A Machine-Learning Approach for Prognosis of Oscillating Water Column Wave Generators

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***Abstract*— Wave excitations cause structural vibrations on the Oscillating Water Columns (OWC) lowering the power generated and reducing the life expectancy. The problem of generator deterioration has been considered for the Mutriku MOWC plant and a machine learning-based approach for prognosis and fault characterization has been proposed. In particular, the use of k-Nearest Neighbors (kNN) models for predicting the time to failure of OWC generators has been proposed. The analysis is based on data collected from sensors that measure various operational parameters of the turbines. The results demonstrate that the proposed kNN model is an excellent choice for reducing maintenance costs by enabling maintenance scheduling months in advance. The model's high accuracy in predicting generator failures allows for timely and cost-effective maintenance, preventing costly breakdowns and improving turbine efficiency. These results highlight the potential of machine learning-based approaches for addressing maintenance challenges in the energy sector and underscore the importance of proactive maintenance strategies in reducing operational costs and maximizing energy production.**

Keywords*— *Machine learning, oscillating water column, wave energy.

I. Introduction

Based on data from global energy forecast, it is projected that the demand for energy will witness a significant surge of 4.6% in 2030, primarily due to climate change and the growth of emerging and developing economies [1]. Consequently, the global energy market is shifting its focus towards sustainable energy sources to cater for the basic energy requirements. Despite the availability of multiple renewable energy options, ocean energies, and wave in particular, have observed a substantial increase in their adoption in the last decade, as depicted in Figure 2. In line with these environmentally conscious policies, several studies have been conducted on ocean energy resources, such as [2-3].

As per the energy roadmap, Europe is under the obligation to establish a marine energy infrastructure capable of meeting roughly 10% of its energy consumption through wave and tidal energy by 2050 [4]. In the course of this development, Wave Energy Converters (WEC) have acquired significant importance [5]. In particular, by 2050, it is expected that 337 GW will be harnessed from the oceans throughout the world, and the technology needed will be developed by then [6]. It will be possible to generate 16 PWh of wave energy per year. Thus, approximately 50% of the expected energy by 2040 could be achieved by means of wave energy.

In the case of Basque Country, the Mutriku Wave Power Plant uses the Oscillating Water Column (OWC) principle to generate electricity from waves. This working principle is quite simple. It works as a result of oscillation of the internal water column within a chamber, which has an opening below the water level. The incoming and outgoing waves make the internal water column oscillate, and consequently the air within the chamber (see Figure 1) is compressed and decompressed. Therefore, there are pressure gradients across the turbine. The turbines deployed are unidirectional, and in this particular case Well´s turbines. For this reason, the generated bidirectional air flow passes through the unidirectional

Figure 1: Capture chamber for an OWCs in Mutriku MOWC

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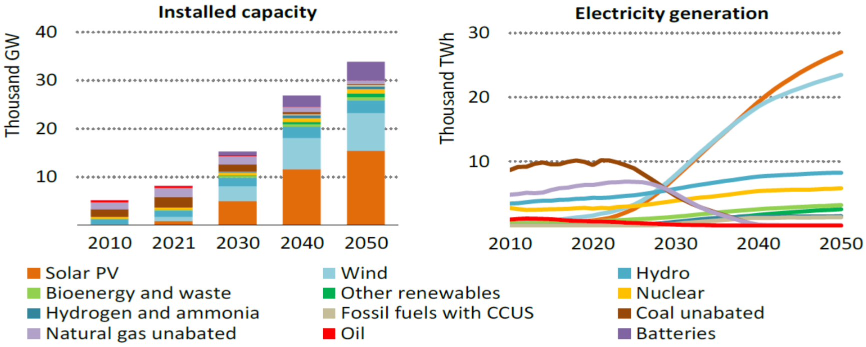

Figure 2: Renewable electricity installation and generation growth by technology by 2050. World Energy Outlook IEA

turbine, thus generating electricity (Garrido et al., 2022). Only onshore devices, such as the multiple OWC Mutriku Wave Power plant in the Basque Country, have shown consistent power generation and can be classified as TRL 8 [7].

