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Detecting the Faults of Subsea Power Cables of Wind Farms with Boosting Ensemble Methods

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***Abstract*—The power transmission system is very critical to the functionality and efficiency of offshore wind farms. The system uses subsea cables spanning from deep offshore to the shores for effective integration with other power sources within the transmission and distribution grid. These cables operate under harsh environmental conditions and, as a result, are susceptible to failures. With over 80% of insurance claims so far in offshore wind energy sector, subsea cable failure has huge economic implications. These failures occur as result of fault development within the subsea transmission cable network. This research aimed to develop a supervised machine learning approach to identify and predict these fault developments because if a fault development can be predicted at the incipient stage, planned maintenance or proactive measures can be carried out to avoid degeneration into failure. This paper describes our earlier experiments in applying the extreme gradient boosting ensemble, Gaussian Naïve Bayes and decision tree algorithms in solving this problem. The testing results showed that the ensemble algorithms performed accurately and consistently in classifying the faulty cables with an average classification accuracy over 90%.**

***Index Terms*—Wind farm, subsea power cable, faults, machine learning**

I. Introduction

The unsustainable nature of conventional energy resources, the continuous increase in atmospheric greenhouse gases, and the prevailing global warming, have made the need for alternative energy resources a global emergency [1]. Researchers have risen to this challenge by identifying potential renewable energy resources to replace fossil fuel [2]. One source for generating electricity is wind power [3]. The development of wind energy systems, especially offshore windfarms, is a strategic energy policy in some European countries including Denmark, Sweden, United Kingdom, Germany, and even United States of America and Canada. An offshore windfarm is built with a cluster of wind turbine generators in the bodies of offshore sea water and has been proven to be more efficient than conventional inland windfarms [4]. The United Kingdom alone has installed capacity of 8.4 GWatts of electricity generated via offshore windfarms, and over 14.8 Gwatts in the pipeline to materialise very soon [5].

The electricity generated by the offshore windfarms needs to be transmitted via subsea cables to an onshore power station before feeding into the national grid. These cables span from the wind turbines offshore, and run through an offshore substation or conversion station to the transmission substation onshore. This usually represents a quite long distance, depending on the capacity of the windfarm, as high output capacity windfarms are usually situated deep offshore for better efficiency. These cables are subjected to different environmental and internal changes that impact functionality negatively, thereby causing various failures of the entire system. These failures not only cause the loss of the generated power but also cost considerable time and resources to repair. It is estimated that these failures have constituted over 80 percent of insurance claims of the offshore windfarms in the UK [6]. Therefore, being able to detect the cable failures and taking necessary maintenance can make the operation of a windfarm more cost-effective.

This research aims to develop some machine learning techniques to identify the faults in subsea power cables, based on the data collected from protection relays installed along the cables.

II. Related Work

The application of machine learning in solving our type of problem is still in the development stages, thereby placing a limit on the amount of existing literature. Therefore, the study reviewed related works that have sufficient correlation with the subject matter. In their research, [7] studied the life expectancy of transmission cables used in offshore windfarms. They implemented a mathematical model to determine major physical events that affect subsea cable functionality. The derived mathematical model which was coded into a desktop software called CableLife by [7], considered these factors majorly for its prediction: cable scouring depth, cable wear mechanism, sliding distance, cable life, with respect to its abrasion wear coefficient, the coating material, and its lost overtime due to abrasion. The mathematical model performed at 30% prediction accuracy upon cross validation with the test data. On a critical review of the failures considered in the model and its importance, it is imperative to state that most of the failure modes considered are more useful pre-installation

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of the cable, nothing was mentioned in the analysis of installation induced failure, and with a 70% misclassification rate, the model requires a lot of improvement and optimisation.

In the analysis of failure rate in offshore windfarm cable, [8] revealed that the unavailability of operational data on failure incidences in offshore transmission systems, due to the organisational policy of the various owners and operators, remains a major impediment in proffering solutions to the costly problem of subsea cable failure. The authors' identified under-reportage of failures by industry operators, stating that on average, the failure rate in real time is higher than the figures being reported in the industries. More than one alternative cable installation, as a contingency plan, was advocated by the authors, although considering the cost per cable installation, it is not a cost-efficient suggestion.

