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

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Declaration

I declare that this document is an original work of my own authorship and that it fulfills all the requirements of the Code of Conduct and Good Practices of the Universidade de Lisboa.

Note: This document has been edited to preserve confidential information, including the removal of critical units and scales, and much of the content being moved to Appendix C. Appendix A through Appendix C are confidential.

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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

Resumo

Este trabalho apresenta um método para detecção de vazamentos de óleo no mecanismo hidráulico do subsistema pitch de uma turbina eólica. Vazamentos de fluido hidráulico no sistema de passo têm efeito cascata, gerando problemas mais significativos em outras partes da turbina, como deterioração de pás e rolamentos por infiltração de óleo, perda de óleo e menos de tempo de produção da turbina. Os efeitos ambientais também devem ser considerados quando o óleo é expelido ao meio ambiente, com impactos sociais, políticos e biológicos negativos. Assim, a mitigação de vazamentos de óleo e falhas hidráulicas é fundamental para a longevidade e sustentabilidade das turbinas eólicas. Da literatura, três abordagens principais para detecção de falhas foram investigadas; baseados em dados, baseados em modelos e baseados em sensores. Métodos híbridos foram investigados para desenvolver um processo robusto e preciso. Um 'gêmeo digital' foi criado no Simulink/Simscape para provar a compreensão do sistema e uma base de validação para os métodos de detecção, os resultados confirmaram que a solução proposta representa o sistema com precisão usando dados reais de uma turbina. Dois métodos de detecção foram criados, baseado an estimação do volume e um outro baseado no fluxo de óleo. Ambos os algoritmos foram validados através de simulação usando dados de uma turbina com e sem fugas. O sensor de nível do tanque foi investigado com base no ruído elevado e esquemas de filtragem foram introduzidos.

Palavras-Chave: Turbina eólica, Sistema pitch, Sistema hidráulico, Algoritmo de Detecção de Vazamento, Gêmeo Digital

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Nomenclature

Latin symbols

A	Area [m^2]
B	Bulk modulus [Pa]
C_p	Specific heat at constant pressure [$\frac{\mathrm{J}}{\mathrm{kg}*\mathrm{K}}$]
C_v	Specific heat at constant volume [$\frac{\mathrm{J}}{\mathrm{kg}*\mathrm{K}}$]
D	Diameter [m]
h	Height [m]
K_p	Compression coefficient [-]
K_HP	Hagen-Poiseuille coefficient [-]
m	Mass [kg]
M	Molar mass [kg/mol]
P	Pressure [Pa]
q	Flowrate [m^3/s]
$\mathrm{R_u}$	Universal gas constant [$\frac{\mathrm{J}}{\mathrm{mol}*\mathrm{K}}$]
r_v	Ratio of entrapped air [-]
s_act	Actuator stroke length [m]
T	Temperature [K]
t	Time [s]
T_S	Simulation Length [s]
U	Internal Energy [J]
V	Volume [m^3]
W	Work [J]
x	Displacement [m]
Y	Pump displacement [m^3/rad]

Greek symbols

α	Thermal volume expansion coefficient [1/K]

η	Efficiency [-]
κ	Isentropic exponent [-]
$\hat{v}$	Molar specific volume [m^3/mol]
ν	Viscosity [m^2/s]
ρ	Density [m^3]
τ	Time constant [s]
ω	Angular velocity [rad/s]

Acronyms & Abbreviations

ANFIS	Adaptive Neuro-Fuzzy Inference Systems
ANN	Artifical Neural Network
BWR	Benedict-Webb-Rubin
CK	Correlated Kurtosis
COE	Cost of Energy
EKF	Extended Kalman Filter
FFT	Fast Fourier Transforms
HAWT	Horizontal Axis Wind Turbine
HHT	Hilbert-Huang Transform
HPU	Hydraulic Power Unit
LPV	Linear Parameter Varying
O&M	Operation and Maintenance
RMS	Root Mean Squared
SAEKF	State Augmented Extended Kalman Filter
SCADA	Supervisory Control And Data Acquisition
STFT	Short Time Fourier Transform
SVM	Support Vector Machine
UKF	Unscented Kalman Filter

Chapter 1

Introduction

1.1 Motivation

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]. To effectively mitigate these losses of production, fault detection methods are earnestly needed.

To focus further on the problem defined by the company, there are a number of important considerations regarding hydraulic oil leakages. The social impact on communities with close relations to wind parks is of great importance, ideally having a positive relationship where turbines are eagerly adopted. Oil leakages in large quantities can have undesirable environmental implications, where political intervention can occur. The financial impact of this issue relates to settlement payments, loss of future investment, loss of production time, and the repair cost of affected turbines. In addition to this, degradation of the turbine is possible when leakages occur. As it is easy to comprehend, this issue needs attention to be effectively addressed, and as oil leakages have a large impact, it is imperative to investigate this topic.

1.2 Objective

The objective of this project is 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.

The area of focus of this work is to develop a fault diagnosis method for the specific case of oil leakages in the pitch system of wind turbines. A fault diagnosis system is a procedure used to detect faults and determine the type, size, time, and location [6]. The company's turbines incorporate a type of sensor that could be used for estimating leakages. This spurred interest in the appropriate and effective use of the sensor to detect oil leakages, including other data and model-based methods. The company has previously developed an algorithm for detecting oil leakages, but it is currently not implemented due to limitations and shortcomings. Thus, improving this algorithm is worthwhile to inspect, in addition to creating new algorithms or models.

This master's thesis 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.

1.3 Methodologies

Literature was reviewed to understand standard practices, not only in the wind turbine industry but also in industries that operate hydraulic systems. The research was broken up into sections to aid in the organization of the large amount of information. A background of hydraulic systems was needed to fully understand the system at hand, which led to an overview of fault detection in wind turbines. Once more in-depth inspection was required, the three possible avenues of fault detection were individually analyzed. The order was based on complexity, in the order of simple detection using signal methods, model-based, and finally, data-driven.

To take a systematic approach, a model in Matlab/Simulink was created to simulate a basic hydraulic system, and additions were inscribed as the model demanded more complexity to represent the model fully. Then this basic model was expanded to include all the major components, mirroring the turbine. Once the model was confirmed to represent the real-world system accurately, the model outputs were extracted and used to validate the developed algorithms. The company provided actual turbine data for testing and validating.

The aforementioned algorithms developed included Algorithm A and Algorithm B as the main detection strategies. Before the project commenced, the company developed an algorithm, the basis for Algorithm A. During the project, Algorithm B was developed based on another strategy. These algorithms were tested using simulation and turbine data to prove the adaptation possibility. Variations of each were compared against key performance indicators and against the previously developed solution at the company. The influence of the tower movement was suspected of having considerable influence on a key sensor, and thus inspected. A filtering scheme for the sensor was developed, comparing multiple strategies to filter the raw signal to a clearer output.

1.4 Limitations

The testing campaign for this project was done solely with a specific turbine. Other turbines in the similar class were assumed to have highly similar operation, however, other turbines were not inspected as data was most widely available for this specific turbine. The number of data sets was also limited for testing the algorithms and models. The use of real turbine data in the project to test algorithms impeded the ability to confirm the algorithms, for the following reasons. In all of the non-leaking data sets, it was impossible to know for certain the turbine's system wasn't leaking. For the cases where the turbine was assumed to be leaking, it was unknown how much oil had been evacuated from the system. This was because data was coming from actual turbines in operation, and no tests were run to gather data for this specific campaign.

Matlab and Simulink were used for modeling, data processing, and calculation. Inherent assumptions or errors in models can create rifts in the similarity between the real-world system and the model. One such limitation comes from the fact that the Simscape model could only take in a certain density, viscosity, and bulk modulus for the full simulation. This is acceptable for short run times where these parameters can be averaged, but over longer runs when the oil properties change this can become a source of error in the model.

The turbine controller's abilities for the computation were discussed, but no analytical boundaries were given to asses if the developed models or algorithms would be suitable to run on an actual turbine. Thus, computation time was considered, but not the most critical factor. Additionally, the designs were based on current instrumentation, meaning if upgrades take place in the future, the models need to be validated once again.

1.5 Structure

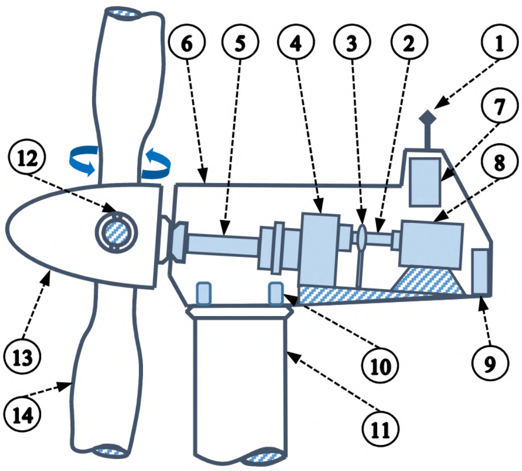
The thesis consists of 5 chapters, which are organized as follows:

- Chapter 2 presents findings from a thorough literature review across industries concerning fault detection and condition monitoring. The wind power industry is not the only industry that employs hydraulic systems, nor is it the only industry looking into fault detection. Through these findings, a 'state-of-the-art' is outlined.
- Chapter 3 describes in depth the developed Simulink models that gradually increase in complexity until reaching the full-scale system. The two main algorithms are analyzed and variations are described in detail, as well as additional work with the special sensor.
- Chapter 4 summarizes the findings and compares the results for the various fault detection methods, as well as recapping the results from the Simulink models.
- Chapter 5 outlines the findings and presents recommended future work.

Chapter 2

Background and State-of-the-art

Figure 2.1 outlines the standard 3-blade horizontal axis wind turbine (HAWT). HAWTs represent almost all commercially produced multi-megawatt wind turbines and are the state-of-the-art system developed by the company [7]. Figure 2.1 describes a wind turbine's main components, generalizing each subsystem's complexity but providing an overview. The development of turbines is considered a multidisciplinary field connecting several branches of engineering sciences [8]. The components of the pitch system (12) are housed in the hub and the nacelle, explained in detail in Chapter 2.1.



Number	Description
1	Anemometer and wind vane
2	High-speed shaft
3	Brake
4	Gearbox
5	Low-speed shaft
6	Nacelle
7	Control and power electronics
8	Generator
9	Cooling system
10	Yaw system
11	Tower
12	Pitch system
13	Rotor hub
14	Blades

Figure 2.1: Three-blade horizontal axis wind turbine overview. Source: [9].

