for 2000 images, corresponding to 13-15 complete cycles, every 1000 cycles. The values for each recording are thus aggregated to give median, maximum, minimum and standard deviations for these geometric features. The thermal camera was set to sample at 100 Hz for 2000 images, resulting in a 20 seconds video for each period. This was sufficient to record at least one full cycle in the CBOS test. Temperatures are only available for the lumped zone SZ, SBZ and DBZ and the temperature values within the rope part of each relevant image are aggregated as average, maximum, minimum and standard deviation. A complete list of features used in this study is shown in Table 1.

3.2. Data Pre-processing

After recording the data is treated for outliers and missing data. Outliers in the geometric measurements are handled using mean absolute deviation. This is due to the morphological operations in the width and length calculations occasionally detecting points outside of the rope region of interest in the images. Therefore, this is applied to both length

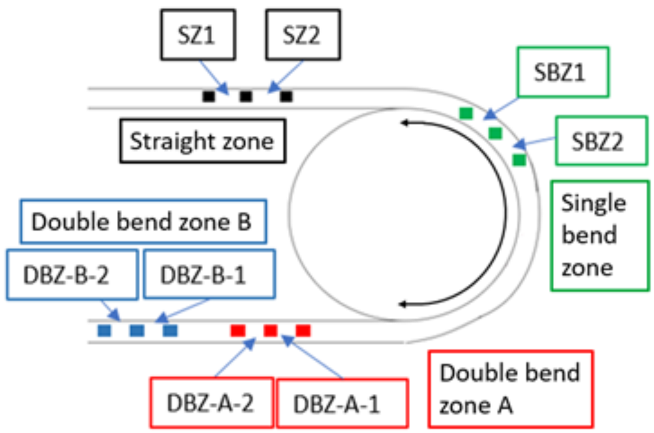

Figure 2. Summary of bending zones monitored during CBOS testing.

Table 1. List of features used for condition classification in data sets A and B.

Data type	Feature (zone)	Parameter
Geometric	Local length: SZ1, SZ2, SBZ1, SBZ2, DBZ-A-1, DBZ-A-2, DBZ-B-1, DBZ-B-2 Width: SZ1, SZ2, SBZ1, SBZ2, DBZ-A-1, DBZ-A-2, DBZ-B-1, DBZ-B-2	median, maximum, minimum, standard deviation
Thermal	Temperature: SZ, SBZ, DBZ	average, maximum, minimum, standard deviation

and width measurements and will exclude outliers from the median, maximum, minimum and standard deviation calculations.

Missing data may occur as a result of instrumentation issues. The machine learning algorithms applied in this study omit the whole record if any feature has missing data, meaning useful data can also be left out. Therefore imputation of missing data points is done through interpolation.

After these steps, the raw measurements from the data acquisition phase are scaled by subtracting the mean value and dividing by the standard deviation. This done for each rope tested to improve comparability between the rope samples and is a standard step to prepare data for machine learning application.

3.3. Labelling

To perform classification predictions on the ropes, the records need to be appropriately labelled. This study is a binary classification problem, therefore the ropes can be considered either Healthy (HE) or Close To Rupture (CTR). The development of the global length resembles a creep curve with three distinct stages: primary, secondary and tertiary creep. The tertiary creep stage encompasses the accelerated creep phase after the transition point. Fitting the global length development to a polynomial allows a quantitative definition of the transition from secondary to tertiary creep, thereby labelling each sample as “HE” or “CTR”, as shown in Figure 3. The “CTR” labelled examples equate to the accelerated creep phase. This labelling process allows an automated, quantitative definition of rope condition to be implemented.

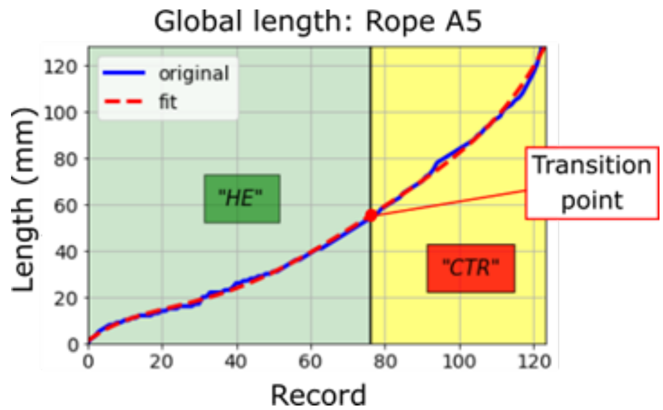

Figure 3. Example of labelling process on rope A5 with transition point between both classes.