The study by [9] revealed that by exciting the fault resonance frequency, measurable changes in voltage amplitude and phase can be obtained which can help in identifying faults at incipient stage. The research centred its fault mode on the possibility of treeing effects because of failure in cable insulation. The result showed a pronounced variation in voltage and current profile, representing high impedance fault which symbolises treeing effect. Although the work was based of HVDC transmission mode, the result sufficiently proved that instantaneous rise in current profile of a transmission system is a potential failure in view. The challenge of inconsistency [10] in conventional relays which serves as measuring device, affects this process. This device measures power swing as a fault, most times tripping the entire transmission system because of this false alarm [11].

Fault classification and prediction using machine learning algorithm is the future of power transmission system. Feed forward Artificial Neural Network with back propagation algorithm was deployed by [12] in classifying fault development within a 33kv MVAC transmission line in Nigeria. The instantaneous current and voltage values were used in training the model, which was thereafter evaluated based on MSE and confusion matrix. The model evaluation result proved encouraging with MSE of 0.00004279 and model accuracy of 95.7%, in classifying line to ground, line to line and double line to ground faults. The evaluation result is impressive, but there was no mentioning of how the model can be deployed in handling live fed data and detecting fault propagation from incipient stage. [13] deployed SVM in classifying transmission system faults. The modelling was carried out with 150 input data and the evaluation result showed 70% classification accuracy. Although the performance of the model is not encouraging, considering the few samples it had to learn with, the researcher proved a point by considering SVM, in difference from the conventional ANN.

In reviewing the application of machine learning algorithm in system failure prediction, [14] identified Decision Tree Classifier as high performing algorithm, stressing on the efficacy of the algorithm, as against SVM and Random Forest. The study by [15], in which special type of ANN, MLP, was applied on 2500 samples with features on the health of underground amour cable made of cross-linked polyethylene (XLPE) insulation material. With 80% and 20% training and test data partitioning, the model evaluation produced an accuracy score of 96%, corroborating existing literature on the high performance of MLP in pattern recognition. Although conventional MLP form of ANN accomplishes high performance in classification by altering network weights, [16] identified that this weight penalty factor results in overfitting sometimes. Stating how Bayes theorem solves this, [16] opined that with prior knowledge of event occurrence that share the same probability density function with the new input data, their class relationship can be estimated.

III. Data and Feature Extraction and Selection

The data used in this research were acquired through Intelligent Electronic Devices (IED) [17] installed at the two ends of a power transmission system from a windfarm to an onshore station. The IEDs monitor and protect a power system and store the data in the IEEE Standard COMTRADE format. COMTRADE [17] files record oscillography and brief variations of Voltages and Currents in a protected power system. These variations can be results of some faults occurring in the subsea power cables in the transmission system. The dataset contains 343 sets of abnormal variations in power transmission. Each set contains the waveforms (time series) of four current phases: A, B, C, and Neutral phase of AC, and some of these phases may have different asymmetric and symmetric faults. So putting all the phases together, there are 1,372 events.

A. Data Labelling

Each phase of 1,372 time series was visualised and manually labelled as Normal or Fault. The binary classes of faulty cables and good cables are distinguished from each other by the transmission current value flowing through the cable at the time of measurements. Figures 1 and 2 show two examples of faulty and normal waveforms. From Fig. 1, it is obvious that phase A, with transmission current value ranging between -2A and 2A as against -0.002A and 0.002A in the other phases, is faulty. Also, from Fig. 2, all the current values of phases A, B, and C suddenly changed to relatively high values, compared to the transmission current value in the neutral phase, therefore all the three current phases began some sort of fault at that time point. In this way, all 1372 samples were labelled. In summary, the dataset formed from the samples contains 393 faults and 979 good cables.

B. Feature Extraction

As the data are essentially represented as time series, some features need to be generated for training machine learning models. Two approaches were applied for doing this. Firstly, some basic statistical features were computed from these time series data, which include *mean, std (standard deviation), max, min*, etc.

Then, an existing popular package *TSFEL* [18] was used to extract more features from the data, using the spectral domain. In total, 389 features were extracted.

