

Building an Air Turbine Conditional Anomaly Detection Approach for Wave Power Plants

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ABSTRACT

The Mutriku Wave Power Plant (WPP) is a wave energy conversion plant based on the oscillating water column technology (OWC). The energy production and the health state of the plant are directly dependent on the sea-state conditions along with component-specific operation efficiency and failure modes. In this context, this paper presents a preliminary air turbine conditional anomaly detection (CAD) approach for condition monitoring of the Mutriku WPP. The proposed approach is developed based on an ensemble of Gaussian Mixture models, where each anomaly detection model learns the expected air turbine operation conditioned on specific sea-states information. Early results show that the integration of sea-states in the anomaly detection learning process improves the discrimination capability of the anomaly detection model.

1. INTRODUCTION

The Mutriku WPP is a wave energy conversion plant based on the OWC technology commissioned by the Basque Energy Agency. From the beginning of the operation of the Mutriku WPP, different degradation and failure events have been reported for WPP components (Lekube, Ajuria, Ibeas, Igareta, & Gonzalez, 2018). However, the lack of experience in similar systems hampered the development of condition monitoring strategies, and maintenance actions have been adopted through intuition and expert knowledge.

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The Mutriku WPP is located onshore into the breakwater at the harbour in Mutriku (Bay of Biscay). Although grid-connected, the main goal of the WPP is promoting the development of OWC components, auxiliary systems and control strategies. Therefore, the operational consequence of unplanned maintenance actions are not as critical as in future commercial open ocean WPPs. However, the monitored information of the plant operation can be used to develop health monitoring models that integrate statistical learning strategies with expert knowledge, and accordingly, assist engineers in the maintenance decision-making processes of future WPPs.

Technological solutions for wind energy have been developed for many years now, and accordingly, most of the proposed turbine condition monitoring solutions focus on wind turbines (de Novaes Pires Leite, Araújo, & Rosas, 2018). Anomaly detection models for wind turbines have been addressed in the literature through probabilistic power curve models (de Novaes Pires Leite et al., 2018). However, there are limited health monitoring solutions for marine energy applications (Mérigaud & Ringwood, 2016). Existing anomaly detection models developed for wind energy applications may perform appropriately under stable operation conditions, however, when the WPP operation and degradation is strongly influenced by metocean conditions that can impact on the operation of the air turbines, it is necessary to integrate sea-state information in the modelling process.

One possibility to achieve this objective is the adoption of conditional anomaly detection (CAD) modelling concepts (Song, Wu, Jermaine, & Ranka, 2007), where the main goal

is to learn and model the normal operation condition of the system as a function of the operation context.

2. CAD APPROACH FOR AIR TURBINES

The expected operation of an air turbine can be modelled using its characteristic power curve, which relates the rotation speed with the produced power. Deviations from the characteristic power curve may indicate early warnings or abnormal turbine operation states.

In the context of anomaly detection models, it is crucial to reduce false positives and maximize accuracy. Different operation conditions may result in different performance indicators, and therefore, it is very important to learn the normal behaviour of the turbine with respect to its operation context. Accordingly, Figure 1 defines a framework to jointly model expected turbine performance conditions along with the corresponding expected sea-state.

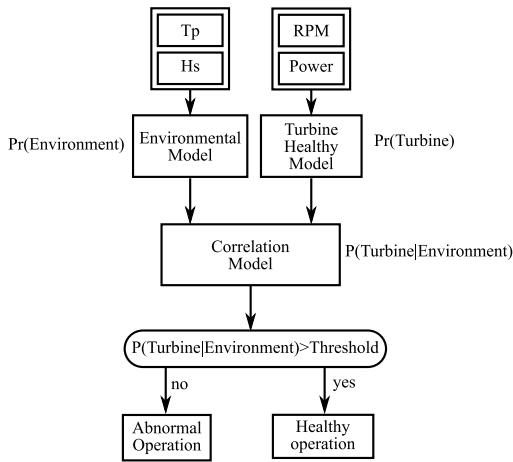


Figure 1. CAD framework for air turbines.

The environmental model will be determined through the combination of significant wave height H_s and the peak period T_p , which are common statistical parameters to characterize a sea-state. Subsequently, probabilistic multivariate models are developed based on Gaussian Mixture models for the turbines to characterize the corresponding probabilistic power curve. Finally, their probabilistic correlations are defined so as to estimate the probability of a turbine being healthy, given the operational information.

3. CASE STUDY & DISCUSSION

In order to evaluate anomalies taking into account sea-state conditions, firstly, sea-state conditions are grouped into wave energy flux (WEF) intervals: very low energetic sea-states (WEF1) 0-5 kW/m, low energetic sea-states (WEF2) 5-15 kW/m, medium energetic sea-states (WEF3) 15-25 kW/m, high energetic sea-states (WEF4) 25-40 kW/m, very high energetic sea-states (WEF5) 40+ kW/m.

Figure 2 shows anomaly detection results for the different energetic sea-states along with the model without classification into sea-states. The vertical axis has been transformed into log-likelihood scale for anomaly representation purposes. The threshold level located at -50 reflects the identification of very unlikely events, *i.e.* anomalies, which are below this threshold.

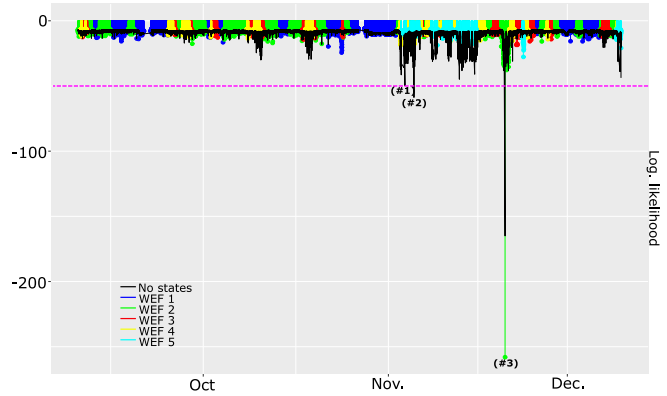


Figure 2. Anomaly detection results.

From Figure 2, it can be observed that there are differences between the classification into different sea-states (WEF groups) and no-classification of sea-states. The no-states configuration identifies two false positive events (#1, #2), while the state-based anomaly detection matches only with one of them, which is effectively an anomalous event (#3).

Early results show the potential of the proposed approach to detect air turbine anomalies through explicit consideration of sea-states along with power curves. It has been observed that without consideration of sea-state information the anomaly detection model is prone to flag false positive events and the integration of sea-state information aids in the discrimination of anomaly events.

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