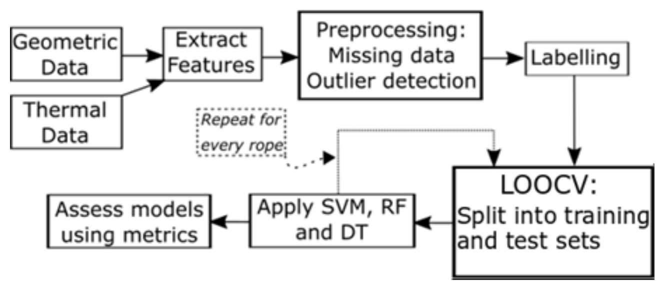

Figure 4. Operations flowchart.

3.4. Model Training and Assessment

Leave one out cross validation (LOOCV) is performed on the CBOS data sets. A summary of the steps in the LOOCV process in this study are detailed in Figure 4.

The results are shown through metrics that are derived from Confusion matrix description, which is shown in Figure 5.

The correct predictions can be summarised as true positives (TP) and true negatives (TN) and the incorrect classifications are quantified as false positives (FP) and false negatives (FN). The negative and positive classes coincide with the HE and CTR classes, respectively. The metrics used for model assessment accuracy (ACC), probability of detection (POD), probability of false alarm (PFA) and Matthews correlation co-

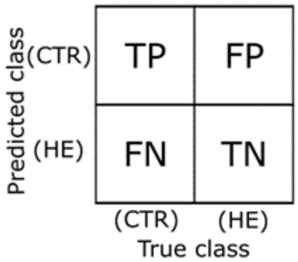

Figure 5. Overview of confusion matrix.

efficient (MCC) are shown in Expressions 2- 5:

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$POD = \frac{TP}{TP + FN} \tag{3}$$

$$PFA = \frac{FP}{FP + FN} \tag{4}$$

$$MCC = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{5}$$

ACC is the most general of the metrics presented in this section and simply takes into account the number of correct predictions across of the whole data set. The closer the value is to 1, the better the model is performing. However, this does not take into account the number of samples present in each class.

POD can be summarised as the likelihood of a CTR being correctly classified. The closer the metric is to 1, the better the model is deemed to have performed in this aspect. A model that fails to detect CTR samples runs the risk of allowing the rope to continue operation until it fails.

PFA is interpreted as the probability of an "HE" sample being mislabelled as "CTR". If a model has a higher tendency to classify samples as CTR when they are HE, it would lead to more false alarms during condition monitoring. This could potentially prove to be costly due to operational stoppages for inspection and therefore a lower value is preferred.

MCC takes into account all four values in the confusion matrix and provides a more balanced assessment regardless of whether one class is disproportionately over- or under-represented. A value close to 1 means that both classes are being predicted well and show that true and predicted classes are correlated.

However, none of the metrics give information about what specific samples have been misclassified. Figure 8 shows an example the classifications predicted by the models at the various stages of the CBOS test. Separate results are presented for data sets A and B and the values of the metrics are averaged over the number of individual ropes in each data set. The algorithms are then ranked and compared based on the predictions made.

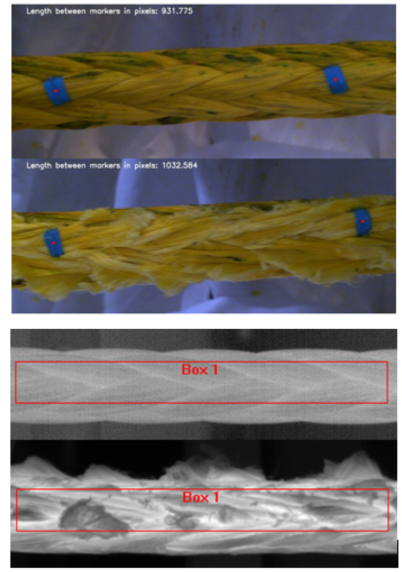

Figure 6. Example of changes in rope in DBZ between the start and the end of a CBOS test.

