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Article

# Bayesian based Diagnostic Model for Condition based Maintenance of Offshore Wind Farms

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**Abstract:** The operation and maintenance costs of offshore wind farms can be significantly reduced if existing corrective actions are performed as efficient as possible and if future corrective actions are avoided by performing sufficient preventive actions. In this paper a holistic multi-agent diagnostic model for fault detection and condition based maintenance of offshore wind components is presented. The diagnostic model presented is based on a probabilistic confidence matrix, which based on Bayes' rule can be updated once observations on the state of components are available. The presented diagnostic model defined in this paper is further explained within a case study for three wind turbine drivetrain components and based on information on vibrations, temperature and oil particles as diagnostic agents.

**Keywords:** diagnostic; condition based maintenance; offshore wind; O&M; confidence matrix; diagnosis matrix; Bayesian updating; vibration; temperature; oil particle; holistic model.

## 1. Offshore Wind O&M

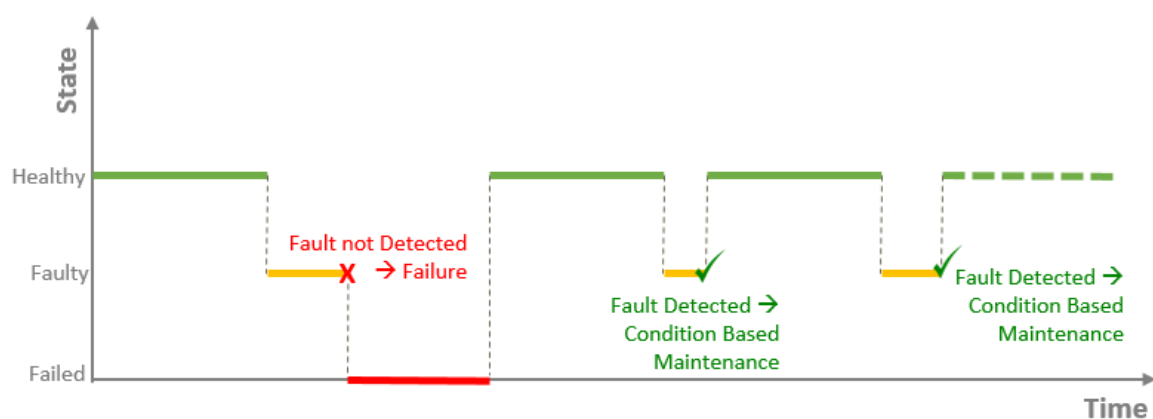
Wind energy with 153.7 GW installed capacity by the end of 2016 is the second largest power generation capacity in Europe [1]. The majority of installed wind capacity in Europe is currently in form of onshore wind. However, recent rapid cost reductions within offshore wind has motivated European governments to shift their focus into more and more offshore wind development tenders.

The majority of O&M costs of offshore wind farms is due to unplanned failure of wind farm components. The O&M costs can be reduced significantly if the faults of wind farm components can be predicted (before they occur) or be detected (as soon as they occur and before they lead to a complete failure). This paper focuses on fault detection or diagnostic of offshore wind components. In the following first a holistic diagnostic model is introduced and then, a case study for condition based maintenance of offshore wind components is presented.

## 2. Diagnostic

According to EN 13306:2010 [2], fault is “state of an item characterized by inability to perform a required function, excluding the inability during preventive maintenance or other planned actions, or due to lack of external resources”. Faults in wind farm components are usually pre-existing, meaning that there is an opportunity to detect faults before they lead to a failure. The state of a component with undetected faults leading to failure and detected faults leading to condition based maintenance is shown in Figure 1.