Effective monitoring and maintenance strategies are essential for achieving high availability, capacity factor, and Annual Energy Production (AEP) in power plants. Good maintenance practices can help maintain steady operations, which has a strong influence on reducing downtime and increasing availability, power production, capacity factor, and AEP. Therefore, reducing Operational and Maintenance (O&M) costs is a critical approach to controlling the Levelized Cost of Energy (LCoE) [8].

To achieve optimal maintenance, scheduling adequate frequency and implementing the best strategy is crucial. Frequent maintenance can be costly, but neglect can lead to higher failure rates and longer downtime. An optimal maintenance system can reduce O&M costs by 11% to 18% [9]. Predictive maintenance is critical for identifying potential failures before they occur, and analyzing data plays a vital role in this regard. Collecting and analyzing data on turbo generator performance can enable the development of predictive models for scheduling maintenance proactively, reducing downtime, minimizing repair costs, and improving operational efficiency. In ocean industries that heavily rely on equipment, such as manufacturing and transportation over a narrow time-window, predictive maintenance is particularly important. By analyzing data, valuable insights into equipment performance can be obtained, enabling proactive measures to ensure optimal offshore device operation and minimize the risk of unexpected failures.

Maintenance strategies are classified into reactive, proactive, and opportunistic categories based on the timing of the tasks. Reactive maintenance strategy, also known as corrective maintenance, is a failure-based maintenance method that involves performing maintenance only after a failure has occurred. This strategy is efficient for small farms with high reliability, where downtime-related maintenance operations are negligible and can achieve high availability [10]. On the other hand, proactive maintenance strategy is an approach that involves scheduling inspections and replacements before the occurrence of failures to avoid small faults from developing into major failures. Preventive, condition-based and predictive maintenance are examples of proactive maintenance strategies [11]. Opportunistic maintenance strategy is the grouping of different planned preventive and corrective maintenance actions with unplanned preventive tasks that were meant for some worn-out components in the future [12-15].

To develop and implement an adequate maintenance strategy in onshore and offshore power plants, time-based and sensor-based information is gathered. However, processing this data is complicated due to the enormous amount of data gathered and the number of variables measured. Feature extraction is used to reduce redundant information and dimensionality in many fields [16-17] including maintenance. Principal Component Analysis (PCA) is the most common feature extraction algorithm, which extracts important information from data and represents it as a set of new orthogonal variables called principal components [18]. Another well-known feature extraction method is Linear Discriminant Analysis (LDA), which involves finding the projection hyperplane that minimizes the interclass variance and maximizes the distance between the projected means of the classes [19].

In Section II a comprehensive overview of the manipulation and analysis of data from the Mutriku MOWC turbo generators will be presented. Initially, data is collected by the PLCs using the data acquisition system, which must be imported, formatted, and stored in appropriate files. Subsequently, the data from each turbine is analyzed using various group statistics, and different data sets may be merged. The modified data can then be utilized in Section III to train a kNN classification model that predicts the health status of the turbo generator. The performance of the model will be evaluated in Section IV and any necessary improvements and future work will be presented in the Conclusions section that ends the article.

II. IMPORT PLC DATA

In order to incorporate data from the output file of a Programmable Logic Controller (PLC) into the programming language of preference, a suitable method must be established. This may be accomplished by defining distinct sets of tables for each turbine, associated with specific time frames, thereby facilitating the import of data from the PLC into tables. Each column of the table represents a variable, allowing for a straightforward analysis and interpretation of the data.

In order to comprehensively explore the data characterization of various diagnostics, an analysis will be conducted using data obtained from three distinct turbines. Each turbine has been identified to exhibit a specific issue, namely bearing, resonance, and unbalance. Consequently, the output data will be closely associated with the corresponding turbine issue, allowing for a comprehensive examination of the data characteristics.

A. *Bearing Analysis*

In this section, a systematic approach is delineated to cluster and preprocess data from a turbine, with the aim of rendering it amenable for classification as exhibiting bearing deterioration. To accomplish this, the data tables are methodically refined through the elimination of any row that contains an undefined or missing value, as well as those rows or columns deemed extraneous for the purpose of the analysis.