4. RESULTS

4.1. CBOS test results

Figure 6 shows an example of changes observed in the rope from the start and end of the CBOS test. Using the images captured from the computer vision set-up (top image), it is possible to monitor changes in both local length and width. In this example there is significant localised increase in length, as well as the presence of ruptured strands and extruded loops. These defects can also be observed using the thermal monitoring set-up (bottom image). The ropes structure changes as the test progresses and the temperature difference between warmer compact core and the cooler ruptured strands is clearly visible.

The number of cycles each rope had at failure is summarised in Table 2. It can be seen that the number of cycles counted for data set B is fairly consistent, however there are slight variations with data set A. These "earlier" failures for ropes A1 and A4 are attributed to the splicing used in these rope samples. Due to experimental limitations, a portion of this splice was in contact with the driving sheave, resulting in failure there instead of at the test sheave.

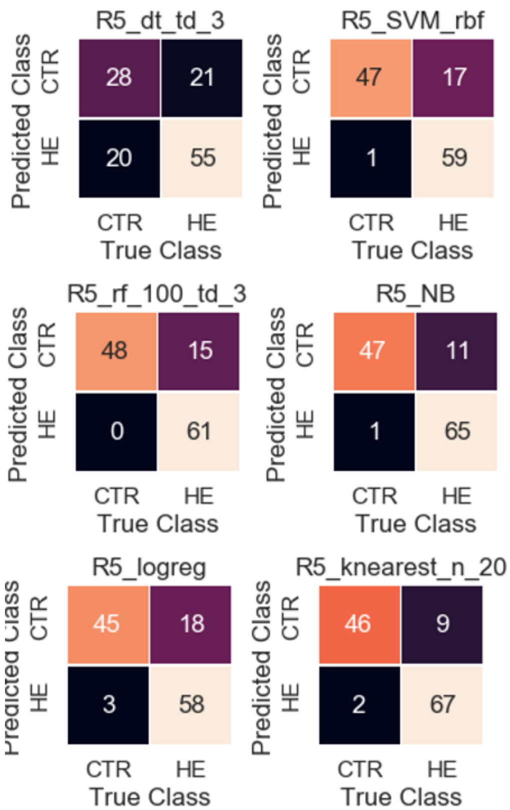

Figure 7. Confusion matrices for results on rope A5 for six different algorithms.

4.2. Classification Comparison

Figure 7 shows an example of confusion matrix results for the six different techniques applied to rope A5. Figure 8 shows an qualitative example of the six different techniques applied and the results given for rope A5. The true transition point between the HE and CTR classes is highlighted by the vertical blue line.

It is shown that most models identify a too early transition between the classes. There are a substantial number of HE instances classified as CTR before the transition point indicated by the vertical blue line for every different model.

The decision tree is shown to have a particularly poor performance in comparison to the other algorithms. It misclassifies a significant number of both HE and CTR samples. Moreover, when a rope break is imminent it continues to classify the rope as safe for use.

k-nearest neighbor gives a lot more false alarms earlier in the CBOS test than the other algorithms. This could prove costly in terms of operation downtime, as a rope identified as potentially failing requires inspection and remedial actions to ensure continually safe use.

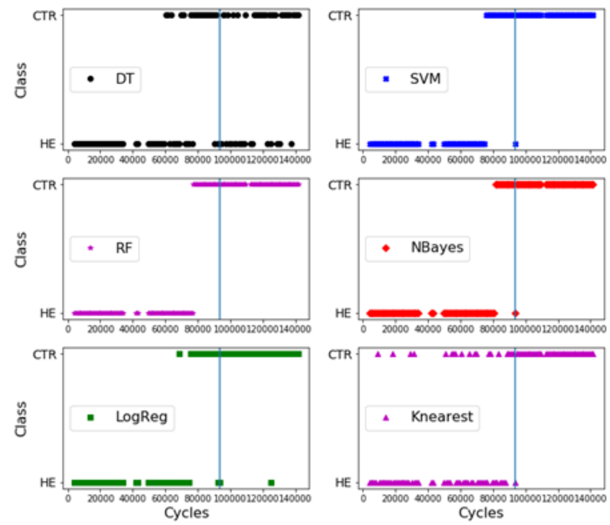

Figure 8. Example of classification results on rope A5 for six different algorithms.