As seen in Figure 2.2, there are different regions of wind speed where the control regime changes [10]. There are two regions where the operation is shut down, below cut-in speed (1) and above cut-out speed (3), using the pitch system in the second case to pitch the blades to feather. The shutdown is due to low energy density in the wind, and safety concerns, respectively. Between cut-in speed (1) and the rated wind speed (2), the turbine will try to extract the most possible power from the wind until the maximum power output is reached, or rated power [11]. From rated wind speed (2) until cut-out speed (3), the aforementioned pitch control strategy is implemented to regulate power production by reducing the aerodynamic rotor torque, which yields the desired rotor speed [8].

To achieve the climate goals outlined by world leaders, wind power aims to be a large part of the

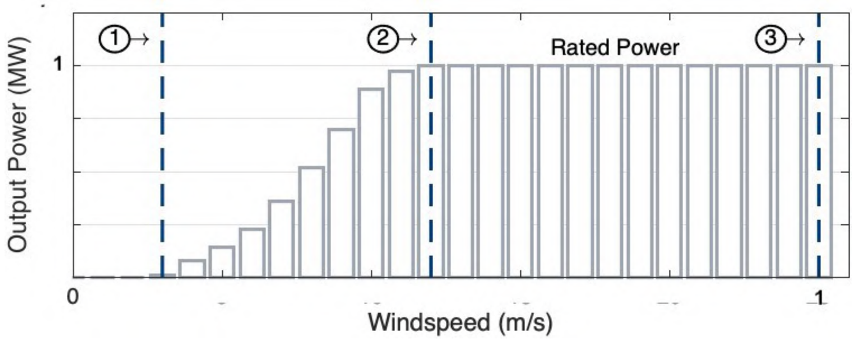


Figure 2.2: Generic power curve of turbine.

renewable energy generation mix of the future. Resources used in renewable energy generation, such as wind, are copiously available around the world [2]. Traditional energy resources today have growing problems; examples include a decrease in exploitable sources, an increase in prices, and the pollution of the environment on a global scale [12]. The number of offshore and onshore wind farms continues to increase due to wind turbines' high promotion and capability [13]. Figure 2.3 depicts the growth over the last decade, with the total installed capacity increasing four-fold, rightfully dubbed the world's fastest-growing renewable energy source [8]. This growth is not projected to slow down, with the net zero scenario quoting upwards of 3000 GW of installed wind by 2030 [14].

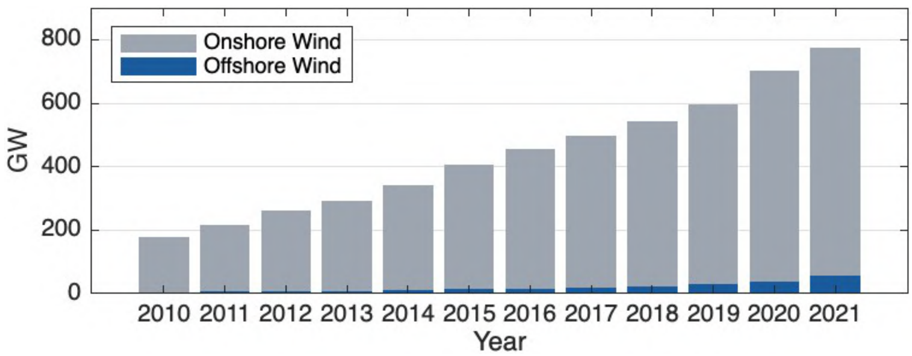


Figure 2.3: Capacity of global wind power 2010-2021. Source: [14].

The nature of wind turbines is to capture the energy from the wind, leading these machines to be sited in areas with high wind characteristics. Thus turbines are sometimes installed far from living zones [6]. O&M costs have been a major contributor to the total cost of wind farm projects and will continue to rise, especially in these remote locations, unless monitoring systems to raise aptly timed alarms are effectively utilized [15]. The nonlinear aerodynamics and the stochastic behavior of wind become a challenge to model and ensure reliable operation [16]. With respect to the frequency of faults, the pitch system can be responsible for as much as 20% of total downtime in wind turbines [17]. In an offshore turbine study of 35,000 down events, the pitch system was at fault for more than 20% of the total failures, making it the leading cause of wind turbine faults in the study [18]. Each turbine subsystem has failure modes, including power electronics, blades, electronic controls, brakes, yaw systems, generators, pitch control systems, etc [19]. Lost production factor implies downtime and therefore lost money due to no production when generation is possible; in some situations, reimbursement is demanded in the case of a high LPF.

For further understanding of the reliability needed in wind turbines, consider a motor vehicle with a design life of 150,000 km, where the system always has an operator present and is frequently inspected and maintained. If this well-understood system is operated continuously, the system's design life would total four months [2]. On the other hand, wind turbines have a lifetime of 20 years and are expected to be in operation for a large part of that time, almost entirely unattended. Thus, large modern turbines are prone to unexpected malfunctions or faults, in large part due to their system complexity and solitary operation over many years [8]. 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, 9].

2.1 Pitch Actuation Hydraulic System

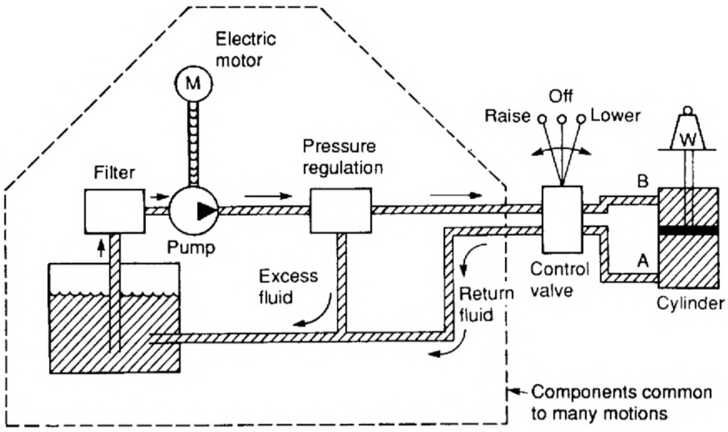


Figure 2.4: Standard hydraulic system overview. Source: [20].

Figure 2.4 depicts a basic outline of the critical components of hydraulic schemes, as understanding the basic principles of each is essential [20]. An electric motor powers a pump, and the pressure regulator ensures suitable and safe pressure in the lines going to the control valve and cylinder. Hydraulic oil is mainly held in the reservoir and is very sensitive to contaminates, which is why a filter in the fluid loop exists. The control valve demands a logical input to operate the system and can perform different actions based on the type of valve. All excess fluid is returned to the tank for future use.

Hydraulic systems are not the only option when considering the actuation of blades in the hub. Electric motor-driven systems achieve the same function with advantages such as larger bandwidth and more rapid actuation but suffer from lower stiffness, more considerable backlash, and faster wear [15]. Conversely, hydraulic systems are advantageous in little backlash, significant stiffness, and higher reliability [15]. But hydraulics can produce noise and incur high-pressure spikes when loads accelerate or decelerate, which can cause wear in the piping [20]. The basis for hydraulic systems is described by the equation $P_{\text{hydraulic}} = F/A_{\text{p}}$, where the pressure in the system is equal to the applied force over the surface area [21].

In a hydraulic system various faults can occur; such as sensor malfunctions, lubrication contamination, and leakages [4]. There are two kinds of leakage in this domain; internal leakage and external leakage

[15]. External leakage occurs when oil escapes from components and connecting hoses, creating a sluggish response and leading to temperature elevation, loss of efficiency, and increased power usage [20]. The system dynamics differ in the event of this fault, seeing that the main pressure drops, which can change the system response [22]. Internal leakage arises when oil escapes past piston seals, showing similar symptoms to external leakages, but is less severe as there is no evacuation of oil which can be costly and dangerous [20]. Leakages are notably found in the pitch cylinders. However, due to powerful non-linearities concerning hydraulic systems and uncertainties in key parameters, fault detection is challenging to implement in practice [23]. External leakages are a serious problem, and this work will focus on this problem specifically.

As stated previously, the blade pitch system is a subsystem that historically accounts for a substantial part of wind turbines' total failures and downtime [24]. Wind turbines operate under highly variable stochastic loads, and the size of modern turbines creates intrinsic reliability issues [4]. The downtime due to the pitch system even outnumbers generator assemblies, frequency converters, and gearboxes for variable pitch turbines [7]. The pitch system is essential for reducing loads, breaking the rotor aerodynamically, and curtailing power production when desired [15]. Stated simply, large turbines rely on pitch systems for start-up, shutdowns, and power control [25]. This is done by rotating each blade individually to adjust the angle of attack, or how the blade's airfoil meets the direction of the incoming wind [26]. This means the active decision can be made in the control scheme whether to pitch the blades to maximize or minimize lift.

The hydraulic reservoir, or tank, is an important component for reliable operation [20]. The tank's volume will vary during operation according to the state of the actuators and accumulators and the temperature of the fluid. The minimum oil level will occur at low temperatures, high-pressure accumulation, and when all cylinders are extended. Inversely, the maximum oil level occurs when all cylinders are retracted, and the accumulators store low-pressure fluid with high temperatures in the system. The hydraulic fluid needs adequate sealing and lubrication properties in addition to power transmission. A fluid with low viscosity flows easily and wastes little energy but increases leakage losses. In contrast, viscous fluids incur pressure and energy losses but reduce the likelihood of a leak [20].

2.2 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 sections. Figure 2.5 depicts the trend of the number of publications explicitly based on wind turbine fault detection. The data was collected using the platform Dimensions.ai [27]; considering the search keywords and the impossibility of finding every work, the total number is undoubtedly much higher. Nonetheless, Figure 2.5 shows a growth in this area in the last 20 years. The year 2023 is included but only contains the number of publications at the time of the search.

For ease of reference, Table 2.1 was compiled to illustrate the publications utilized in the learning and research phase. The papers collected are shown based on publication date to depict the influx of

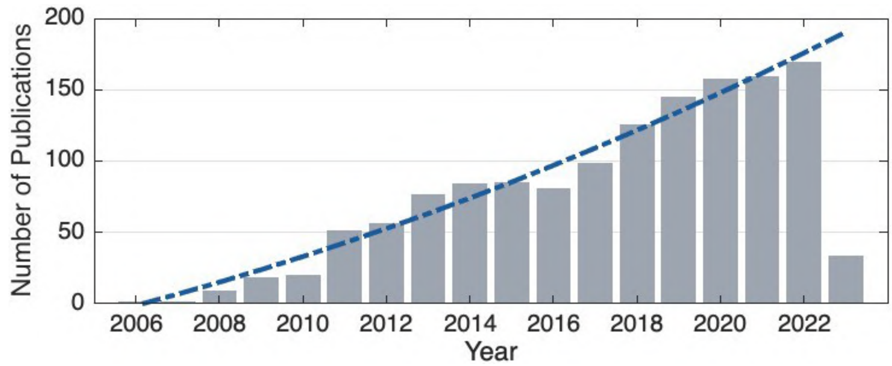


Figure 2.5: Publications on wind turbine fault detection since 2005. Source: [27].

research in recent years, as was confirmed in Figure 2.5. In the last decade, there has been a push towards detection methods based on model and data approaches, as well as works dedicated solely to collecting recent findings and giving an overview of the state of the art. The knowledge gained from these reports was used in conjunction with information provided by the company to fully outline the state of the art for each detection class, as follows.