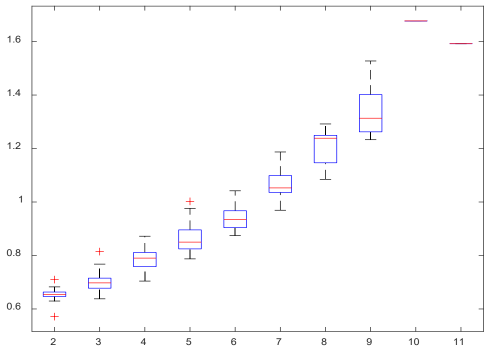

Figure 3: Relationship between the power output (kW) and the amplitude of the vibration (mmps)

The statistical analysis of each turbine on a specific day can be determined by calculating the mean of the grouped values to the first power for each generated pressure. Subsequently, the resulting tables for different days can be combined by joining only those pressure values that appear on all tables. This process ensures that the analysis is consistent and accurate across all the observed days.

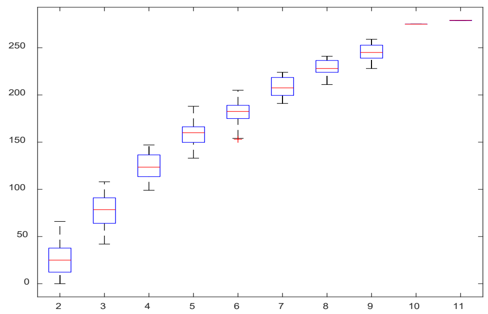

Figure 4: Relationship between the power output (kW) and the pressure across the turbine (dPa)

As observed in Figures 3 and 4, there exists an optimal operating point at approximately 6.5kW, which is characterized by high output power and low levels of vibration. The existence of this is optimal operating point is further underlined when the vibrations are plotted against the pressure, grouped by power output, as illustrated in Figure 5.

B. *Resonance Analysis*

Analogous to Section A, we present a systematic approach for clustering and preprocessing data obtained from a turbine with the goal of facilitating its classification as experiencing resonance. The data tables are subjected to a methodical refinement process involving the elimination of any row containing undefined or missing values, as well as those rows

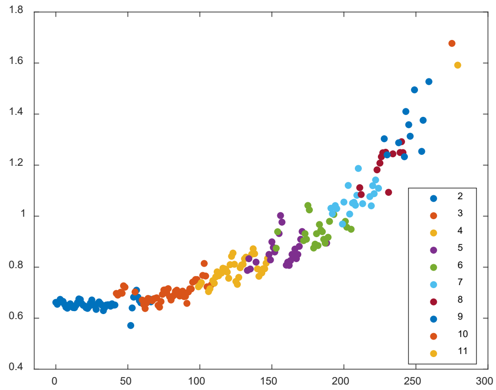

Figure 5: Relationship between the vibration amplitude (mmps) and the pressure across the turbine (dPa) grouped by power output (kW)

or columns deemed extraneous to the analysis. For each turbine and day, the relevant statistics are computed in a similar manner to the previous case. Additionally, the tables obtained from different days are combined and subjected to a joint analysis.

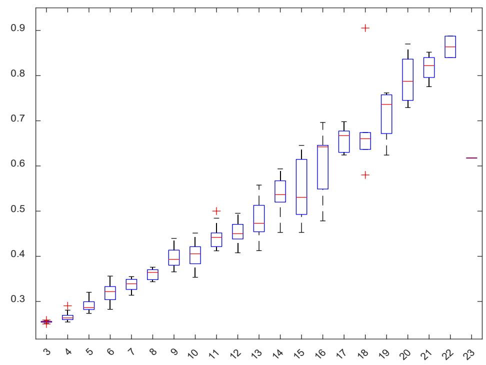

Figure 6: Relationship between the power output (kW) and the amplitude of the vibration (mmps)

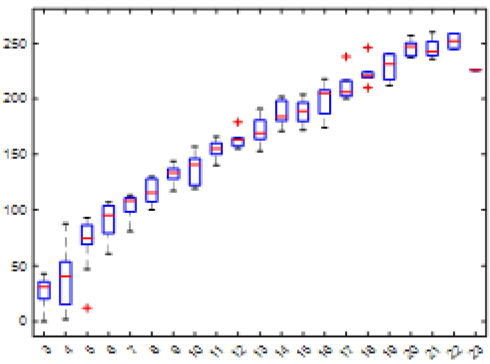

Figure 7: Relationship between the power output (kW) and the pressure across the turbine (dPa)

The study of the data presented in Figure 6 reveals that the turbine subject to vibrations resulting from resonance is comparatively less severely impacted when contrasted with the turbine affected by bearing wear off. This finding is further validated by the information presented in Figure 8, which indicates that the turbine experiencing resonance generates a higher production rate at the same pressure values as the other turbines. These observations provide valuable insight into the differential effects of distinct types of turbine vibration, and underscore the importance of implementing targeted maintenance and repair strategies that are tailored to the specific nature and severity of the observed vibration phenomena.