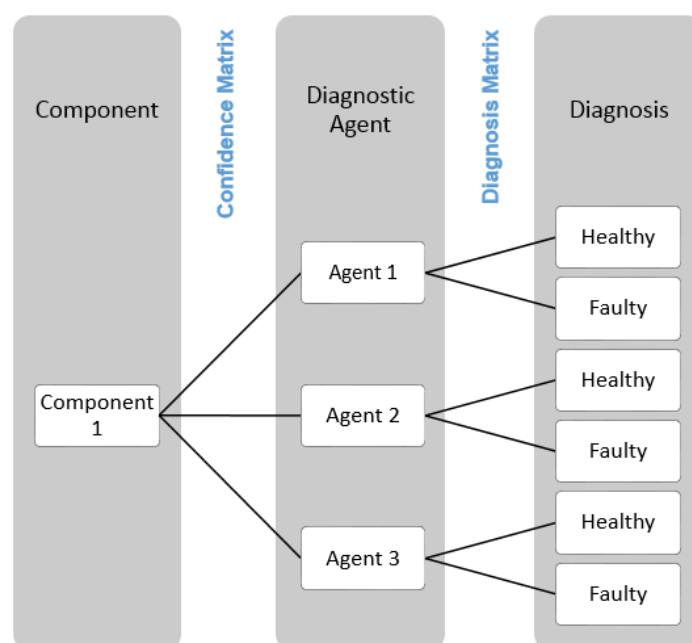
**Figure 1.** State of a component with undetected faults (leading to failure) and detected faults (leading to condition based maintenance)

The Figure 1 shows that if faults are detected before they lead to a failure, a condition based maintenance can be performed to bring back the component to its healthy state.

The detection of a component fault is also known as “diagnostic”. The result of a diagnostic method is known as “diagnosis”. The term diagnosis is from the Greek term *diagignōskein* meaning “distinguish” and the term diagnostic is from the Greek term *diagnōstikos* meaning “able to distinguish”.

Diagnostic or fault detection of wind turbines is mainly done for mechanical and electrical components in the drivetrain, which are known to have high failure rates. The structural components of wind turbines such as blades, tower or foundation are designed according to high safety factors and are known to have very low failure rates. Therefore, instead of diagnostic, degradation monitoring is a more proper approach for structural components.

During the last decades it has been proven that no diagnostic method can single-handedly detect faults in wind farm components with high detection accuracy. Instead, a holistic multi agent diagnostic model can be used, in which results of multiple diagnostic agents can be incorporated into each other to detect faults of a single wind farm component. In Figure 2, an example of such a multi agent diagnostic approach for fault detection of one wind farm component is shown.



**Figure 2.** Multi agent diagnostic of wind farm components



As shown in Figure 2, it is assumed that fault of this component can be optimally detected by a hybrid of three diagnostic agents. The relevance or contribution level of each diagnostic agent is defined within a Confidence Matrix. Once the diagnosis of each diagnostic agent is known, a Diagnosis Matrix can be formulated to incorporate all probabilistic fault detection results into one final verdict.

### 2.1. Confidence Matrix

A probability confidence matrix for diagnostic is a measure for relevance or confidence level of diagnostic agents for a given component. At the beginning of the wind farm lifetime, since no prior operational data is available, the confidence matrix should be defined based on experts' experience on relevance or confidence level of each diagnostic agent for each component. As instance, based on experience it can be assumed that confidence level of temperature, oil particle and vibration based diagnostic agents for detection of faults in a wind turbine main bearing is 20%, 50% and 30% respectively:

$$\begin{aligned} P(A_T)_{Bearing} &= 0.2 \\ P(A_O)_{Bearing} &= 0.5 \\ P(A_V)_{Bearing} &= 0.3 \end{aligned} \quad (1)$$

Once sufficient operational data is available, based on correctness of each fault detection agent determined by inspections, the confidence matrix can be updated. Moreover, the confidence matrix can be defined for each failure mode of each component, if enough information is available.