Table 2.1: Survey of publications on fault detection by approach.

Year	General	Sensor-based	Model-based	Data-based
Pre 2000	[28]	–	[29]	–
2000 – 2010	[2, 19]	[30–32]	[33]	–
2010 – 2020	[7, 8, 12, 34]	[35–39]	[6, 15–18, 22, 23, 37, 40–46]	[13, 47–57]
Post 2020	[1, 4]	[9, 25, 58]	[9, 58, 59]	[26, 60, 61]

It is important to understand the difference between faults and failures. When an unexpected action occurs and the deviation is outside of the assumed allowable system parameters or structure, it is considered a fault [1]. Conversely, if the function of the system is entirely incomplete or deficient and it is not able to fulfill its duties it is considered a failure [28]. This study is focused on leakage faults, as failures are simple to detect when the system ceases operation. Thus, faults can be more subtle to detect and require further work.

There is an ever-increasing need for safe and reliable industrial systems when considering irregularities with more expensive and intensive processes [37]. In literature, definitions have been outlined to differentiate between fault detection, fault isolation, and fault identification. Fault detection is solely to make a binary decision on the state of the system, whether there is a fault or not. Fault isolation is used to locate the fault, and fault identification determines the nature or size of the fault [6]. Of course, installing a large number of sensors and measurement devices to create redundancy and obtain as much data as possible allows easier detection of a fault, but this is not always realistic with respect to economic cost or space and weight [1, 37]. In the end, early detection and location of faults are imperative to preserve maximized availability and minimized maintenance [4]. Additionally, it is crucial for the same reasons to be able to monitor the condition of the turbine in real time [9].

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' [50, 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 [43]. 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].

Data is reported from the turbine using the standard SCADA (supervisory control and data acquisition) benchmark system. Generally, the recorded data is sampled at 1 Hz and converted to 10-minute averages, as well as minimum, maximum, and standard deviation over the 10 minutes [52]. This is favorable as there is less data to transfer and store long-term in databases. A common approach today is to count the number of alarms reported by the SCADA system, if the total is lower than a predefined threshold, the situation is considered safe [48].

Historically, fault finding in hydraulics has been a manual process. A complete knowledge of the system is required, both hydraulic and electrical, as it involves visual inspection and checking the state of electrical outputs to solenoids and limit-switch inputs [20]. However, as wind turbines are essentially remote power plants that are unmanned, this is not always possible [34]. Therefore, the outline of potential paths is described in Figure 2.6.

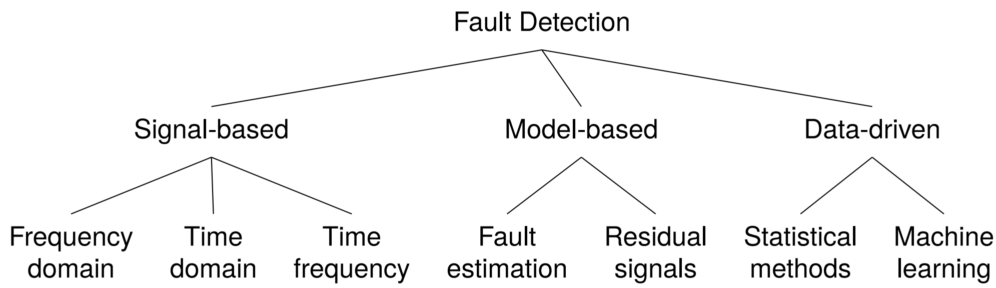


Figure 2.6: Classification tree of fault detection.

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.

All promising methods were investigated until deemed otherwise. However, in 2022 it was reported approaches using artificial neural networks (ANN), adaptive neuro-fuzzy inference systems (ANFIS), and nonlinear state estimation have shown promising results [9]. 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 [12, 33].

2.2.1 Sensor-Based Approach

From a report in 2009, [2], only slightly more than one decade ago, time and frequency signal analysis without explicit mathematical models were the state of the art in supervisory control. This was effective as there was no need for redundant sensors or complex models, but due to disturbances and noise in time series data inaccuracies were imposed [4]. The approach relies on the signals available from sensors in the system, which can be electrical signals, temperature, and vibrational, among many others [4]. The possibility to detect faults comes from the idea of feature or signature extraction. Signals can quite often be noisy and complex to directly understand, so implementing a frequency analysis technique or statistical method can allow feature unpacking and thus a greater understanding of the situation at hand [35].

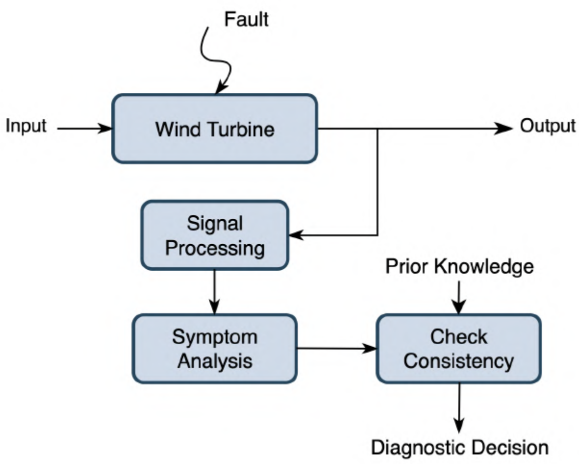


Figure 2.7: Flowchart of signal-based detection. Adapted from: [1].

Sensor-based approaches, also known as signal based, have a general outline as found in Figure 2.7. The sensor output signal is first processed to extract features and effectively manage inherent noise in the system. When a deviation from normal operation is found the symptom of the system is analyzed and checked with prior knowledge, thereby making it possible to determine if a fault occurred.

As discussed and seen in Figure 2.6, the typical classification of sensor-based detection is time domain, frequency domain, and time-frequency techniques. The time domain is the elementary method used when understanding a simple signal. This approach uses linear time parameters such as peak value, root mean square, and kurtosis to prove the health level [1]. Transformation to the frequency domain allows feature extraction from signals that have complex characteristics in the time domain. Such methods include spectrum analysis techniques, such as fast Fourier transforms (FFT) [1]. Finally, if the signal oscillates and varies over time, to reveal time-variant features in non-stationary signals time-frequency analysis can be used, such as wavelet transforms or Hilbert transform [37].

As mentioned previously, hardware redundancy is not always feasible. However, using the hardware and sensors that are installed can be used for feature extraction with a host of techniques that can lead to a robust diagnostic decision [37]. Implementation of these techniques can be convenient as there is no associated model needed, but can be sensitive to external disturbances and load changes [1].

2.2.2 Model-Based Concept

Model-based detection adds another layer of complexity but has the potential to detect faults with a greater breadth and accuracy. This classification uses mathematical models in order to estimate the relationships between inputs and outputs of the system, which can be powerful in real-time monitoring cases [1]. Literature is rife with recent publications for general hydraulic fault detection and specifically pitch system detection with respect to this method. Most of these publications only use standard sensors, along with either a dynamic model to continuously run in parallel or a comparison algorithm [4]. For cohesion, the two categories utilized in this text were described in Figure 2.6 and hold the most common model-based schemes; fault estimation techniques and residual signal strategies [4].

Figure 2.8 depicts standard architecture, with two paths to a diagnostic decision. Contrary to sensor-based, model-based makes use of the output signal and the input signal. Highlighted with the solid line is the residual estimation technique, where a model estimates the healthy output parameters and compares that to the actual output signals. If the difference is large, a large residual remains which leads to a possible fault conclusion, versus fault-free operation with a residual of zero. Highlighted with a dotted line is another possible path of using the input and output to estimate internal parameters, which can again be used for a diagnostic decision.

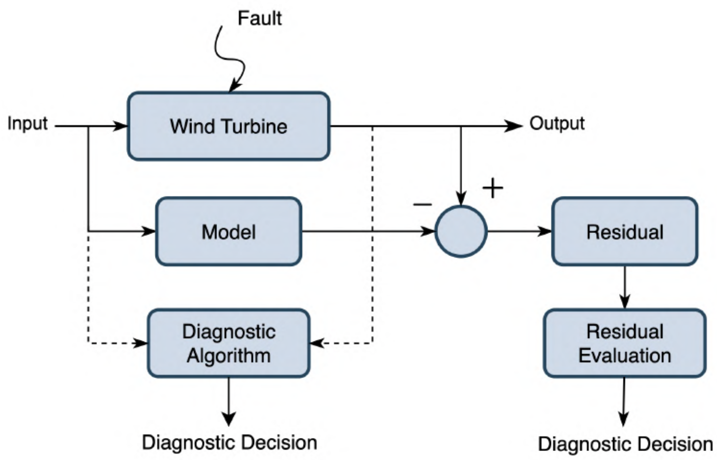


Figure 2.8: Flowchart of model based detection. Adapted from: [1].

To focus more specifically on residual signals, which is a simple calculation once the output valves have been estimated, trend analysis of the residual can be used to detect changing characteristics of the system [2]. Although this appears to be a simple process, decoupling the residual from noise and model uncertainties can be a very challenging problem [4]. The typical steps after calculation of the residual, as seen in the architecture of Figure 2.8, is first to evaluate the residuals that react to a fault by comparison to a predefined threshold [4]. Then decision making includes deciding whether the changes in residual values truly represent a fault, and which elements are still healthy.

Fault estimation is a general term for techniques or algorithms that can sense and estimate the magnitude of a fault by the continuous monitoring of model parameters using input and output data [2]. This can be achieved by using a number of approaches, such as but not limited to; Kalman filters, state observers, set membership approaches, or particle filters [4].

The key factors for the effective and accurate implementation of model-based practices include enhancing the robustness of the model in the presence of model errors and external noise, as well as sensitivity to the occurring faults [1]. Developing an accurate reference model of the healthy operation is crucial if the system hopes to estimate the residual precisely [23]. As the development of the models ensues offline and is used onboard the turbines control system these model types have excellent real-time performance [1]. Today, observer methods, including Kalman filters, are the predominant model-based technique for detecting faults [4, 44].