Additionally, it is evident from Figures 6 and 7 that there exists an optimal operating point at approximately 15 kW. This point is distinguished by its ability to produce high output power while simultaneously minimizing levels of vibration. This optimal operating point is further emphasized when the vibrations are graphed against the pressure, categorized by power output, as illustrated in Figure 8.

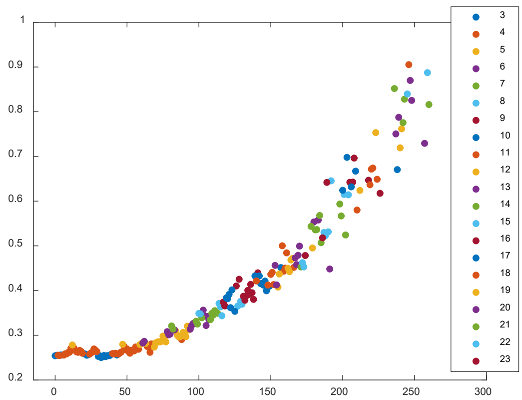

Figure 8: Relationship between the vibration amplitude (mmps) and the pressure across the turbine (dPa) grouped by power output (kW)

C. *Unbalance Analysis*

Finally, we propose a comprehensive methodology for clustering and preprocessing data collected from a turbine, aimed at facilitating its classification as experiencing turbine unbalance. To achieve this objective, the collected data undergo a meticulous refinement process that entails the elimination of any row containing undefined or missing values, as well as the exclusion of those rows or columns deemed irrelevant to the analysis. Subsequently, for each

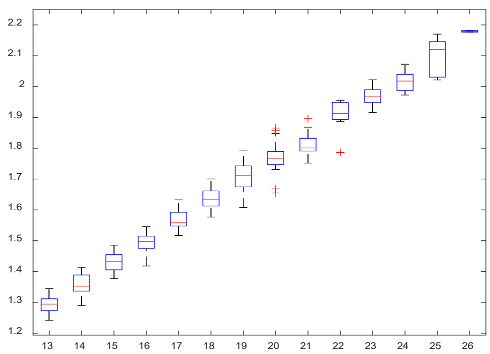

Figure 9: Relationship between the power output (kW) and the amplitude of the vibration (mmps)

turbine and day, pertinent statistics are computed in a manner similar to the previous cases. Furthermore, the tables obtained

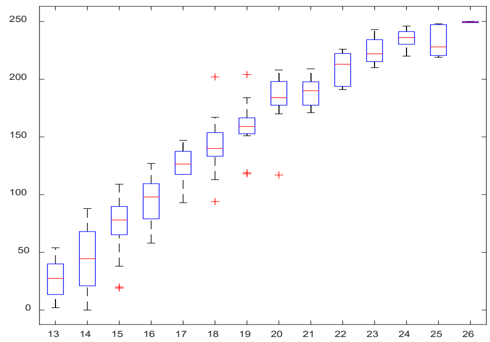

Figure 10: Relationship between the power output (kW) and the pressure across the turbine (dPa)

from different days are combined and subjected to a joint analysis. The proposed approach presents a systematic and rigorous methodology for preprocessing and clustering turbine data, with the ultimate goal of improving the accuracy and reliability of turbine unbalance classification.

The analysis of the data presented in Figure 9 reveals that the turbine vibrations caused by unbalance exhibit a more pronounced linear relationship with the generated power when compared to those vibrations resulting from resonance or bearing wear off. This assertion is supported by the findings presented in Figure 10, which show that the unbalance turbine generates a superior production rate at the same pressure values as the other turbines.