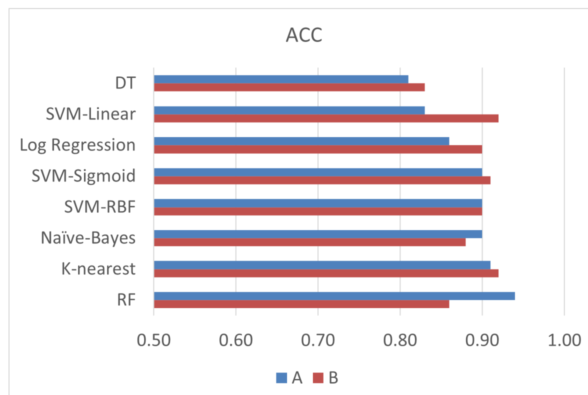

Figure 9. ACC results for each algorithm compared between data set A and B.

4.3. Average Metrics

The average results for metrics ACC, POD, PFA and MCC in data set A and B are shown in Figure 9 to Figure 12. The best performing configuration of each algorithm is presented and assessed for classification performance.

An ACC value that exceeds 90 % generally indicates a very good performance, as it measures how many correct classifications were made across all samples. Random forest and SVM-linear were shown to be best performing machine learning algorithms in data sets A and B respectively.

k-nearest was also shown to have similar scores in data set A to random forest, however as shown in Figure 9, this can be deceptive due to extensive mislabelling of HE samples as CTR in the earlier portions of the rope test time. These misclassification are reflected by the higher PFA score, indicating that there is around a 10 % probability of a HE sample being

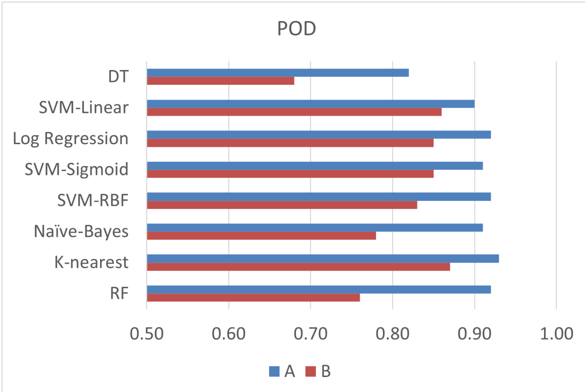

Figure 10. POD results for each algorithm compared between data set A and B.

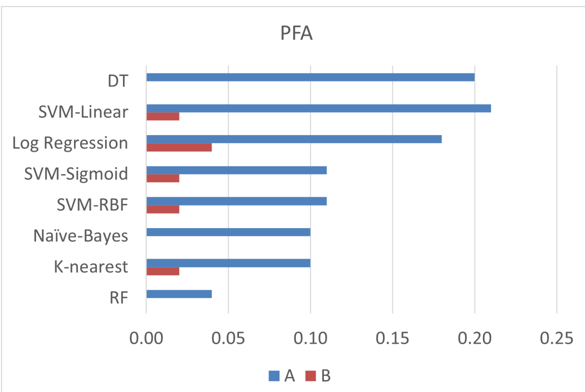

Figure 11. PFA results for each algorithm compared between data set A and B.

misclassified as CTR. These types of misclassification could prove costly due to increased down time for inspections.

Similarly, POD above 90 % also indicates a very good performance as this assesses how effective the model at classifying the CTR class. This was shown to drop between data sets A and B, indicating that the data used in B was to the detriment of successfully classifying the CTR class.

Generally, a lower PFA score indicates better performance. PFA is shown to decrease dramatically between data set A and B. From the outset a zero PFA score is ideal, however in the case of Naïve-Bayes, random forest and decision tree in data set B this indicates the models were biased towards predicting the majority of the samples as HE. There was no misclassification of HE samples as CTR but they failed to identify a number of CTR samples. These models could lead to dangerous operation as a rope that is nearing the end of its usage could potentially be classified as being safe to continue.

SVM linear increases dramatically in performance from A to B. This is reflected in the increase in scores for both MCC and ACC between A and B, indicating that the algorithm was able

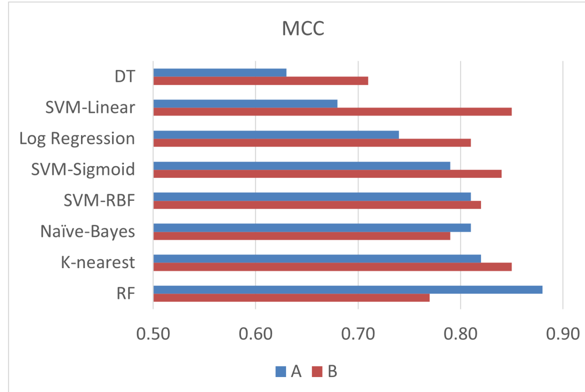

Figure 12. MCC results for each algorithm compared between data set A and B.

to better predict both classes with the change in data used.