### 2.2. Diagnosis Matrix

The probability diagnosis matrix is a hybrid placeholder for individual probabilistic diagnosis of each diagnostic agent. As instance, the probabilistic diagnosis of signal anomaly detection agents can be presented as an exponential CDF:

$$\begin{aligned} P(D = Healthy|A) &= e^{-\lambda_A \Delta_A} \\ P(D = Faulty|A) &= 1 - e^{-\lambda_A \Delta_A} \end{aligned} \quad (2)$$

assuming:

- $P(D|A)$  as probability of the component diagnosis  $D$  being faulty or healthy given agent  $A$
- $\Delta_A$  as the deviation of the actual signal compared to its profile for diagnostic agent  $A$
- $\lambda_A$  as the exponential rate for diagnostic agent  $A$

The exponential rates of these models can be estimated based on experts' opinion. As instance, the exponential rate of a diagnostic agent can be calculated as:

$$\lambda_A = \frac{-\ln(1 - P)}{Deviation} \quad (3)$$

assuming:

- *Deviation* is the condition monitoring signal deviation level from its healthy profile, in which an expert is confident that a component fault is certain
- $P$  is the confidence level of the expert's judgement

As instance, if due to experience it is known that once temperature deviation is above 50 degrees with 90% probability a component is in fault, then the exponential rate of temperature agent can be calculated as:



$$\lambda_{AT} = \frac{-\ln(1 - 0.9)}{50} = 46E - 3 \left(\frac{1}{^\circ C}\right) \quad (4)$$

If temperature diagnostic agent of a component detects 10 degrees temperature deviation compared to its healthy temperature profile, then the probability of this component being in fault given the temperature diagnostic agent is 37%:

$$P(D = Faulty|A_T) = 1 - e^{-\lambda_{AT}\Delta A_T} = 1 - \exp(-0.046 \times 10) = 0.37 \quad (5)$$

In section 3 of this paper within a case study, formulation of the diagnostic matrix is further explained.

### 2.3. Total Probability of Fault

Once both probability confidence and diagnosis matrices are known, the probability of each component being in the faulty state can be calculated using the total probability theorem:

$$P(D = Faulty) = \sum_{i=1}^{i=n} P(D = Faulty|A_i)P(A_i) \quad (6)$$

assuming:

- $P(D = Faulty)$  as the probability of a component being in faulty state
- $P(D = Faulty|A_i)$  as the probability of component being faulty given agent  $A_i$
- $P(A_i)$  as the confidence level of agent  $A_i$

Once the probability of a fault based on the holistic diagnostic is more than a threshold for a given period of time an inspection should be perform to validate the diagnosis. The inspection thresholds should be defined in a way to minimize the false positives and at the same time avoid unplanned failures.

### 2.4. Posterior Confidence

If an inspection outcome confirms that the state of the component is faulty then, a condition based maintenance work order should be created to maintain the component before its failure. Additionally, since after this inspection sufficient operational data is available, the prior estimations of the confidence matrix can be updated by Bayesian updating:

$$P(A|D = Faulty) = \frac{P(D = Faulty|A) P(A)}{P(D = Faulty)} \quad (7)$$

assuming:

- $P(A|D = Faulty)$  as posterior confidence level of diagnostic agent  $A$
- $P(A)$  as prior confidence level of diagnostic agent  $A$
- $P(D = Faulty)$  as the holistic probability of a component being in fault based on diagnosis of all diagnostic agents calculated using Equation (6)

