A method for the detection of oil leakages on the pitch control system of wind turbines

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Abstract

This work presents a method for the detection of oil leakages in the hydraulic mechanism of the pitch subsystem of a wind turbine. Leaks of hydraulic fluid in the pitch system have a cascade effect, creating more significant problems in other parts of the turbine, such as deterioration of blades and bearings due to oil infiltration, loss of oil, and loss of turbine production time. Environmental effects should also be considered when oil is being expelled into the environment, relating heavily to social, political, and biological factors. Thus the mitigation of oil leakages and hydraulic failure is paramount for the longevity and sustainability of wind turbines. From literature, three main approaches for fault detection were researched; data-based, model-based, and sensor-based. Hybrid methods, meaning utilizing multiple methods simultaneously, were investigated to develop a robust and accurate process. A 'digital twin' was created in Matlab Simulink/Simscape to prove understanding of the system and a basis of validation for the detection methods, which was confirmed to represent the system accurately using actual turbine data. Two detection methods were created, which were validated using the simulation, and tested with leaking and non-leaking turbine data. A critical sensor was investigated on the basis of elevated noise, and filtering schemes were introduced.

Keywords: Wind turbine, Pitch system, Hydraulic system, Leak Detection Algorithm, Digital Twin

1. Introduction

Wind turbines continue to grow in size and complexity, and as time goes on, they are being installed in increasingly remote locations on land and in the sea [1]. To be economically attractive, turbines need to be reliable and efficient when converting the kinetic energy in the wind to other forms, such as electrical energy for grid injection or direct hydrogen production [2, 3]. Due to their operation in harsh environments with highly variable stochastic loads, faults become inevitable [4]. Operation and maintenance (O&M) costs are quite significant concerning the total investment costs of projects, especially unscheduled maintenance that can lead to prolonged downtimes and loss of generation [5].

The problem of hydraulic oil leakages in wind turbines, as identified by the company, has significant social, environmental, and financial impacts. This issue can impact community relations, while technical challenges and potential turbine damage make it important to address. Settlements, decreased investments, and repair costs may result in the lack of action. Active mechanical systems are mandatory to control the pitching function in turbines, where the company opted to institute a hydraulic system on their turbines. Thus, the origin of this project related to leaks in the hydraulic system was formed.

The nonlinear aerodynamics and the stochastic behavior of wind become a challenge to model and ensure reliable operation [6]. With respect to the frequency of faults, the pitch system can be responsible for as much as 20% of total downtime in wind turbines [7]. But if well designed, the ever-soaring O&M costs, which can account for 20% of the total cost of energy (COE), could be curbed by appropriate monitoring and detection solutions to improve turbine reliability and availability [5, 8].

1.1. Objective

The objective of this project was to propose a method for the detection of oil leakages in the pitch system. An underlying host of goals are defined as follows to achieve this objective. To understand the inner workings of a pitch system and identify critical components and variables. To propose a method based on data and sensors available on the turbines. Finally, to create a model for the simulation of the pitch system to validate the proposed detection methods.

This paper aims to deduce a more accurate, efficient, and robust detection method in the data, model, or sensor-based fault detection domain than what is currently in place. This is a current research topic in the academic world and has yet to converge on a decided method, as the detection method is highly dependent on the specific situation. As wind turbines become larger, more issues arise, and more effort is needed when considering the machines installed in the future.

2. Detection Methods and Supervisions

2.1. Detection Techniques

To have a succinct understanding of different detection methodologies, three categories clearly define the approaches; sensor-based, method-based, and data-based detection. Each type grows in complexity, and the three classes are the basis for the following discussion. The trend of research publications on wind turbine fault detection has increased dramatically in the last 20 years [9]. In the last decade, there has been a push toward detection methods based on model and data approaches.