In the true application to real systems with realistic operational conditions there are problems with the schemes discussed. In the case of residual calculation, more detail in the model is required to result in accurate values to compare, as well as a drifting problem becoming apparent over time [25]. This leads to the statement in 2022 that the complexity of realistic hydraulic pitch systems with associated operating conditions and uncertainties has managed to stay ahead of any attempts to identify subtle failures consistently, but in the future, nearly perfect digital twins may be possible [25].

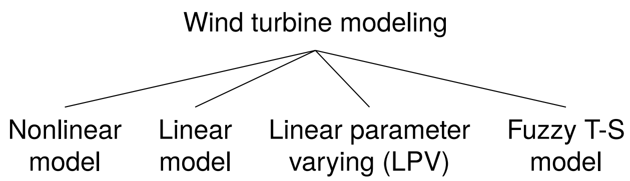


Figure 2.9: Modeling techniques for model-based detection [12].

A report from 2019 has defined the different basis for the modeling of the turbine or subsystem and is referenced for the following discussion [12]. The four types of modeling outlined are found in Figure 2.9; linear, nonlinear, linear parameter varying, and fuzzy modeling. Wind turbines have very nonlinear behavior, thus for a linear model, as this is usually more simple and less computationally heavy, the nonlinear system is linearized with minimized error. Nonlinear models ideally depict the system in a way that is closer to reality but can have more complexity as normally hydraulic pitch actuators are represented as a second-order system [12]. LPV modeling uses multiple linearized models at different operation points, creating a feasible dynamic descriptor set of the turbine. Finally, fuzzy T-S observers estimate the nonlinear behavior and can reduce the uncertainty of the observer performance by using multiple linearized models and fuzzy if-then rules defined by expert knowledge.

2.2.3 Data-Based Method

Data-driven approaches, compared to model and sensor-based methods, can deliver higher diagnostic accuracy, but only if the quality of the data available is sufficient and is from optimal sensor locations [4]. Large amounts of historical data typically come from the SCADA system, which ideally includes full fault scenarios for the approach to learn from. It is also possible for the algorithms to learn from a priori knowledge, or knowledge that can be manually input for specific cases when fault data is not available [4]. Another benefit of this approach is that mathematical models are not necessary, lowering the manual design complexity and eliminating the need to approximate the complex nonlinear system using simulations and theoretical equations [1]. Two classifications of data-driven designs can be derived based on the methods under inspection, also known as knowledge-based designs; that being statistical and machine learning methods, as returned once again from Figure 2.6 [9]. The goal is for this method to search for an implicit relationship among the variables, that would otherwise be inconceivable to generate manually [1].

The general flow of information is included in Figure 2.10. As is similar to the previous two cases, input and output data from the turbine is compared to a 'knowledge base' that has been tuned to the specific system, in which it is possible to detect a fault. Historical data and a priori knowledge are used to train the model or learn statistically from the information given, which builds a knowledge base that is useful in monitoring the system in question.

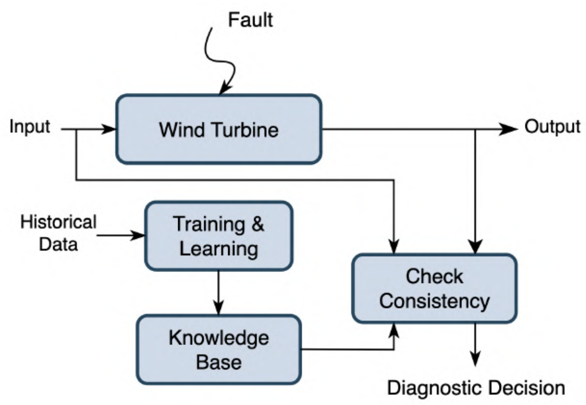


Figure 2.10: Flowchart of data based detection. Adapted from: [1].

Parametric methods have a fixed number of parameters that relate input and output variables, whereas non-parametric methods are able to adapt to the complexity of the data and have a changing number of parameters [62]. Generally, statistical methods are considered parametric methods, and machine learning is considered non-parametric. These methods can be used to analyze data and make inferences based on trends, and is even able to learn patterns and make predictions without explicit directives on how. Many approaches have been appearing recently in the research field, and machine learning is becoming a popular culture hot topic.

Naturally, the previously described processes have further issues that are inherent in the process itself. Data-driven approaches suffer from the inability to determine the origin of a fault, nor can they explain the reason why the fault occurred [40]. Furthermore, if there are flaws in the data used for analysis or training, erratic inexplicable behavior may follow when unseen or fuzzy input conditions are taken in Ref. [48]. SCADA data, as it has a low sampling rate, has been known to have low accuracy and challenges with respect to fault diagnosis [40]. But nonetheless, this is becoming a very popular method for fault detection where applicable and fuzzy logic, neural networks, and adaptive neuro-fuzzy inference systems have been recommended for use in pitch system leakage detection [4].

2.2.4 Hybrid Detection

Hybrid detection is a blend of multiple approaches to obtain a better prognosis [1]. This can be an interesting optimization problem with the conglomerated hybrid method of detection. Of course, this can be a combination of multiple methods of the same domain, per se data-based with another data-based. Or hybrid detection could include different approaches, for example, combining a signal unpacking approach with a data-based method for better results. The list of combinations is endless, nonetheless, this section is dedicated to the possibilities to combine the best parts of inspected detection methods.

As has been discussed, using model-based digital twins to represent a system is currently very difficult. However, strategies to increase the performance of digital twins, which is a digital model designed to mimic a physical system, is possible [63]. An example of this is illustrated in Figure 2.11, which utilizes a mathematical model, then with a data set and model results, can train a neural network to adjust the model outputs to more closely represent reality. This hybrid digital twin theory can become very powerful if a large amount of data is available, and the model can already closely model the system. A large added benefit from this strategy is derived from the tuning of the mathematical model, if the data available can be used in place of manual tuning, this can be widely implemented across different systems with ease.

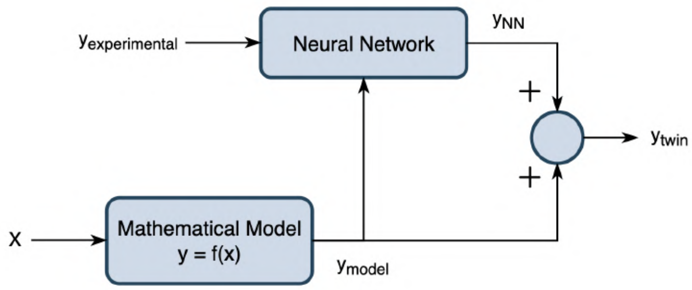


Figure 2.11: Architecture of a digital twin. Adapted from: [63].

Another possible hybrid combination could be using observers, such as Kalman filters, in conjunction with a mathematical model or a data-based approach. A mathematical model that has specific areas that are weak points, could utilize a Kalman filter to reduce error. Other approaches such as the combination of Kalman filters and support vector machine, or neural networks and fuzzy inference systems, among many others, have been developed in literature [12, 41]. It is possible to leverage the strength of various fault diagnosis methods, combining two or more diagnosis methods as seen in a variety of engineering applications, to boost the results of the fault diagnosis system [49].

Chapter 3

Detection Method Proposal

3.1 Simulink Modeling

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. Simscape is a modeling feature in the Simulink environment that allows for physics-based modeling, and it can be powerful in modeling hydraulic-based systems [64].

3.1.1 Basic Simulink Model

To take a pragmatic approach, firstly a simplified model was created using Simulink that included only the basic elements; a system fluid tank, a pump and motor, a proportional valve, a relief valve, a hydraulic cylinder, an accumulator, and a simulated load [15]. Simplified models were tested with this software to determine feasibility and confirm methodologies before adding complexity and adaptation to the full models. Each block used in the basic model was recreated as a Matlab function file to gain a deeper understanding of the logic and to do preliminary flow estimation across key boundaries in the system. However, these methodologies of block reconstruction used much more data than is available in the sensor catalog in the turbine system.

For a more in-depth explanation of the basic Simulink model, refer to Section C.2 in Appendix C.

3.1.2 Full Simulink Model

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. Matching the simulation outputs to the real turbine sensors' outputs meant the simulation model could be confirmed to accurately represent the system. However, the model for the specific turbine needed to be tuned. Of course, running a model that is more demanding computationally than is allowable on the turbine computer system is not suitable. That being said, 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.

For a description of the full Simulink model created, refer to Seciton C.3 in Appendix C.

Data Extraction from Simulink Model

The ability for the model to generate fault scenario data to be used as test cases for the algorithms was discussed, but as real turbine data was not available to test the model accuracy under a fault event, this idea did not progress. Instead, the model outputs tested under non-fault events served as validation data to confirm the developed algorithms with non-noisy sensor inputs.

Upon verification of the Simulink model, the most critical output to compare was the special sensor between the simulated case and the actual case. As it had been previously determined that the measured outputs were very volatile, and had a fluctuation that correlated to a physical change that was not possible given the maximum equipment ability, the calculated sensor value could be used as a guide to filter the measured sensor value.

3.1.3 Simulink Model Reduction

Following the confirmation of the tuned Simulink model, which used minimal sensor input from real data, the model was supplemented with all applicable turbine sensor signals to try and reduce the simulation complexity and time. This study aimed to inspect if the model could run accurately and efficiently enough to be used as a detection tool. In this case, if the simulation could be implemented, many parts of the system could be compared to reality. Localized detection would be possible for not only oil leakages but also faulty valves and actuators amongst other important components.

Refer to Section C.4 in Appendix C for a description of the reduction. Multiple versions of the reduction model were created, henceforth listed as Reduction 1-3, each having its own advantages and disadvantages.

3.2 Special Sensor A

Part of the inspiration for this master's thesis was the inclusion of a special sensor on the newer turbines, henceforth known as variable A. However, as will be seen in Chapter 4, the clarity of outputs from this sensor is an important topic of discussion. For a description of the use and location of the sensor in question, refer to Section C.5 in Appendix C.

Sensor Filtering

The sensor is the critical signal used to estimate a key variable for the algorithms. However, the output 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, and combinations of filters were also applied to advance the results.

Sensor Noise Origin

The volatile activity of the sensor seemed to come from more than just sensor noise. For this reason, another variable, variable B, which had a possible correlation was inspected. The FFT was computed for variable B and was compared to the calculated FFT of the variable A raw signal. This analysis aimed to answer whether variable B, specifically at the frequencies with the highest associated amplitudes, correlated with the frequencies seen in the raw signal of variable A.