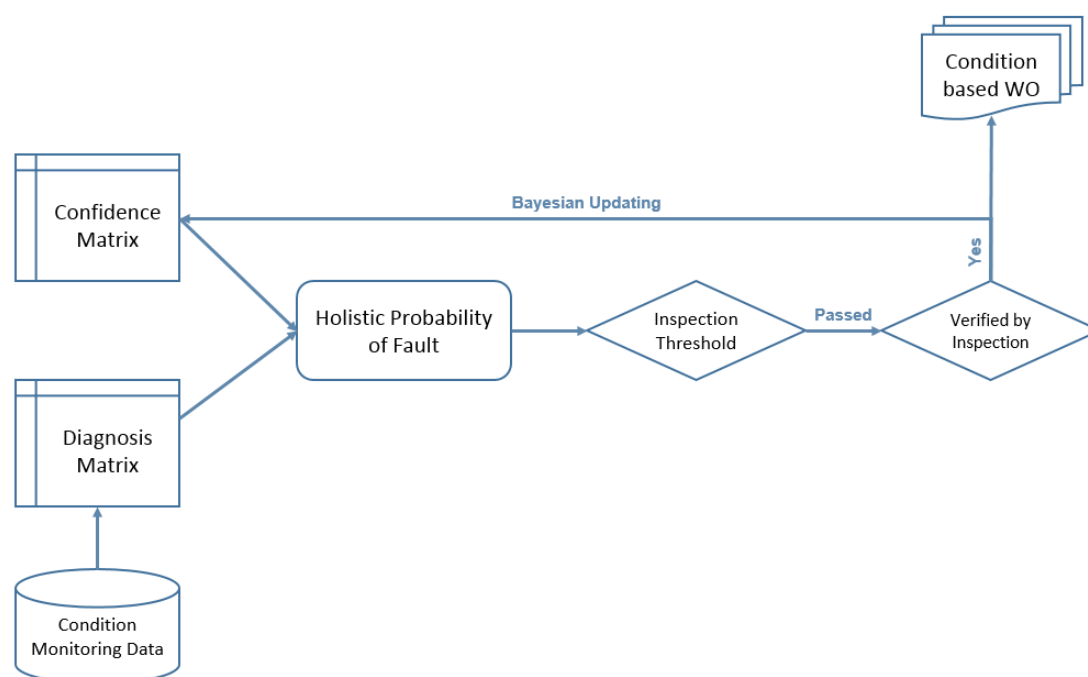
The updated posterior confidence levels of diagnostic agents should be used for future diagnostics to enhance the fault detection made by this holistic diagnostic model.

### 2.5. Holistic Diagnostic Model

Now that confidence and diagnosis matrices are defined and total probability of fault and posterior confidence can be calculated, a holistic diagnostic model can be defined. In Figure 3, the



framework of a holistic diagnostic model with Bayesian updating for offshore wind components is outlined.

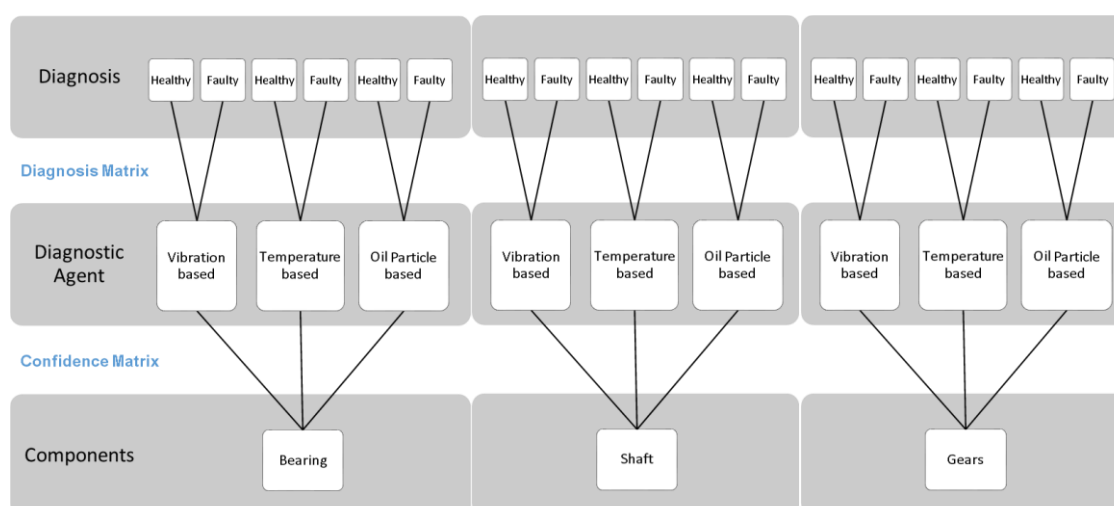


**Figure 3.** Framework of a holistic diagnostic model with Bayesian updating for offshore wind components

In the next section, a case study for fault detection and condition based maintenance of three wind turbine components based on three diagnostic agents is presented.