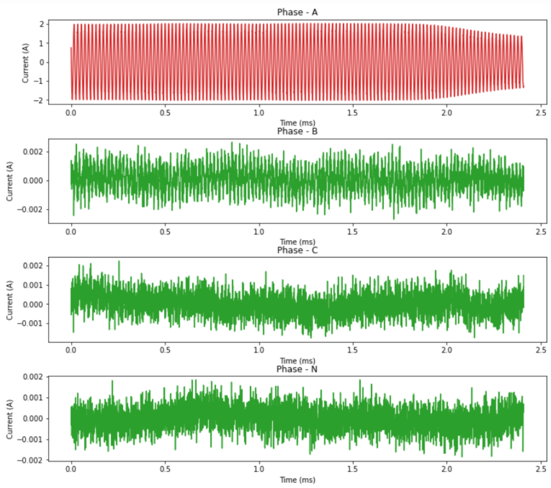


Fig. 1: Phase-wise plots of Current Variation in a subsea power cable with an asymmetrical fault in Phase A.

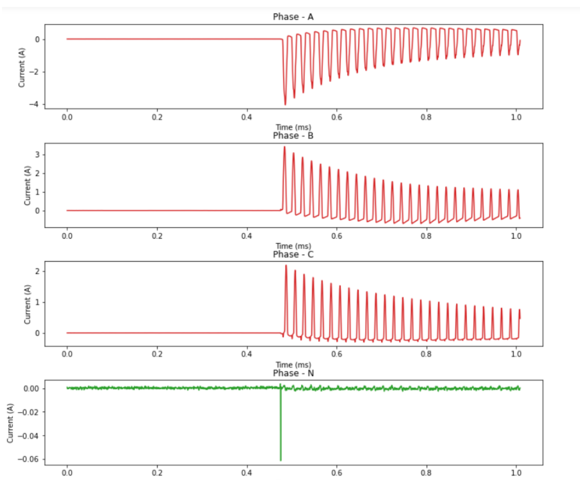


Fig. 2: Phase-wise plots of Current Waveforms in a subsea power cable. It can be seen clearly that in all three Phases, A, B and C symmetrical faults occurred at a time point.

IV. Machine Learning Ensembles

A machine learning ensemble, Φ, is a collection of M models, $\Phi = \{m_1, m_2, ..., m_k, ..., m_M\}$, which are generated by using a learning algorithm on a given dataset and the outputs of those models will be combined with a fusion function to produce a final output. An ensemble does not necessarily produce more accurate results [19] if it is not built with more diverse models as identical or highly correlated models in an ensemble will have the same weaknesses in terms of the knowledge they have learned and hence cannot compensate each other's errors when their outputs are combined.

Various methods have been developed for generating diverse models, although implicitly, to build an ensemble and some popular ones include Boosting [20] and Random Forest [21]. They have been demonstrated to be successful in many applications. Based on the classic Boosting algorithm, some variants have been produced, and a dominant one is XGBoost, that is why we chose it as the main classification algorithm to classify the cable faults.

We also chose Gaussian Naive Bayes (GNB) algorithms, Multi-Layer Perceptron (MLP) neural networks and Decision Tree (DT) for comparison. It should be noted that although deep machine learning methods are nowadays considered as state of the art, but because they normally require a very large dataset to utilize their strong learning capacity to produce good results, and our dataset is quite small, they were not chosen in the first place for this study.

A. XGBoost Algorithm

XGBoost (eXtreme Gradient Boosting) [22] is an extension of Gradient Boosting ensemble technique. It uses classification and regression trees (CART) as the base learners and generates iteratively several CART models by regularizing their objectives with an aim of minimising the total loss function when combining all the generated models.

In a Boosting-based ensemble, M models are generated iteratively with a boosting mechanism with an intention of enforcing (boosting) the current model to correct the errors made by the previous models, and their outputs are combined with their coefficient(weight) γ, to produce the predicted output $\hat{y}$ of the ensemble for an input x, i.e.

$$\hat{y}(x_i) = \sum_{k}^{M} m_k(x_i)\gamma_k \tag{1}$$

The total loss $L(\Phi)$ of the ensemble can be computed by an error measure $l(y_i, \hat{y}_i)$ over the entire dataset.

$$L(\Phi) = \sum_{i}^{n} l(y_i, \hat{y}_i) \tag{2}$$

The XGBoost extended the gradient boosting loss function with an extra regularisation to inhibit overfitting.

$$L(\Phi) = \sum_{i}^{n} l(y_i, \hat{y}_i) + \sum_{k}^{M} \Omega(m_k) \tag{3}$$

where, $\Omega(f_k)$ is the additional regularisation function.