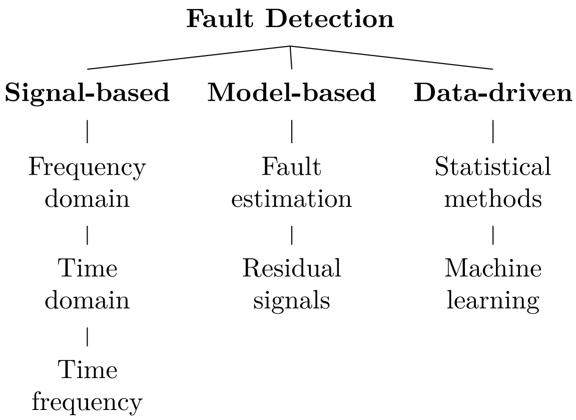

Figure 1: Classification tree of fault detection.

The outline of potential paths is described in Figure 1. Signal-based detection is solely an inspection of the sensor outputs available, and subsequent comparison to known operating conditions. This inspection can be done in three domains currently, the time domain, frequency, and the combination in a time-frequency analysis method. Model-based detection uses a mathematical model to predict the state or behavior of a system and compares this to the actual sensor output, calculating the difference in the case of residual signals. Fault estimation aims to represent the system using a set or model that can generate estimates of the key parameters, and by using sensor and control signals a diagnostic decision is taken. Finally, data-driven detection uses historical data and either through a statistical or machine learning method can classify and intelligently use the data to correlate the current system operation with either healthy or faulty conditions.

As was stated in a 2019 report, 'Hydraulic systems have the characteristics of strong fault concealment, powerful nonlinear time-varying signals, and a complex vibration transmission mechanism; hence, diagnosis of these systems is a challenge' [10, p. 1]. This is not the only report to claim difficulty, others citing condition monitoring of hydraulic systems, particularly to precisely model, to be a very challenging task [11]. This detection system ideally should successfully run under transient and unsteady operation, in addition to steady-state situations [12]. But if achieved, a host of benefits are provided, such as; reduction of maintenance cost, remote diagnosis, avoidance of premature breakdown, and improvement of capacity factor [2]. As the likelihood of fault occurrence is unavoidable, and the severity of repercussions from leakages in the pitch actuation system is high, the identification of leaks is well understood to be a sizeable concern [13, 14].

3. Methodologies and Limitations

As part of the research, literature was examined on standard practices in the wind turbine and hydraulic system industries. The study was organized into sections to manage the large amount of information, starting with a background on hydraulic systems and fault detection in wind turbines. Three avenues of fault detection were analyzed, progressing from simple signal methods to model-based and data-driven approaches. A Matlab/Simulink model was developed to model the hydraulic system and later expanded to simulate the turbine's major components during operation. The company provided real turbine data for validation. The two detection algorithms developed were Algorithm A and Algorithm B. These algorithms were tested using simulation and actual turbine data, with comparisons made against key performance indicators. Additionally, the influence of sensor B on sensor A was examined, leading to the development of a filtering scheme for sensor A to enhance signal clarity.

The testing campaign focused exclusively on a specific turbine, assuming similar operation for other models, but lacking sufficient data to inspect them. Limited data sets and the use of real turbine data for algorithm testing hindered the confirmation of the algorithms due to uncertainty about non-leaking cases and the amount of oil evacuated from the system during assumed leaks. Matlab and Simulink were utilized for modeling, data processing, and calculation in the project. It is crucial to acknowledge that the models possess certain inherent assumptions and errors that can lead to discrepancies with the real-world system. Certain limitations, such as fixed oil properties in the Simscape model, could introduce errors in longer runs when oil properties change. The practicality of the developed models and algorithms to run on an actual turbine was discussed in terms of computation time, but not in terms of specific boundaries of complexity. The designs were based on current instrumentation on the specific turbine in question, requiring validation again for future implementation on other turbines.

4. Novel Contribution

Simulink is a powerful tool to simulate environments that can be otherwise hard to estimate, using a block library to generalize components of the system at hand. This software can interface with Matlab for data analysis and was used extensively in this project.

4.1. Simulink Modeling

To take a pragmatic approach, a simple model was created using Simulink that included only the basic elements. Simple models were tested with this software to determine feasibility and confirm methodologies before adding complexity and adaptation to the full models.