In the context of this specific failure, a definitive optimal operating point for the turbo generator module is difficult to ascertain from the information presented in Figures 9 and 10. Moreover, a more evident linear relationship between the vibrations and the pressure, grouped by power output, can be discerned from the data plotted in Figure 11. This visualization highlights the complexity of the underlying factors contributing to the failure, and underscores the importance of employing comprehensive and multifaceted analyses to diagnose and address such issues in a rigorous and effective manner.

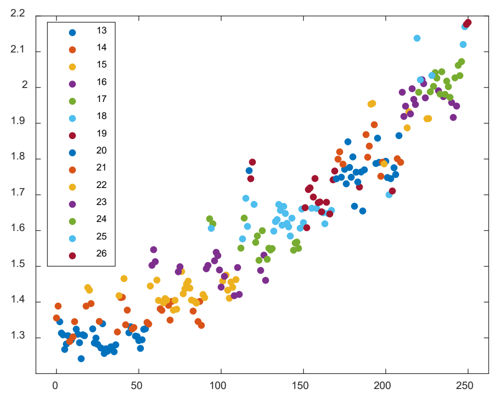

Figure 11: Relationship between the vibration amplitude (mmps) and pressure across the turbine (dPa) grouped by power output (kW)

The aforementioned observations serve as compelling evidence for the potentially significant impact of turbine unbalance on the efficiency and productivity of the overall system. These findings underscore the critical importance of implementing timely and effective maintenance interventions to mitigate this issue and minimize any adverse effects on the system's performance. Such interventions may include the implementation of regular monitoring and inspection procedures, the incorporation of predictive maintenance strategies, and the utilization of advanced diagnostic tools and techniques to facilitate the early detection and remediation of turbine unbalance issues.

III. Train a Model. Supervised Learning

The findings of the preceding section provide a compelling rationale for proposing a classification model dedicated to prognosis. The objective of the model is to effectively classify the data output obtained from the Programmable Logic Controller (PLC) that governs the aforementioned turbines, each exhibiting distinct issues: bearing, resonance, and unbalance. Notably, the PLC generates individual data sets for each turbine, with a unique label assigned to delineate these specific data sets. This proposed classification model seeks to efficiently analyze and categorize the data output, thereby facilitating accurate prognosis of turbine conditions based on their identified issues. Then, a partition object using a holdout method is created, where the data is divided into training and testing sets. The testing set comprises 30% of the total data, while the training set contains the remaining 70%. Subsequently, a k-Nearest Neighbors (kNN) algorithm will be employed to construct a model capable of classifying the operational state of the turbine based on an instant of PCL data. The classification model shall be trained using the training set and then leveraged to make predictions for the testing set.

The k-Nearest Neighbors (kNN) is a supervised machine learning technique that was initially introduced by Evelyn Fix and Joseph Hodges in 1951 [20] and later expanded by Thomas Cover [21]. The kNN algorithm does not explicitly learn or optimize model parameters during training. It simply retains the training data to establish a database of labeled examples and then leverages the stored data to make predictions based on the principle of similarity. In kNN classification, the input data consists of the k closest training examples in a dataset. The output is a class membership assigned to the object being classified. The algorithm works by taking a plurality vote of its neighbors, with the object being assigned to the class that is most common among its k nearest neighbors. Since kNN relies on distance for classification, it is important to normalize the training data if the features come in vastly different scales. This normalization can significantly improve the accuracy of the algorithm.

Initially, the data undergoes the customary procedures of cleansing and scaling as a primary step. Within this specific physical system, absolute values will be adopted to consider the pressure, as both pressure differentials induce a unidirectional rotation. Moreover, it is assumed that a given pressure differential will yield similar power generation by the turbine.

The distance metric that measures the similarity between two data points in the feature space, is chosen to be the Euclidean distance because it presents an excellent performance in this case. Therefore, the model calculates the distance between the new turbine data output and the data in the training set using the Euclidean distance formula as follows:

$$d = \sqrt{(p_n - p_i)^2 + (w_n - w_i)^2 + (v_n - v_i)^2} \quad (1)$$

where p_n, w_n and v_n are the pressure, power and vibrations of the new turbine, and p_i, w_i and v_i are the pressure, power and vibrations of the i^{th} turbine in the training set.