In modelling with the XGBoost algorithm, hyperparameter configuration or tuning is instrumental in improving the performance of the algorithm. In this work, Scikit Learn GridSearchCV was utilised to obtain the best predicting parameters. The study also considered validation of the model on different variants of the datasets, this was achieved through a series of different partition and random sampling process.

B. Gaussian Naive Bayes(GNB) Algorithm

The GNB classifier is a simplified Bayes theorem based probabilistic classifier [23], or called Naive Bayes(NB), which naively assume that the features are independent from each other. NB operates by creating a probability model for every feature vector in the training input data based on their categorical description. The algorithm determines the probabilities of an object belonging to a specific class or having certain associated characteristics with a specific group, meaning that, GNB is a collection of probabilistic predictive models. GNB algorithm works with the condition that if the characteristics' class is specified, the presence or absence of one attribute has no bearing on the presence or absence of another.

$$P(c|x) \;=\; \frac{P(x|c)P(c)}{P(x)} \tag{4}$$

Where $P(x)$ is called the independent probability of x and $P(c)$ is the class probability of c, or the likelihood, $P(x|c)$ represents the posterior probability of x with respect to the value of c, the likelihood. GNB classifiers can deal with many categorical and continuous independent variables [16]. Therefore, for a given set of variables, $X \;=\; x_1, x_2,\; ...x_n$, the future or posterior probability can be achieved for an event C_j in the set of possible outcomes $C \;=\; c_1, c_2,\; ...c_n$. X represents the predictor, where C is the set of categorical stages in the dependent variable.

$$p(C_j|x_1x_2,\; ..., x_n) \;\propto\; p(x_1x_2,\; ..., x_n|C_j)p(C_j) \tag{5}$$

Considering that the structure of GNB presumes that the conditional probabilities of variables that are independent are statistically independent, the likelihood factor can be eliminated by

$$p(X|C_J) \;\propto\; \prod_{k\;=\;1}^{n} p(x_k|C_j) \tag{6}$$

For more details on the function derivation, [16] and [23] covered it extensively up to the derivation of map.

V. Performance Evaluation Metrics

The studied models of XGBoost, MLP, GNB, and DT Classifier were evaluated using the same parameter. The evaluation parameters include the *accuracy, precision, recall, F1 score*, the *auroc* curve score, which relates to the specificity and sensitivity of the models, and the *mcc* that represents the model ability to distinguish between the binary class. The built models were also validated for performance consistencies on different values of training and testing data. This was achieved through different partitioning and stratification of the input training and testing datasets. Each of the algorithms was trained and evaluated 60 times, each time with a different variant of the dataset. The different variants of the dataset were obtained through changes in the training and testing data splitting criteria, as mentioned earlier. The means and standard deviations of 10 runs for each investigation are reported in this paper later.

VI. Experiments and Results

A. Experiment Designs

The pre-processed dataset consists of 1372 entries with 342 features. The faulty cable represents the target label in the binary classification modelling, and it is denoted by 1, whereas the 0 digit denotes the good condition of transmission cable.

The experiments were designed to investigate the accuracy of the chosen models by using different numbers of the features through dimensionality reduction and the size of the training data.

1) Dimensionality Reduction: As there are 342 features extracted and some of them may be less relevant or even irrelevant, which can not only confuse machine learning algorithms to not generate better models, but also slow down the learning process considerably. So, it is usually helpful to reduce the dimensionality of the data by eliminating some useless and less important features. In this study, a hybrid method—Random Forest Elimination (RFE), based on the *XGBoost* technique, was used to select the features with most predictive power.

The process can select a given percentage of the initial dimensionality. In our study, we selected 50%, 25%, 15%, 10% and 5%, respectively, in order to find out a smallest possible subset of the more relevant features.

2) Sizes of training data: The data with the selected features were partitioned into training and testing datasets in a stratified manner for a given ration. This ensures that the subsets have the same distributions of the classes as that of the original dataset. We varied the ratio from 40%:60%, 50%:50%, 60%:40%, 67%:33%, 70%:30%, and 80%:20% respectively, to examine the effect of training data size.