Generally the ACC, POD, PFA and MCC show distinct groupings in data set A. When only assessing ACC and POD, the best performing algorithms could be interpreted as performing at the same level. However, when considering PFA and MCC scores, there is a clearer separation between the algorithms indicating that these metrics have to be used in combination to properly assess a model.

5. DISCUSSION

The performance of each method is assessed and discussed individually in the following sections. Then the performance of the machine learning algorithms against the classical statistical methods is also considered and discussed. Despite discrepancies between the rope lifetimes, it is possible to achieve good condition classification results using both machine learning and statistical approaches with all the viable data from the zones outlined in Figure 2.

5.1. Decision Tree

The decision tree method implemented in this study performed worse than all other algorithms, both machine learning and statistical based. Decision tree is an example of a heuristic algorithm and will classify instances based on the feature that has the lowest Gini index value. This approach causes the results of individual trees to vary, as a feature may produce the same "impurity" but the resulting segmentation point could classify samples differently. Unless explicitly programmed to make consistent data splits on the same features, the decision tree will produce variation in results.

The method is however shown to be useful for exploratory analysis of the features best suited to distinguishing between the two classes established in this study. For fibre rope condition monitoring of CBOS testing it highlights that the features derived from the SBZ and DBZ are more relevant than those from the SZ section. This is as expected, since more bending occurs in these zones leading to greater deformation and more variation in width, length and temperature to form data splits. The method should not be used as a stand-alone classification method but can be used as a technique for feature reduction before repeating the modelling process with other machine learning or statistical approaches.

5.2. Random Forest

Random forest was the most effective method for data set A but performed worse than all other algorithms apart from decision tree in data set B. Data set B had less data than data set A, so therefore the decrease in the amount of data to split the records contributes to the detriment in performance. This is due to the model not being able to achieve the same model complexity at shallow tree depths with fewer samples. This highlights the importance of having an extensive data set to make predictions when using random forest as indicated in data set A.

The technique is robust due to the properties of the algorithm, with random sampling with replacement and the majority vote system of trees contributing to more stable predictions. It is also possible to achieve excellent predictions with shallow tree depths, which limits the need for excessive computer capacity. However again, both of these characteristics are reliant on substantial and good quality data to achieve the model complexity needed to give the good results achieved through random sampling and the majority vote system.

5.3. Support Vector Machine

The linear kernel was not as effective in data set A, however was the best performing machine learning algorithm in data set B. The linear kernel is the simplest implementation of SVM, which puts a straight hyperplane in the higher dimensional space to separate the samples into classes. In data set A, there is lower temperatures in the bending zones during the experiment compared to data set B. Features with measurements that change little contribute noise to the process of finding the optimal hyperplane. In data set B there were larger temperature differences between the bending zones due to greater tension, allowing a more optimal split to be found due to more distinctly scaled values.

SVM using both the radial basis function and sigmoid kernels performed to more or less the exact same levels in both data sets, indicating the hyperplane shapes imposed were more adaptable to the differences between data sets A and B. While the linear kernel is limited in the separating hyperplane it can impose for class separation, the other kernels presented here can form a more complex hyperplane that can serve to separate the classes more effectively. Compared to decision tree and random forest, the SVM is a much more adaptable and consistent algorithm as reflected in the results presented.

Table 2. List of cycles at failure during CBOS testing in data sets A and B.

Data type	SF	Rope ID	No. cycles at failure
A	11	A1	73,324
		A2	122,368
		A3	120,430
		A4	87,314
		A5	143,374
B	8	B1	14,948
		B2	13,883
		B3	13,901
		B4	13,998

5.4. Machine Learning and Statistical Methods Comparison

Both the machine learning and classical statistical approaches were shown to be valid methods for classifying condition of fibre ropes during CBOS testing. The k-nearest neighbours algorithm was shown to perform just as well or slightly worse than the best performing machine learning algorithm when assessed using only metrics. However, Figure 8 demonstrates that there is a possibility that k-nearest neighbours produces a substantial amount of false alarms at earlier stages of testing. The false alarms for random forest occur closer to the transition point between classes and avoid very early stoppages.