### 3. Case Study

As discussed in the previous section, instead of assessing results of each diagnostic method individually, a holistic or multi-agent diagnostic approach can be used, in which the results of all available diagnostic methods are taken into account at once and as result, the diagnosis (state of the component) is determined. In this case study, a holistic multi-agent diagnostic model for one wind turbine with three main components (main bearing, shaft and gears) based on three diagnostic agents is discussed in detail. In Figure 4, an overview of wind turbine components and diagnostic agents covered in this case study is shown.



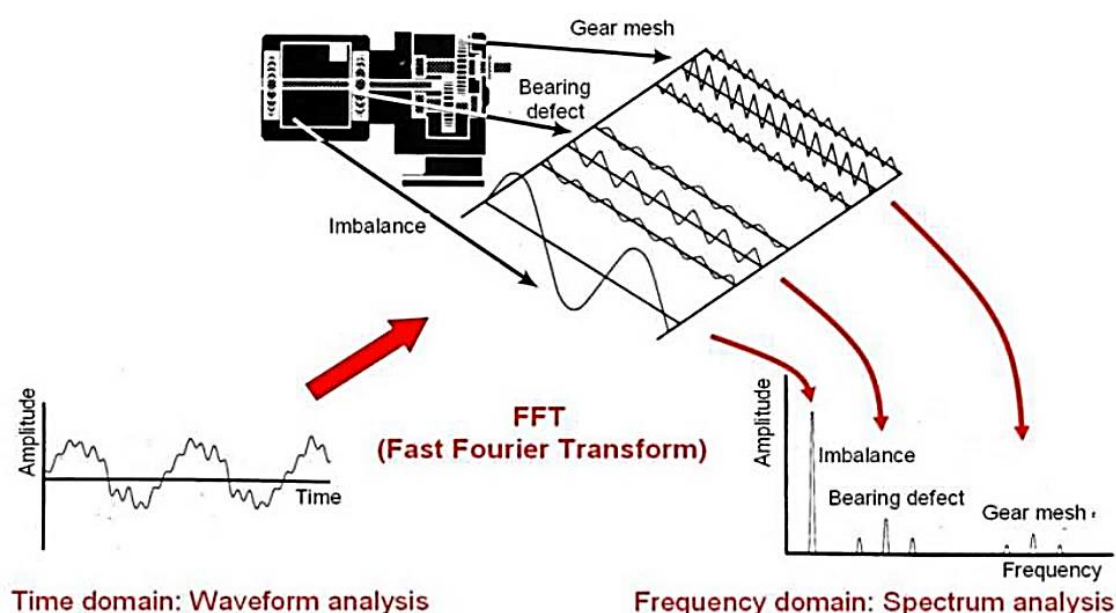
**Figure 4.** Wind turbine components and diagnostic agents in the case study



As shown in Figure 4, it is assumed that vibration, temperature and oil particle are independent diagnostic agents for drivetrain main bearing, shaft and gears. As result of each agent, the diagnosis (state of the component) can be estimated as a probability. These diagnostic methods are briefly explained in the followings.

### 3.1. Vibration based

Vibration analysis is the most reliable method for diagnostic of drivetrain mechanical components. The vibration analysis is based on data from 6 to 10 accelerometer, velocity and displacements sensors installed on bearings, shafts, gearbox, coupling and generator of wind turbines. These sensors are not a part of SCADA system and therefore a separate network infrastructure is required for their data acquisition, transfer and storage. As illustrated in Figure 5, the vibration analysis can be done in time domain (such as trend analysis) or in frequency domain (such as envelop analysis). The time and frequency domain analyses for vibration based condition monitoring are further explained in [3].



**Figure 5.** Time and frequency domain analyses for vibration based diagnostic [3]

Once the state of a component deviates considerably from its healthy vibration signature a warning is generated. The vibration based analysis can detect drivetrain mechanical faults a few month prior to their potential failure, which provides sufficient time for preparation and planning of the subsequent condition based work orders.