3.3 Estimation Algorithms

3.3.1 Algorithm A

The base case to try and improve off of was the original Alrogithm A developed by internals in the company previously. Then, improvements were made and two new algorithms were created, listed as Algorithm A1 and Algorithm A2. The goal and specifications of these algorithms can be found in Section C.6 in Appendix C.

3.3.2 Algorithm B

A new type of algorithm, following a different theory than that of the company previously was created and titled Algorithm B. The outline and description of this algorithm can be seen in Section C.8 in Appendix C.

3.4 Input data

The input data for the Simulink models and algorithms were sourced by a team member. The data sets for the Simulink models were taken from the specific turbine in question. Multiple data sets were made available to be used in the Simulink model.

For the algorithms, data with leaks and without leaks were available. However, the maximum window of time that was possible due to the size of the data files was 24 hours. In reality, this is not how the operation would commence. When installed on an actual turbine, the algorithm could be run over many months. Nonetheless, the given 24-hour data was tested in the algorithms, along with data from the Simulink model, with results compiled in Chapter 4.

Chapter 4

Results and Discussion

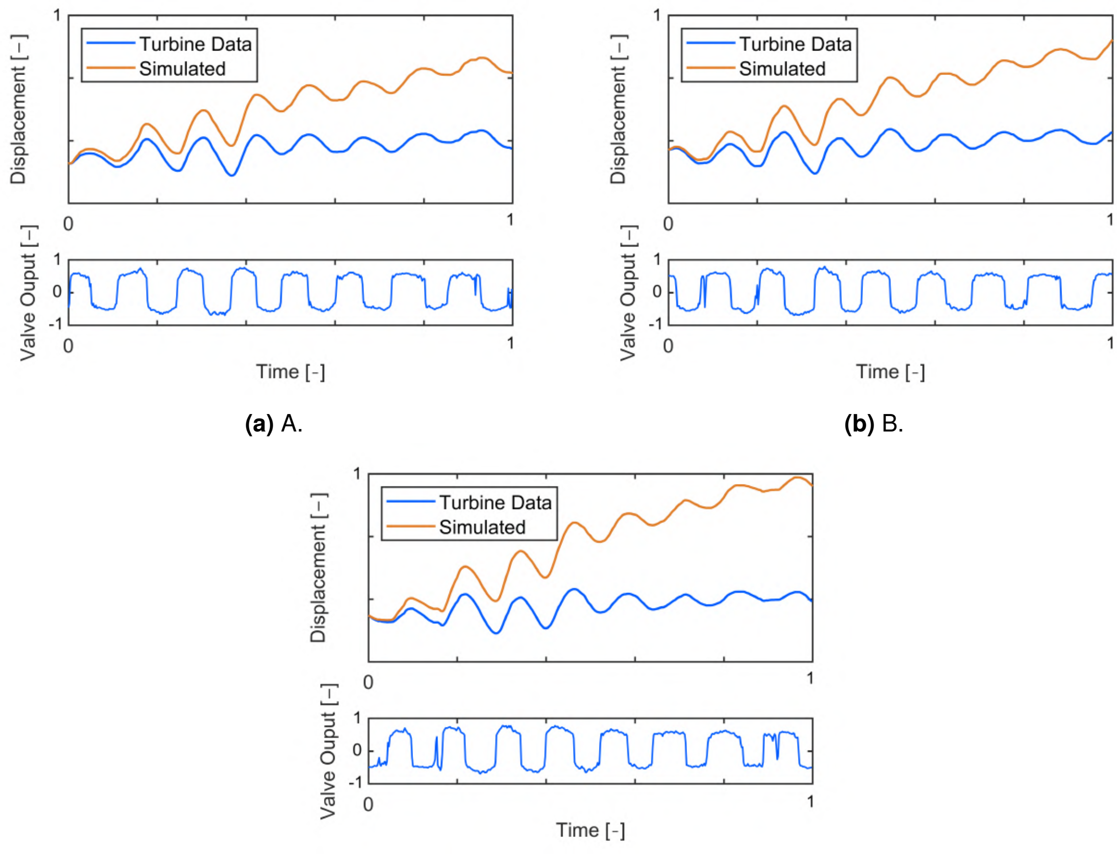
The results section aims to discuss the major findings and present the developments from the discussion in the previous chapter. This section serves as a platform to present the outcomes of the Simulink simulations and provides a comprehensive understanding of the findings obtained from the research process. Additionally, the discoveries from the filtering schemes and developed leakage detection algorithms are presented and examined below.

4.1 Simulink Results

The Simulink models were created with the goal of creating a model to match the operation of the actual turbine. The critical components are the key indicators to compare the simulation to the turbine data, which are listed in Section C.9 in Appendix C. The full-scale model, when tuned, was able to function particularly close to turbine data.

Untuned Simulink Model

The untuned Simulink model results are an important starting point for understanding how critical the tuning of a specific component in the model is. This can be seen in Figure 4.1, where the simulated values deviate over the simulation time. The data set chosen for this study and the subsequent tuning of the valves was under high-pitch actuation.

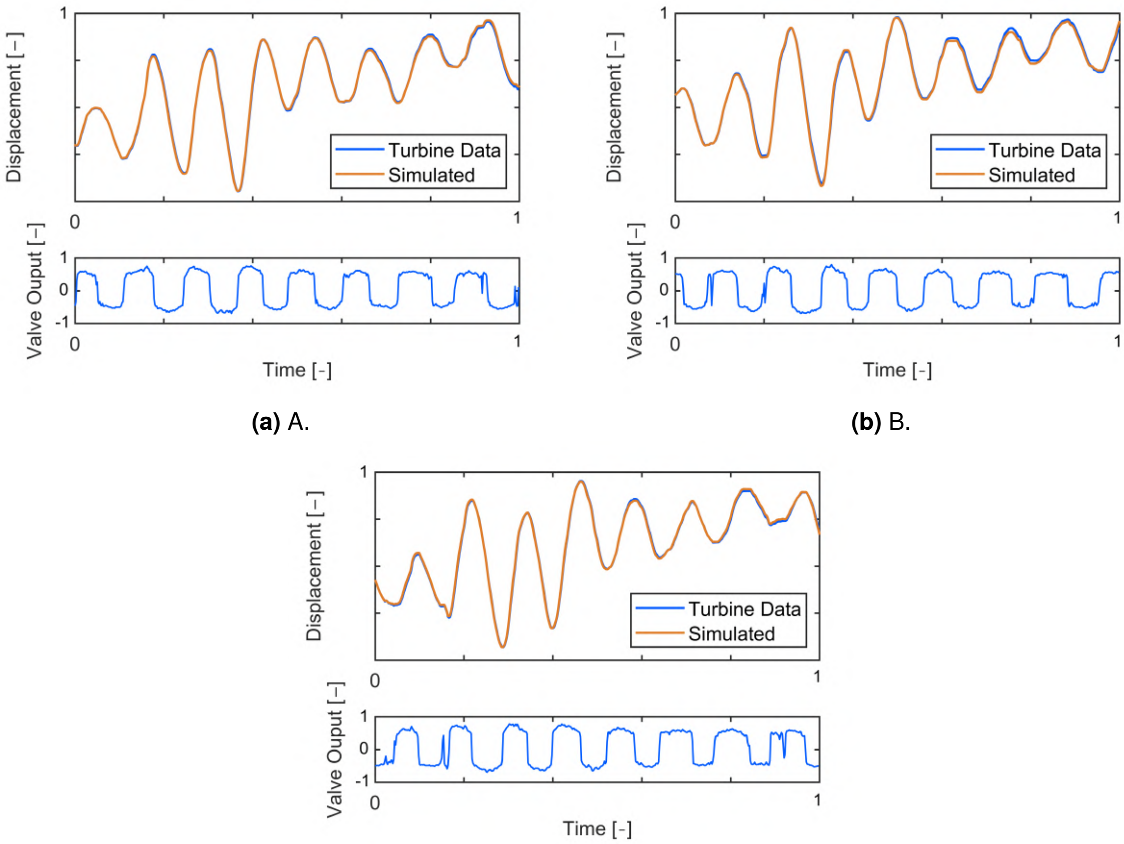


(a) A. **(b)** B. **(c)** C.

Figure 4.1: Untuned comparison of key variables.

Tuned Simulink model

The model was re-run using the same data set as the initial simulation, but with the tuned key elements. Figure 4.2 is an important figure depicting the comparison between the real turbine variable and the simulated variable. The simulation matches the turbine's raw data nearly perfectly in all plots. Figure 4.2 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 needed to be tested under more cases to prove its capability.



(a) A.

(b) B.

(c) C.

Figure 4.2: Tuned comparison of key variables.

1st Confirmation Simulation

To confirm the Simulink model closely resembled the actual turbine, the model was run under two additional data sets. As the model was tuned under the previous conditions, the model was not expected to operate as precisely as the tuned case. The two new data sets were taken from other periods of time. As such, nothing was changed in the model excluding the input data.