The full Simulink model was created to include all the critical valves and components used in normal operation, this was then adapted to run using a minimal number of inputs from real data of a turbine. The Simulink model was used to compare the sensor outputs and test the developed algorithms, thus deducing if noise on the turbine signals was having a considerable effect on the algorithm capabilities. Furthermore, having an accurate base Simulink model allowed for the reduction in the complexity of the model and the inclusion of more turbine signals, where if the results were still acceptable, the model could be used as a detection method itself. Detailed information about the model can be found in Section C.4 in Appendix C from Ref. [15].

Upon confirmation of the Simulink model, the most critical output to compare was sensor A between the simulated case and the actual case. The model outputs tested under non-fault events served as validation data to confirm the developed algorithms with non-noisy sensor inputs.

4.2. Sensor A

Part of the spark for this master's thesis was the inclusion of a special sensor on the turbines. Refer to Section C.5 in Appendix C from Ref. [15] for further information.

Sensor A is the critical signal used to estimate a critical variable for the algorithms. However, the reading can become obscured due to the noise during normal operation. The results from the Simulink model was used as a guide to filter the raw signal. Several filtering techniques were tested, including filter A, filter B, filter C, filter D, and filter E. Combinations of filters were also applied to advance the results.

The volatile activity of sensor A seemed to have more proponents than just the uncertainty of the sensor. For this reason, sensor B was inspected. The FFT was computed for sensor B and was compared to the calculated FFT of sensor A's raw signal. This analysis aimed to answer whether sensor B, specifically at the frequencies with the highest associated amplitudes, correlated with the frequencies seen in the raw signal of sensor A.

4.3. Algorithm A

With respect to the detection algorithms, the base case to try and improve off of was Algorithm A developed by company internals previously. Two more alterations were created from this algorithm, Algorithm A1 and Algorithm A2. Refer to Section C.6 in Appendix C from Ref. [15] for a detailed explanation of the algorithm.

4.4. Algorithm B

The second algorithm created, Algorithm B, looked at the problem from another perspective, therefore having new challenges with respect to Algorithm A. For information on this algorithm, refer to Section C.8 in Appendix C from Ref. [15].

5. Results

The results section aims to discuss the major findings and present the developments from the discussion in the previous section. The discoveries from the filtering schemes and developed leakage detection algorithms, as well as the Simulink model, are presented and examined below.

5.1. Simulink Results

The Simulink models were created with the goal of creating a model of the hydraulic system. The untuned Simulink model results are an important starting point for understanding how critical the tuning is in obtaining an accurate simulation. This can be seen in Figure 2, where the simulated displacement deviates over the simulation time.

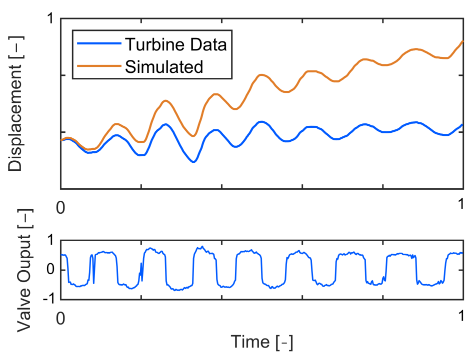

Figure 2: Displacement comparison - untuned model.

Figure 3 is an important figure depicting the comparison between the real movement and the simulated movement. The simulation matches the turbine's raw data nearly perfectly. Figure 3 depicts the final results from the tuned Simulink model for the data set in question. The operation of the model compared to the actual turbine data revealed striking similarities, leading to increased confidence in the output data for other sensors in the simulation. However, to confirm the model was an accurate representation of the hydraulic system of the turbine, it was tested under two more data sets, which depicted similar results.

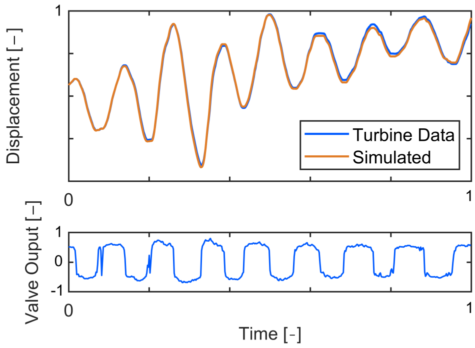

Figure 3: Displacement comparison - tuned model.