3) Repetition of the experiments: To test the consistency of the models, for each experimental setting, we varied the random seeds for 10 times to generate 10 sets of training and testing subsets in order to test the consistency of the chosen learning algorithms.

The modelling process also varied the dataset dimensionality to ascertain dimensional effect on the algorithm performance. This was achieved using XGBoost-RFE, and the resultant datasets were trained and evaluated using the same algorithm parameters. The dataset was also modelled in Decision Tree, Gaussian Naive Bayes and Multi-Layer Perceptron algorithms. The resultant models' performances were compared with the ensemble model performance.

B. Results and Evaluations

All the models built with XGBoost algorithm performed very well upon evaluations. Cross validation using different subsets of the dataset, obtained from the various data partitionings deployed, showed excellent performance in all the evaluation parameters. As shown in the confusion matrix in Fig. 3, the algorithm was able to perfectly distinguish between the transmission cable status. The error bar plot of the model performance accuracy as shown in Fig. 4a, that of AUROC in Fig. 4b, proves the model consistency across all the data subsets used for the modelling and evaluation processes. With an average model performance accuracy of 0.996, the AUROC score, which defines the model sensitivity and specificity to the target class, averaging at a high score of 0.995, and the MCC with an average of 0.990, the model showed high efficiency in classifying the transmission cable status.

The research scope also covered comparison analysis of some selected algorithms with the sole purpose of identifying

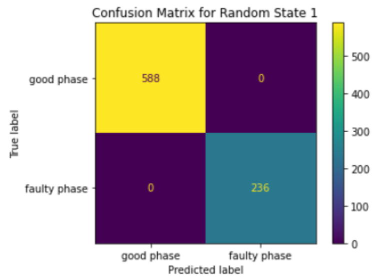
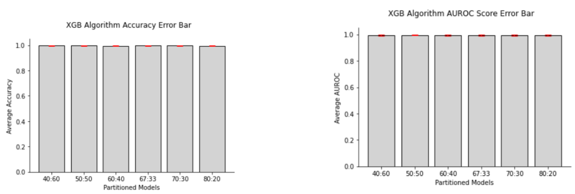


Fig. 3: The confusion matrix of a “perfect” classification.



(a) Accuracy

(b) AUROC

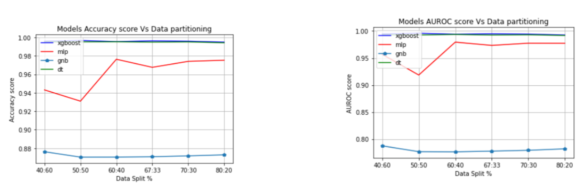
Fig. 4: The performance of the trained models.

the algorithm with the best performance efficiency. Therefore, the various models built using the XGBoost, MLP, GNB and DT algorithms were compared with each other. The comparison analysis involved the average values of performance Accuracy, AUROC score and Computational Time of all the models considering the various data partitioning criteria observed.

From Fig. 5a, which compared the various models in terms of performance Accuracy across all the data partitioning criteria, the following were observed:

i) XGBoost and DT are the best performing, with approximately equal values across all data partitioning criteria.
ii) The performancse of XGBoost and DT are not affected by changes in the training or testing data, as the plot showed consistency throughout.
iii) MLP models’ performance grew with the training data, peaking at 60% training data, and just slightly below XGBoost and DT.
iv) Relatively, GNB is the least performing algorithm, but it produced consistent results across the different data subsets.

The comparison analysis with AUROC, as presented in Fig. 5b, showed the same pattern as the performance Accuracy plot.



(a) Accuracy

(b) AUROC

Fig. 5: Performance of models as the training data sizes vary.

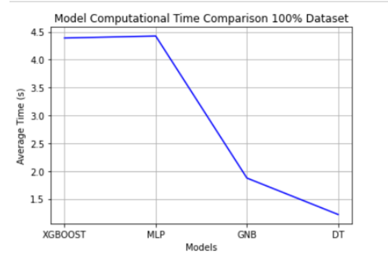


Fig. 6: Comparison of models’ computational time.

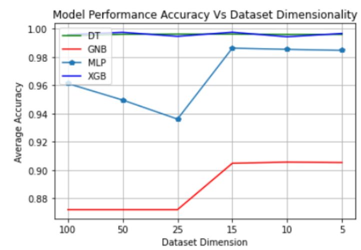


Fig. 7: Model accuracy vs feature reduction.