However, the results presented in this paper show that there is merit in applying machine learning for fibre rope condition monitoring. In a machine learning application, the models created can only perform if there is enough data available. In situations where data is limited a classical statistical approach can suffice, as shown by the robust performance of logistic regression and k-nearest neighbours across both data sets. Logistic regression was also shown to be less hampered by smaller data sets as reflected by the stronger performance in data set B than in data set A. Some machine learning algorithms in this study, such as decision tree and random forest, performed worse in data set B than in data set A and failed to adapt to the smaller data set. Also SVM-linear showed an increase in performance with a smaller data set.

This also highlights the adaptability of different machine learning models for different circumstances. In situations where there is both enough and good quality data, machine learning should be used as the approach for condition classification. However, in situations where there is a smaller data set, a classical statistical approach could be more appropriate before attempting machine learning to find potential improvements in condition classification.

6. FUTURE WORK AND ADAPTATION FOR FIELD DEPLOYMENT

Further work is required to develop machine learning applied to fibre rope condition monitoring. There is a possibility of improving on the current feature set by considering the time each rope spends at elevated temperatures, which could give further insight into rope lifetime. Moreover, embedded magnetic or electric threads could be weaved into the rope, which would allow additional data processing techniques to assess rope degradation. Combining these techniques with the features outlined in this paper can also improve prediction results.

Another potential improvement could be through limiting the number of features used for training. Features that vary very little throughout the experiments essentially contribute noise to machine learning models and hamper classification performance. This can be done by assessing the difference between using only geometric data and comparing it to using both geometric and thermal data. There is also the possibility to test the effect of limiting features from certain bend zones on performance and focusing only on features related to the SBZ and DBZ. The sensitivity of classification results to data loss can be further explored. The effect of using only visual features or temperatures can be further explored to assess the effect on what type of data is the best for achieving the best classification results.

In this study, the two different data sets are tested independently of one another. Combining data from two different rope types can also be assessed to see if it improves algorithm performance. With respect to field application, this would be useful as an industry-wide approach, where different sizes of cranes would use potentially several different diameters and types of rope in the same fleet of ships. Implementing the sensors detailed in this paper at a location near one of the main sheaves would give insight into how the measurements fluctuate during a real offshore lifting operation. Additionally, the rope sections would have to be properly tracked and marked, as different parts of the rope could be subject to extended bending periods and heat build up due to active heave compensation during lifting operations. The historical data could then be used to analyse the measurements and assess for patterns. Predictions on ropes in use can be continually updated as ropes are maintained or replaced based on the historical data from other equipment.

Data availability is also highlighted as an important factor in algorithm performance. Due to lack of operational data for fibre ropes of offshore lifting, CBOS testing is chosen as the approach to simulate similar forces and movements in a laboratory environment. However, CBOS testing is a long and expensive process to perform, so therefore robust intelligence maintenance algorithms that work would be of great advantage. Data recording was limited during these experiments, in particular for data set B, which highlighted the need for more frequent data recording to create larger data sets.

Furthermore, there are other machine learning approaches that can be implemented for classification problems. Neural networks are a suitable candidate as a machine learning technique, in addition to the algorithms presented in this paper. Similar to the techniques used previously, there is potential to use and adapt different network architectures and configurations for different data sets, such as the fibre rope measurements presented in this paper.

In addition to condition classification, the algorithms can also be adapted for remaining useful life estimation. Rather than simply assessing a class, a continuous variable could be developed to give a more accurate number or fraction which predicts the rope lifetime.

7. CONCLUSION

The research in this paper has indicated that both machine learning and classical statistical approaches based on computer vision and thermal monitoring are viable methods for condition classification in fibre ropes. Both were shown to effectively classify fibre rope condition during CBOS testing. However, it has also highlighted the need for a greater amount of data to truly gain advantage from different machine learning approaches. This was shown by the inconsistent performance of random forest between both data sets presented.

Ultimately, the methods proposed in this paper have the potential to be developed further for condition classification in fibre ropes. Additionally, with an established framework for machine learning there is further possibility to adapt these methods for remaining useful life estimation in fibre ropes subject to CBOS regimes.

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