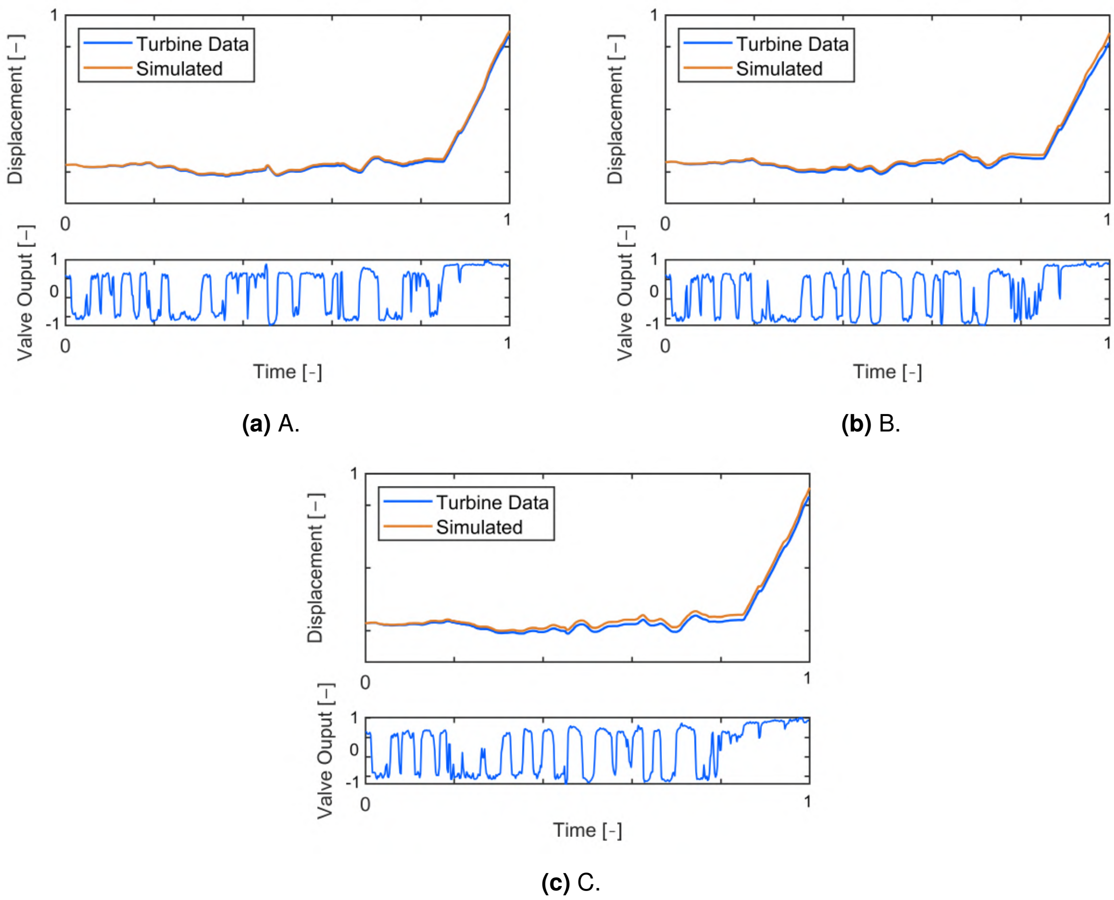
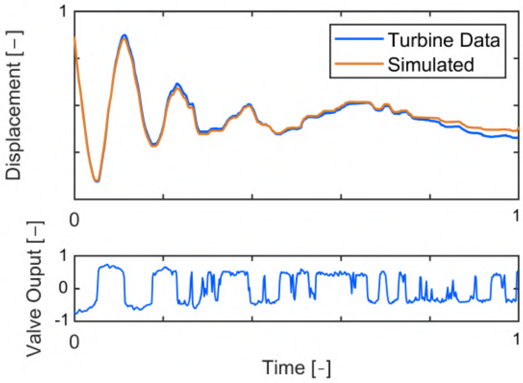


Figure 4.3: Tuned comparison of key variables - 1st confirmation data set.

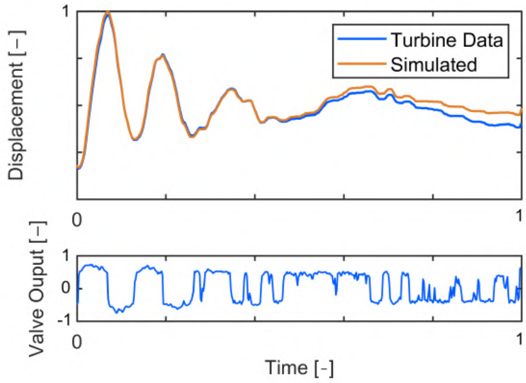
Figure 4.3 depicts the critical variables for each plot, similar to previous plots seen. This data set is during lower movement. However, towards the end of the set, a command was sent that drove the plots upwards. The simulation values closely match the turbine data in all three plots both in the region of low movement and high movement.

2nd Confirmation Simulation

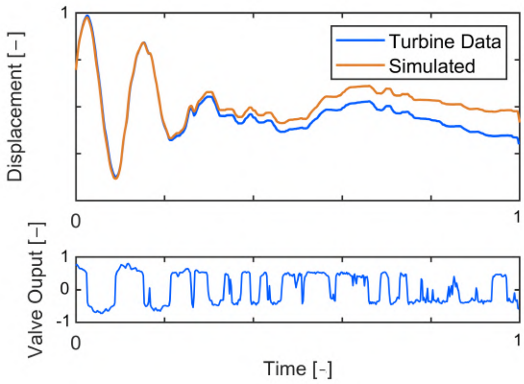
The second simulation run to confirm the Simulink model was taken during a time of heavy movement to little movement. The reason for this selection was to test the robustness of the system. In the heavy movement section, there was more likelihood for the simulation to deviate from the turbine data. Then, this deviation would likely hold for the duration of the simulation. But in fact, what is seen in Figure 4.4 is that of extremely similar movement during the heavy movement phase of the simulation, but deviation in the lower movement phase. This divergence can especially be seen in Figure 4.4c, which leads to the conclusion that the tuning of the system was not perfect for all possible inputs. The outcome of the 2nd confirmation study meant the data from the Simulink model could be used in the latter part of the study, utilizing the sensor outputs to test the developed algorithms, assuming no noise on the sensor values.



(a) A.



(b) B.



(c) C.

Figure 4.4: Tuned comparison of key variables - 2nd confirmation data set.

Special Sensor A Comparison

From the original tuned data set, the simulated sensor A output was extracted from the model and compared to the raw signal seen from the turbine. As seen in Figure 4.5, the same signal, does not match. Obviously, there is a high level of noise in the real turbine signal, which will be discussed in the next section. But to preface, sensor A is a critical signal for the developed algorithms. This variation seen dramatically reduces the ability of the detection algorithms to effectively deduce if a leak is occurring.

4.2 Simulink Reduction Results

The full-scale Simulink model was confirmed in its ability to model the real-life turbine. Subsequently, as there is much knowledge to gain from an accurate model, the reduction of complexity of the model commenced as it was very computationally expensive. The reduction needed to still ensure accurate estimation, but also reduce complexity and simulation time, to potentially be a detection method of its own. The results from the three final reduction versions will be presented. All the versions removed different parts of the model to test various avenues, and are described in detail in Section C.10 in Appendix C. Figure 4.6 shows the critical aspect of this simulation, the displacement of key variables. The reduction model does not boast perfect results, but does an adequate job keeping the system deviation to a minimum.

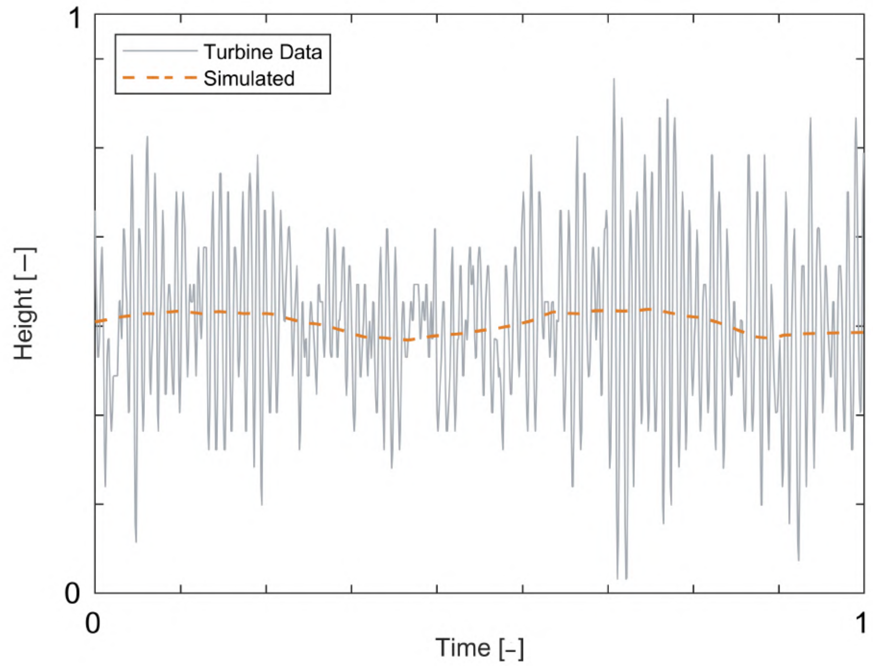
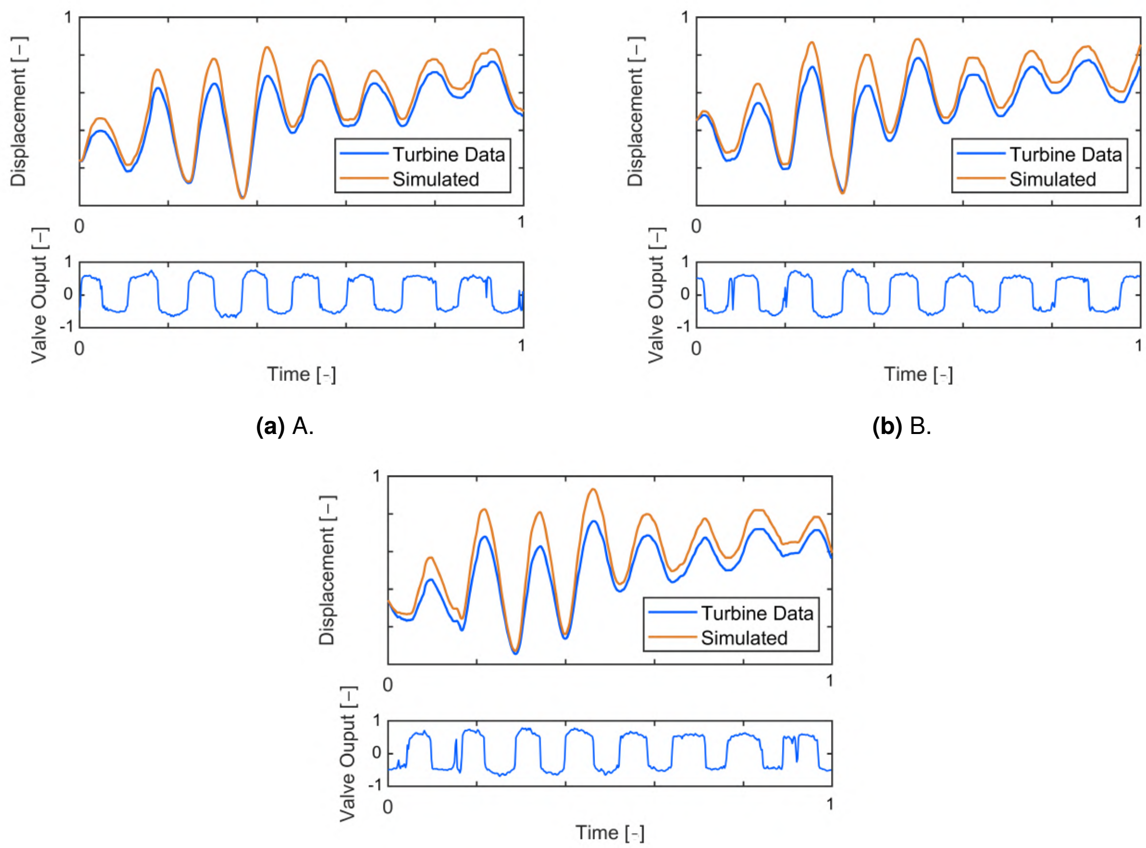


Figure 4.5: Sensor A of measured and simulated.