The plot in Fig. 6, which compares the average computational cost of each the algorithms, shows XGBoost and MLP on a par. With average computational time of about 4.5 Seconds, both algorithms took longer than the others to compute. The GNB algorithm took approximately 2 Seconds, while the DT algorithm, with the least computational cost, took 1.22 Seconds.

The effect of dataset dimensionality on performance evaluation and computational efficiency was also covered in the research. The process involved systematic reduction of the training data features using XGBoost-RFE. The reduction process generated five subsets of the original datasets, which were modelled with the four different algorithms, and evaluated using the same testing data. The evaluation process prioritised the performance accuracy and computational time of each of the models. The line plot in Fig. 7 and Fig. 8 captures the behaviour of the different algorithms with respect to performance accuracy and computational time, respectively, as the dataset dimensionality changes. From the performance accuracy plot in Fig. 7, it is important to note that DT and XGBoost models maintained almost the same performance across all the datasets sub-divisions. Whereas, the models of MLP and GNB made better predictions as the training data features reduced. Therefore, it is pertinent to state that the performance of MLP and GNB can be improved by feeding the algorithm with few best predictors. The computational cost analysis, represented in Fig. 8, showed MLP algorithm computing time drastically increasing as the training data features reduced. This implies that, unlike other models of XGBoost, DT and GNB, that processed at lower time rate as the features reduced, the MLP requires more time in handling datasets with fewer attributes.

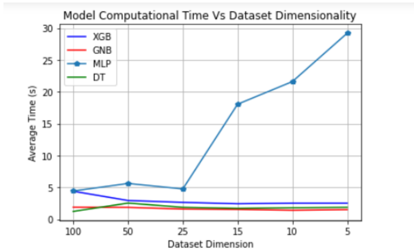


Fig. 8: Model computational time vs data dimensionality.

VII. Conclusions

The need to lower the running and maintenance cost of offshore energy transmission system prompted this research. As the world aims to switch from petrol and diesel engine driven cars to electric cars, the demand for electric power will increase drastically. This additional surge in energy demand, together with the ambition of decarbonising our power generation system, makes research like this of high value.

This research implemented a systematic approach with a view to solving the increasing challenges of transmission cable failures in offshore windfarm systems. The study covered implementation of ensemble machine learning techniques in solving this problem. Other supervised learning algorithms were also deployed to ascertain the algorithm that is of better performance.

The evaluation process considered the different model performance accuracy, precision, sensitivity, specificity and MCC value. The sensitivity and specificity of the various models were obtained in terms of the AUROC curve value. The evaluation process produced excellent results from the various algorithms, with XGBoost and DT performing optimally, with average performance Accuracy, AUROC values and MCC values of 99%, 98% and 100%, respectively, across all the training data subsets. Although, the performance of MLP and GNB are not so high and consistent as XGBoost and DT, they performed relatively well with average performance Accuracy, AUROC value and MCC values of 90%, 92% and approximately 100%, respectively, proving the models' ability to distinguish between the class labels efficiently. The study also considered the effect of training data dimensionality on the performance metrics and computational time of the various models. The evaluation projected XGBoost and DT as the best, with consistency in performance accuracy and decrease in the computational time, as the training data attributes reduced.

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References

[1] A. Khosravi, L. Machado, and R. Nunes, "Time-series prediction of wind speed using machine learning algorithms: A case study osorio wind farm, brazil," *Applied Energy*, vol. 224, pp. 550–566, 2018.

[2] S. Dyatlov, N. Didenko, E. Ivanova, E. Soshneva, and S. Kulik, "Prospects for alternative energy sources in global energy sector," in *IOP Conference Series: Earth and Environmental Science*, vol. 434, no. 1. IOP Publishing, 2020, p. 012014.

[3] A. Kusiak and W. Li, "The prediction and diagnosis of wind turbine faults," *Renewable energy*, vol. 36, no. 1, pp. 16–23, 2011.

[4] P. Bresesti, W. L. Kling, R. L. Hendriks, and R. Vailati, "Hvdc connection of offshore wind farms to the transmission system," *IEEE Transactions on energy conversion*, vol. 22, no. 1, pp. 37–43, 2007.