The full-scale Simulink model was confirmed in its ability to model the real-life turbine. Subsequently, the reduction of complexity of the model commenced as it was very computationally heavy. The results from the reduction can be seen in Section C.9 in Appendix C from Ref. [15].

5.2. Sensor A

Sensor A is a critical component in the algorithms, thus an accurate estimation of the sensor is needed. The raw signal demanded post-processing to be used adequately and effectively in the algorithms.

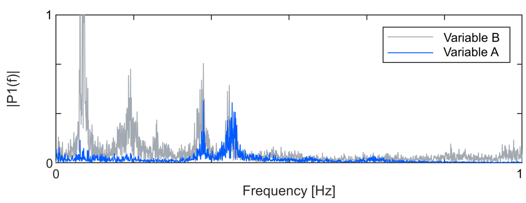

Figure 4: FFT of X-Direction & sensor A.

FFTs were computed with the data from sensor B in two directions; Y-direction and the X-direction, as well as sensor A itself. The results from Figures 4 and 5 reveal a strong link between the highest amplitude frequencies of sensor B and the frequency with the highest excitation of sensor A. The discussion of this topic can be found in Section C.11 in Appendix C from Ref. [15].

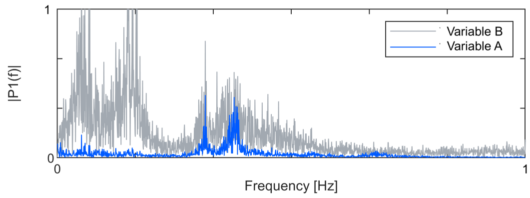

Figure 5: FFT of Y-Direction & sensor A.

A host of filters were inspected to effectively filter the noise on sensor A to give an accurate reading. First, as seen in the previous discussion, filter A was implemented. After inspection of various filtering techniques, filter A in conjunction with filter D was implemented in the algorithms to obtain a more accurate reading for sensor A, as depicted in Figure 6.

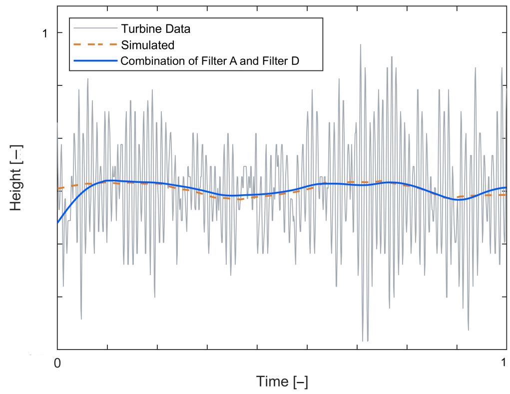

Figure 6: Filtering and raw signal comparison.

5.3. Algorithm A

To track improvement, Algorithm A was used as the base case. Algorithm A1 was based on Algorithm A, as was Algorithm A2. Each progressed in complexity and the quality of the results. Refer to Section C.12 in Appendix C from Ref. [15] for a detailed description.

5.4. Algorithm B

Algorithm B estimates the leakage of oil in a different way than Algorithm A. Refer to Section C.13 in Appendix C from Ref. [15] for further information.

6. Conclusions

The project aimed to develop an accurate oil detection strategy for the company's turbines, offering several benefits like cost savings, environmental protection, safety enhancement, and increased trust. The project followed three major steps: a literature review, a modeling phase, and an analysis of results. A Simulink model successfully resembled real turbine data. Two detection algorithms, Algorithm A and Algorithm B, were developed. Algorithm A showed good results and Algorithm B needs further development, but sensor A filtering proved to be effective. Correlations were found between sensor B and sensor B.

6.1. Recommendations

Three variations of the Algorithm A were inspected. Based on performance alone, Algorithm A2 showed the best results. Algorithm B demands further work before implementation on a turbine. Filtering schemes such as those discussed should be implemented on sensor A, and a possible redesign of the measurement of sensor A could be helpful to ensure clear operation.

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