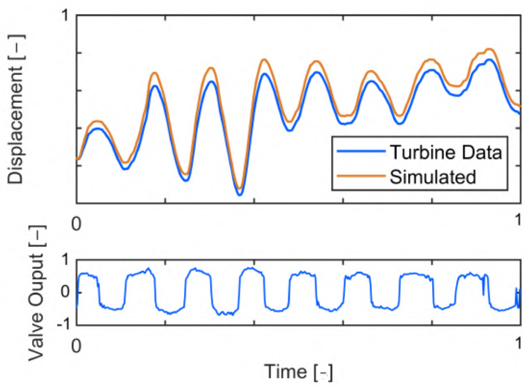
(a) A.

(b) B.

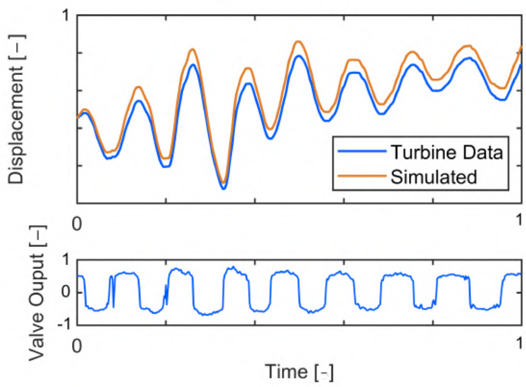
(c) C.

Figure 4.6: Displacement comparison - reduction model 1.

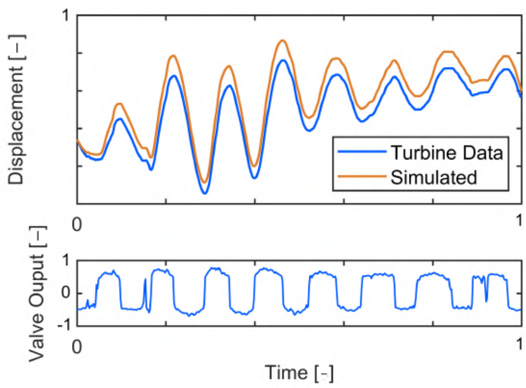
The second reduction model goes one step further in the removal process than the first reduction model. The movement in the second reduction model, seen in Figure 4.7, is very similar to the previous reduction model. The specifics of the results can be found in Section C.10 in Appendix C.



(a) A.



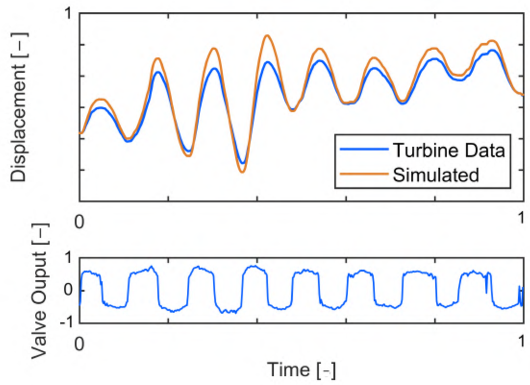
(b) B.



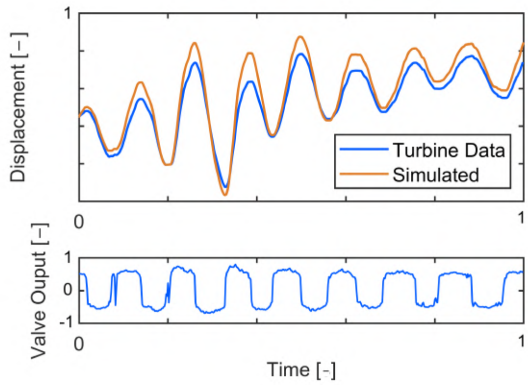
(c) C.

Figure 4.7: Displacement comparison - reduction model 2.

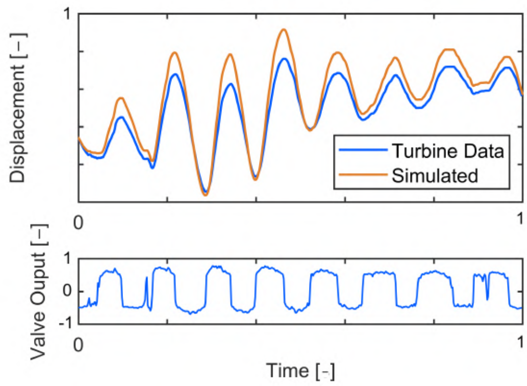
The final version of the reduction built off of the second reduction model, but kept some aspects the same as the first reduction model. The simulated movement, seen in Figure 4.8 saw some overshoot during the heavier movement cases, but overall saw similar results to the previous cases.



(a) A.



(b) B.



(c) C.

Figure 4.8: Displacement comparison - reduction model 3.

Table 4.1 illustrates the simulation time for each model, given the same input data set. The original tuned model can be seen to have the highest simulation time, with a low ratio of real-time to CPU time. The first reduction model readily improved the simulation time, cutting the total time by a factor of three. The further removal of components in the second reduction model decreased the simulation time once again. It is worth noting this was the only model able to run the simulation faster than the simulation time itself. The third reduction model, with the inclusion of the extra aspects, saw an increase in simulation time, but was still more than twice as fast as the original model.

Table 4.1: Simulation time comparison - reduction models.

Simulation name	**Computation Time** (T_C) [-]	**Ratio** (T_S)/(T_C) [-]
Original Model	1	0.269
Reduction Model 1	0.34	0.791
Reduction Model 2	0.25	1.057
Reduction Model 3	0.44	0.608

Reducing the models also meant taking out parts of the model that help to paint the full picture of the turbine operation. In essence, during the reduction there has to be a focus, and what is not the focus is what is removed from the model and replaced with less complex submodels or components. For a full description of the Simulink models and further inspection of results, refer to Section C.9 in Appendix C.

4.3 Special Sensor A

Sensor A is a critical component in Algorithm A, thus an accurate estimation of sensor A is needed. On the turbines, there is no redundancy to measure sensor A. Therefore, the raw signal demanded post-processing to be used adequately and effectively in the algorithms. For a more detailed explanation, refer to Section C.11 in Appendix C.

4.3.1 Sensor Noise Origin

Theories were inspected to explain the results seen in Figure 4.5, as it became apparent that the sensor outputs exuded a high noise level. The sensor, manufactured by an undisclosed manufacturer, has a tight tolerance. As seen in Figure 4.5, the variance of the measurement around the expected value is much higher than the specified tolerance. Therefore, further inspection ensued with regard to the frequency of oscillation of variable B, expecting there to be a link between variable A and variable B. A Fast Fourier Transform (FFT) was computed on the tank height sensor, and the results are seen in Figure 4.9. As can be seen, the two highest amplitudes of the frequency are located around the center of the chart, which is an excitation frequency of the system. Even though the movement of the variable B is inducing noise on the sensor, it is not the only source, other sources are discussed in Section C.11 in Appendix C.

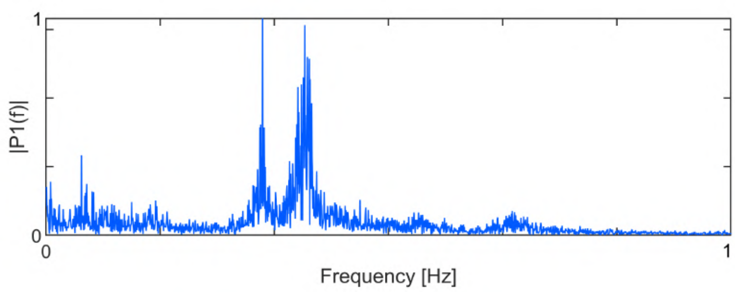
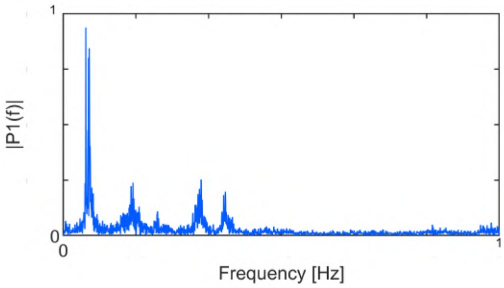
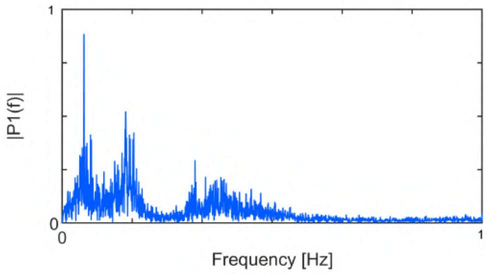


Figure 4.9: Single-sided amplitude spectrum of sensor A.

FFTs were computed with the data from the variable B in two directions; the Y-direction, and the X-direction. Figure 4.10 displays the results from the FFT of the two directions. The X-direction shows clearer peaks at certain frequencies, whereas the Y-direction has more noise at lower frequencies from the data set.



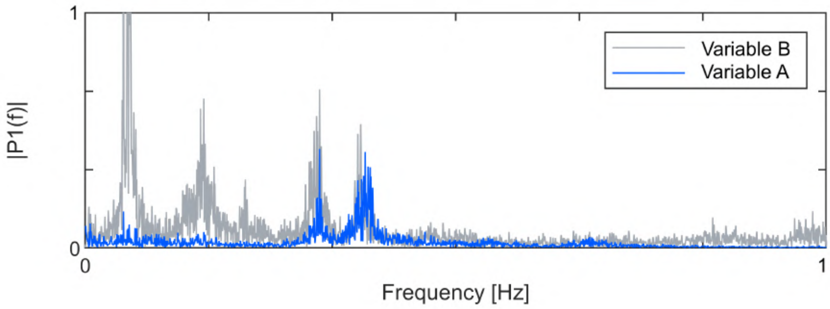
(a) *X*-Direction.



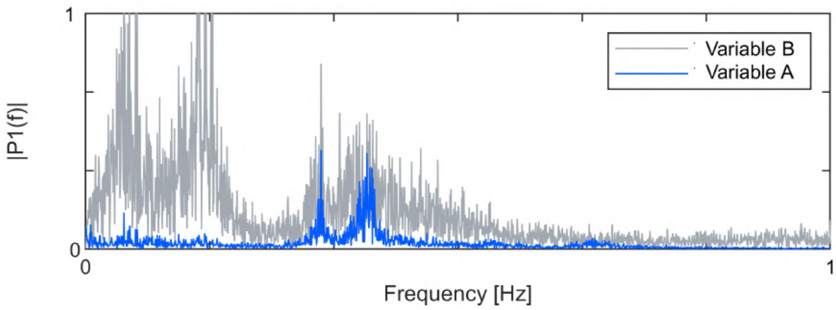
(b) *Y*-Direction.