[5] C. Strang-Moran, "Subsea cable management: Failure trending for offshore wind," *Wind Energy Science Discussions*, pp. 1–11, 2020.

[6] R. Wilson, "Best practice guideline for the complete condition monitoring (cm) of offshore wind farm (owf) cable networks," 2015.

[7] F. Dinmohammadi, D. Flynn, C. Bailey, M. Pecht, C. Yin, P. Rajaguru, and V. Robu, "Predicting damage and life expectancy of subsea power cables in offshore renewable energy applications," *IEEE Access*, vol. 7, pp. 54 658–54 669, 2019.

[8] J. Warnock, D. McMillan, J. Pilgrim, and S. Shenton, "Failure rates of offshore wind transmission systems," *Energies*, vol. 12, no. 14, p. 2682, 2019.

[9] A. P. Magalhães, J. P. Salvador, A. C. Lima, and M. T. C. de Barros, "Identification of incipient faults in subsea hvdc systems," in *2016 Power Systems Computation Conference (PSCC)*. IEEE, 2016, pp. 1–7.

[10] M. M. Saha, J. Izykowski, and E. Rosolowski, *Fault location on power networks*. Springer, 2010, vol. 2.

[11] S. Singh, K. Mamatha, and S. Thejaswini, "Intelligent fault identification system for transmission lines using artificial neural network," *IOSR Journal of Computer Engineering*, vol. 16, no. 1, pp. 23–31, 2014.

[12] A. A. Ayokunle, O. M. Peter, and A. S. Isaac, "Artificial neural networks for intelligent fault location on the 33-kv nigeria transmission line," *Artificial Neural Networks for Intelligent*, vol. 54, no. 3, pp. 147–155, 2017.

[13] M. R. Singh, T. Chopra, R. Singh, and T. Chopra, "Fault classification in electric power transmission lines using support vector machine," *Int. J. Innov. Res. Sci. Technol*, vol. 1, no. 12, pp. 388–400, 2015.

[14] T. Rashmi *et al.*, "Predicting the system failures using machine learning algorithms," *International Journal of Advanced Scientific Innovation*, vol. 1, no. 1, 2020.

[15] R. Sahoo and S. Karmakar, "Health index prediction of underground cable system using artificial neural network," in *2021 1st Odisha International Conference on Electrical Power Engineering, Communication and Computing Technology (ODICON)*. IEEE, 2021, pp. 1–4.

[16] E. Aker, M. L. Othman, V. Veerasamy, I. b. Aris, N. I. A. Wahab, and H. Hizam, "Fault detection and classification of shunt compensated transmission line using discrete wavelet transform and naive bayes classifier," *Energies*, vol. 13, no. 1, p. 243, 2020.

[17] F. Ferro, O. Utterbäck, V. Gliniewicz, and L. Nordström, "Leveraging a service oriented architecture for automatic retrieval and processing of comtrade files for analysis needs of maintenance of circuit breakers," 2020.

[18] M. Barandas, D. Folgado, L. Fernandes, S. Santos, M. Abreu, P. Bota, H. Liu, T. Schultz, and H. Gamboa, "Tsfel: Time series feature extraction library," *SoftwareX*, vol. 11, p. 100456, 2020.

[19] W. Wang, "Some fundamental issues in ensemble methods," in *2008 IEEE International Joint Conference on Neural Networks (IEEE World Congress on Computational Intelligence)*, 2008, pp. 2243–2250.

[20] J. H. Friedman, "Greedy function approximation: A gradient boosting machine." *The Annals of Statistics*, vol. 29, no. 5, pp. 1189 – 1232, 2001. [Online]. Available: https://doi.org/10.1214/aos/1013203451

[21] T. K. Ho, "Random decision forests," in *Proceedings of 3rd International Conference on Document Analysis and Recognition*, vol. 1, 1995, pp. 278–282 vol.1.

[22] T. Chen and C. Guestrin, "Xgboost: A scalable tree boosting system," *CoRR*, vol. abs/1603.02754, 2016. [Online]. Available: http://arxiv.org/abs/1603.02754

[23] G. Tzanos, C. Kachris, and D. Soudris, "Hardware acceleration on gaussian naive bayes machine learning algorithm," in *2019 8th International Conference on Modern Circuits and Systems Technologies (MOCAST)*. IEEE, 2019, pp. 1–5.