Given a new turbine data, the kNN method has the capability of classifying a new turbine data by associating it with the most commonly occurring label type among its k nearest neighbors. This technique is rooted in the principle of similarity, whereby the classification of a data point is based on the identities of its closest neighbors as defined by equation (1) in a high-dimensional space. Through this approach, the kNN algorithm seeks to classify the new turbine data as belonging to the same type as the turbines that have the highest frequency of occurrence among its nearest k neighbors.

IV. Simulation, Validation and Discussion

Using the kNN method, we can calculate the distances to each turbine in the training set and select the type of those turbines with the shortest distance. Choosing the optimal value of the hyperparameter k, the number of nearest neighbors to be considered, is a critical aspect in the algorithm. Large values tend to smooth out the decision boundary or prediction surface, while small values ender the system more sensitive to noise and overfitting. This value has been tuned to k=5 in order achieve optimal performance on the validation set.

The Hold-out validation method has been used to estimate the performance of the model, randomly partitioning the available dataset into two subsets: a training set with 70% of the data and a validation set with 30%. This technique has been used because the available dataset has 21710464 entries, so that it is large enough to support a random partition into training and validation sets. Thus, the kNN model offers a convenient approach for estimating performance through a single training phase and subsequent evaluation on a validation set. This method eliminates the need for iterative training processes commonly seen in other machine learning models. Once the k-NN model is trained using a labeled training dataset, it can be applied directly to a validation set to assess its performance. By calculating the accuracy or other relevant metrics on the validation set, we can quickly estimate how well the trained k-NN model is likely to perform on unseen data. This efficient evaluation process allows for a rapid assessment of the model's effectiveness without the need for further iterations of training and validation.

The evaluation of the accuracy for thr kNN classifier involves determining the number of correct predictions made and dividing that by the total number of observations within the test set as follows

$$a = \frac{1}{size y_t} \sum (y_p == y_t) \quad (2)$$

where y_p is a vector of predicted labels generated by the classifier for the test set, y_t is a vector of true labels for the test set, and $sizey_t$ represents the total number of labels within the test set. Upon performing this evaluation, the resulting accuracy score of the kNN classifier (2) was found to be 0.9129. This score, which is indicative of the model's effectiveness, can be deemed as excellent.

A. *Validation of the Results*

The validation has been carried out once the kNN model has been designed and trained. To evaluate the model's performance, a confusion chart is employed, which provides a comprehensive analysis of a classification model's accuracy. The confusion chart displays the counts of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) for each classification task (bearing, resonance, and unbalance).

In the confusion chart displayed in Figure 12, the rows correspond to the true class labels, and the columns correspond to the predicted class labels. Each cell in the table represents the number of predictions that were classified as a certain class. The diagonal cells represent the number of instances that were correctly classified, while the off-diagonal cells represent the number of instances that were misclassified.

In this example, it may be read in Figure 12 that the model correctly predicted 10539388 instances for the bearing problem, while misclassifying 583275 instances as resonance and 179615 as unbalance. It also predicted correctly 8088515 instances for the resonance problem, while misclassifying 868993 instances as bearing and 103003 as unbalance. Finally, it predicted correctly 1192596 instances for the unbalance problem, while misclassifying 104716 instances as bearing and 50363 as resonance.

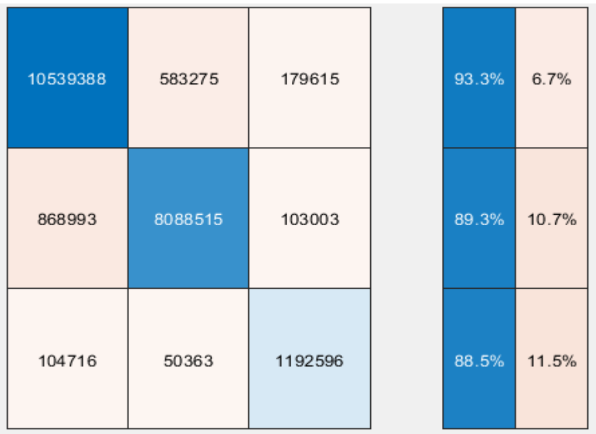

Figure 12: Confusion Chart illustrating turbine classification performance with respect to bearing, resonance and unbalance issue using the kNN model.