Figure 4.10: FFTs of variable B in *X* and *Y* Directions.

The results from Figure 4.11 reveal a strong link between the highest amplitude frequencies of variable B and the frequency with the highest excitation of variable A. This is most likely due to the design and orientation of the special sensor A. Referring to Figure C.6, a description of the most likely cause of this can be seen in Section C.11 in Appendix C.



(a) FFT of X-Direction variable B & variable A.



(b) FFT of Y-Direction variable B & variable A.

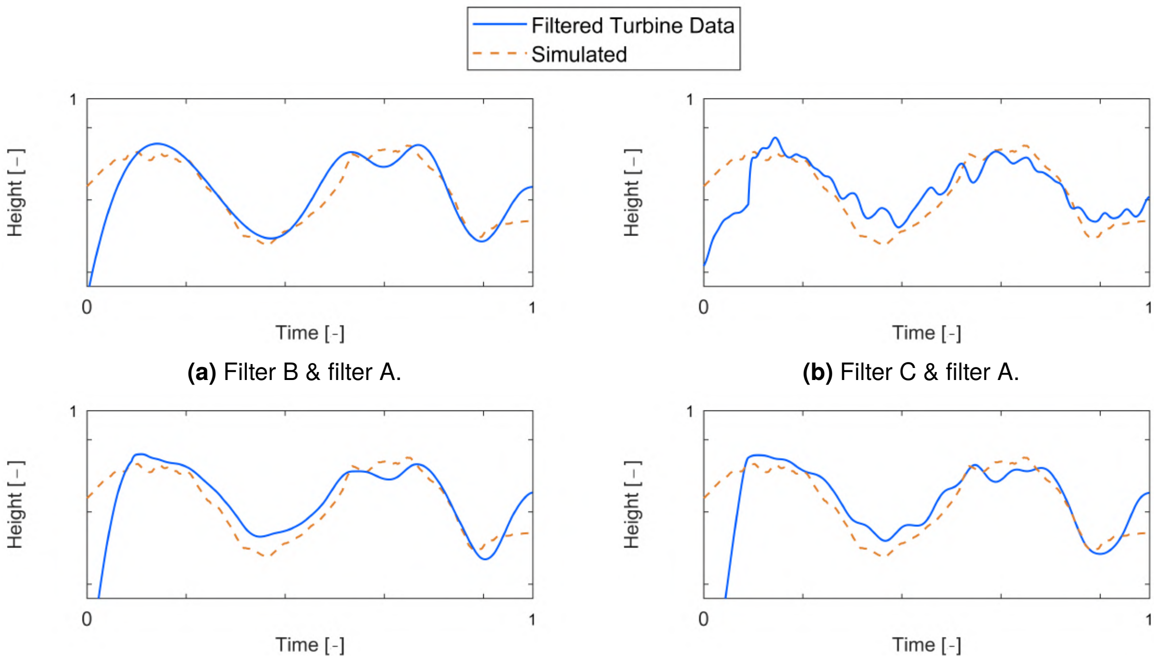
Figure 4.11: Comparison of FFTs of variable B in X and Y Direction to special sensor A.

With the current design, filtering the results is the only way to get a more accurate reading without redesigning the system. But the design could also be improved, perhaps by adding redundant sensors to get an average value of the variable A, amongst other improvements discussed in Section C.11 in Appendix C. For reference, Figure A.1 in Appendix A describes this idea visually.

4.3.2 Sensor A Filtering

A host of filters were inspected to effectively filter the noise on sensor A to give an accurate reading for the variable in question. First, filter A was implemented to reduce the noise from variable B and other sources. This was used as a base for the filtering to follow, as this filter removed only part of the noise, but it did not filter the signal completely to the desired output.

Figure 4.12 shows the results from the four filtering strategies, which are applied on the results of filter A. Each filter has an operation window in which the filter is applied. For that reason, the first part of the plot sees poor results as the moving window is still developing. Figure 4.12a uses a filter B. Filter B displays very good results with a smooth curve matching very closely to the final results. Figure 4.12b used filter C with the same window size to filter to the actual output, but has a small amount of agitation and is less smooth than the other filters. Figure 4.12c implements filter D. The final filtering method is seen in Figure 4.12d, which uses filter E. This filter is heavier computationally than the others and provides similar results.



(a) Filter B & filter A. **(b)** Filter C & filter A. **(c)** Filter D & filter A. **(d)** Filter E& filter A.

Figure 4.12: Filtering methods compared to the simulated ideal case for sensor A.

Filter B is not possible to do in real-time. The other three filtering schemes can operate in real-time and have similar results. However, as it has the most optimal balance of computation power and smooth results, Filter A and Filter D were implemented in the algorithms to obtain a more accurate reading for the sensor A, seen in Figure 4.13.

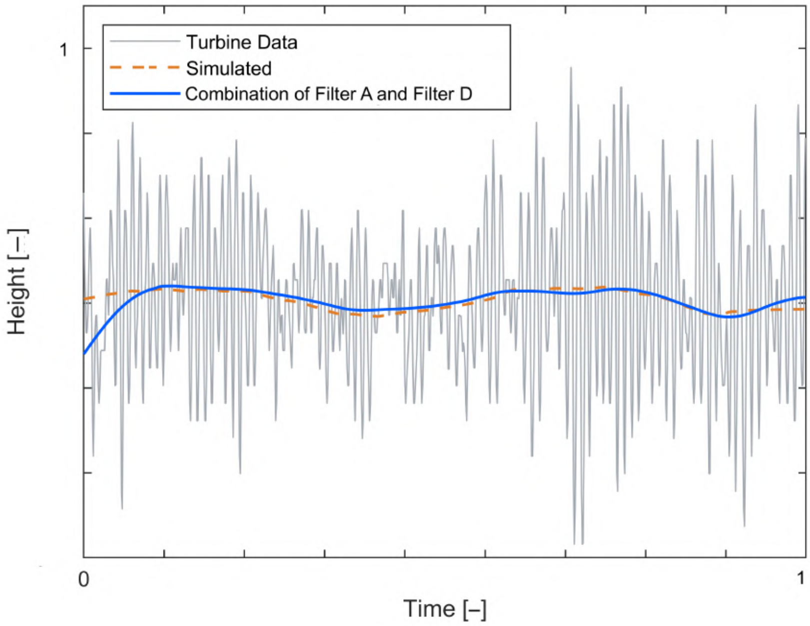


Figure 4.13: Filter A and Filter D comparison.

4.4 Algorithm A

Algorithm A is an oil leakage measurement tool. The results of this section are split up into multiple sections. First, the results of the base case of Algorithm A are outlined. Then, the improvements are discussed and results are compiled. The data sets utilized are a leaky data set, a case with no leak, and the Simulink output data. It is worth noting the size of the leak in the leaky data set is unknown, however. The non-leaking data set is only assumed to not be leaking, but that is not certain. Finally, a sensitivity analysis is discussed with the most critical variables in the algorithm.

4.4.1 Base Case - Algorithm A

As stated, the original algorithm was used as the base case to track improvement. The recreated model description is outlined in Section C.12 in Appendix C along with the results of the base case.

4.4.2 Algorithm A Modification Results

All of the following results include the discussed sensor A filtering scheme, as that was an improvement needed globally for each variation. The three versions of Algorithm A under examination were Algorithm A, Algorithm A1, and Algorithm A2. The results from algorithms A1 and A2 are listed in Section C.12 in Appendix C.

4.4.3 Sensitivity Analysis

Due to the sensitive information described in the framework of the sensitivity analysis, this section has been moved to the appendix, specifically Section C.12 in Appendix C.

4.4.4 Simulation Time

The simulation time is an important comparison between the proposed models. As even if one model shows better results, it may not be the best solution to implement if it is extremely computationally heavy. Table 4.2 tabulates the difference between the three versions of the algorithm run with the data sets. As is depicted, Algorithm A ran the fastest, with a ratio of real-time to CPU time of 3777. Algorithm A1 ran half as fast, and Algorithm A2 ran three times slower than Algorithm A1. Of course, this should be a factor when weighing the direction of the implemented solution. However, compared to the Simulink models, these algorithms are able to run much faster.

Table 4.2: Simulation time comparison - Algorithm A.

Simulation name	Computation Time (T_C) [-]	Ratio (T_S)/(T_C) [-]
Algorithm A	1	3777
Algorithm A1	1.93	1964
Algorithm A2	5.75	655

4.5 Algorithm B

Algorithm B estimates the oil leakage in a different way than Algorithm A. As the basic framework of this algorithm is different, the comparison of results will differ. However, the goal of the algorithms is the same, thus comparing the final verdicts is possible. For a more in-depth description of the algorithm's results, refer to Section C.13 in Appendix C.

4.5.1 Simulation Data

As the Simulink model data allows inspection of the key variables in any location desired, data was taken from the simulation to aid in the development of the algorithm. The results from the algorithm given the simulation data can be referenced in Section C.13 in Appendix C.

4.5.2 Real Turbine Data

The model was run under two data sets, the same as Algorithm A, one leaky data set, and one non-leaky data set. The results and the discoveries from this study is outlined in Section C.13 in Appendix C.

Chapter 5

Conclusions

This project aimed to develop an oil leakage detection method for use on the company's turbines. Oil leakage in the present is a source of concern. Developing an accurate oil detection strategy comes with a host of advantages, such as cost savings, environmental protection, enhanced safety, and increased trust. The company requested an improvement in the current system on the turbines. Three major steps took place in the timeline of the project; first, a thorough literature review of the current state of the art occurred. Then the modeling phase, which included the creation of Simulink models, detection algorithms, and the sensor A investigation. Finally, the third step of the project started with analyzing the results, which included comparing model variations and computation time, which is important for the detection approaches.

The full-scale Simulink model was successfully developed to act as a digital twin, with confirmation derived from the comparison of main variables in the system to real turbine data. Thereafter the output data was used as ideal inputs for the algorithm development and confirmation as well as the sensor A filtering. The model was subsequently altered to reduce complexity, computation time, and special variables. This proved to be possible with important changes to the model.

Two detection algorithms were developed in parallel, Algorithm A and Algorithm B. Algorithm A, after the inclusion of the discussed improvements, showed promising results.

A filtering scheme was developed for sensor A, combining filter A with filter D, which showed good results filtering sensor A to the expected results. Correlations were drawn from the link between the variable B and sensor A. The learning process of this project proved to allow positive growth.

5.1 Recommendations and Future Work

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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