B. *Discussion of the Results*

Our findings suggest that the kNN classification model achieved an accuracy of approximately 90%, indicating that it correctly classifies the failure type for the majority of the turbine output data. This level of accuracy suggests that the model is reliable and has the potential to be useful to correctly classify bearing, resonance, and unbalance, turbine issues using the PLC output data. It suggests that this kNN classification model has wide-ranging implications for maintenance planning, cost optimization, asset management, safety, and overall turbine performance. It empowers operators to make informed decisions, implement targeted repairs, and improve the reliability, efficiency, and profitability of turbine operations.

There are certain limitations that need to be considered in relation to these findings. One important limitation is the quality and representativeness of the dataset used for training and testing the kNN model. Although the chosen datasets were sufficiently large to provide robust results, it is essential to ensure that the data accurately captures the variability and complexity of the turbine systems. Moreover, adequate coverage of all possible scenarios is crucial for achieving optimal model performance. This requires a thorough understanding of the physical system and its faults, as any bias or inadequate coverage in the data can negatively impact the accuracy of the model and reliability.

In terms of sample size availability, it is important to note that this study did not encounter any issues, as the dataset size was considered adequate. However, it is worth acknowledging that sample size can be a limitation in certain cases, particularly when dealing with smaller datasets. Generalizability is not a concern in this study, as the training set only requires data from the new turbines under study, without the need for parameterization or iterative processes. The model can be applied to similar turbines without extensive modifications.

Nevertheless, it is essential to recognize that the performance of the model heavily relies on the availability of comprehensive and unbiased data. If certain fault scenarios are not adequately represented in the dataset, the predictive capabilities of the model may be compromised. Therefore, prior knowledge of the physical system and its faults is crucial for ensuring that the data collection process encompasses a wide range of scenarios.

In summary, while the chosen datasets and the approach used in this study offer advantages such as robustness and generalizability, it is important to be aware of the limitations associated with data quality, representativeness, and coverage of fault scenarios. Future research should focus on expanding the dataset to include a broader range of scenarios, ensuring that the data collection process is comprehensive and unbiased to further enhance the model's performance.

V. Conclusions

In this article, the authors have presented a study on the development and evaluation of machine learning models for prognosis and fault characterization of oscillating water columns (OWCs) using Mutriku data. The data collection involved the use of sensors to measure the mechanical and aerodynamic properties of the entire OWC system. A k-Nearest Neighbors (kNN) model has been proposed for the replication of the OWC system behavior and structural performance. The model has been trained with appropriate parameters while adhering to a low Mean Squared Error (MSE) target function. The efficacy of the model has been successfully tested on a validation set to ascertain its computational efficiency, validity, and accuracy. The presented work has potential implications for improving the prognosis and fault characterization of OWCs through machine learning-based approaches.

The results of the evaluation indicate that the proposed kNN model outperformed existing methods in accurately predicting turbine failures, further underscoring its potential for enhancing the prognosis and fault characterization of OWCs. The findings presented in this study contribute to the existing body of research on turbine maintenance and fault diagnosis. While previous studies have explored classification models for identifying and classifying turbine failures, the novelty of this research lies in several key aspects.

Firstly, the high percentage of agreement observed among different failure types is a noteworthy finding. This indicates that the classification model, specifically the kNN approach employed in this study, exhibits a significant level of accuracy and consistency across various failure scenarios. This level of agreement sets this research apart from prior studies, as it demonstrates the robustness of the model in handling diverse turbine failures.

Secondly, the consideration of data bias is another important aspect of this study. By acknowledging the potential variations in turbine conditions due to their distinct locations within the breakwater, this research offers a nuanced understanding of the impact of data bias on classification performance. The successful application of the kNN model in the presence of data bias provides a novel perspective on how such biases can be effectively addressed.

Finally, the examination of the dataset pertaining to turbine unbalance, which contained a smaller number of instances compared to the other failure types, introduces a unique element to this study. This analysis highlights the ability of the kNN model to handle imbalanced datasets and still achieve satisfactory classification results. This aspect of the research contributes to the existing knowledge by showcasing the robustness and adaptability of the kNN approach, even in scenarios with data availability of different orders.

Overall, the novelty of this research lies in its comprehensive consideration of agreement among failure types, the exploration of data bias, and the investigation of imbalanced datasets. These findings advance the understanding of classification models in turbine maintenance and fault diagnosis, providing valuable insights for future research and practical applications.

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