In the wind industry vibration analysis is incorrectly known as the Condition Monitoring System (CMS) since it is the most used CMS for wind turbine components. However, besides vibration based sensors there are several other wind turbine sensors which can be used for condition monitoring, such as temperature or hydraulic oil based sensors.

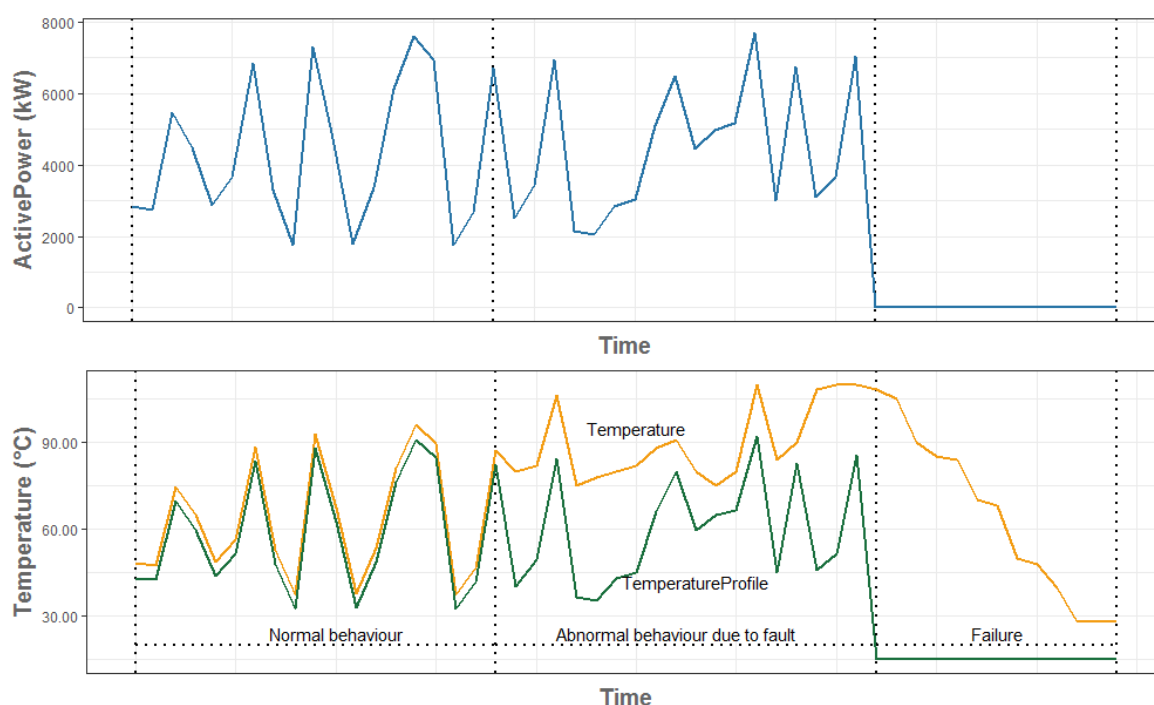
### 3.2. Temperature based

The majority of drivetrain components of wind turbines are equipped with temperature sensors. The data acquisition of temperature sensors is typically handled by wind turbine SCADA system. This makes temperature analysis an interesting diagnostic method as it can be done almost for any turbine platform without demanding any additional sensor or network infrastructure.



There are several methods for temperature analysis of drivetrain components. A typical temperature analysis is based on automated anomaly detection. Once the actual temperature of a component is considerably higher than its temperature profile a warning is generated.

The temperature profile of a component can be calculated using historical temperature data of the component. A component's temperature is dependent on turbine produced active power, duration that the turbine is continuously in run and weather condition such as ambient temperature or humidity. In other words, the temperature profile of a component should be binned for each power bin and run time and it should be corrected by ambient temperature and humidity. By doing so, the number of false positives or wrong warnings of temperature analysis is reduced to their minimum. In Figure 6, a hypothetical example of temperature based diagnostic is shown.



**Figure 6.** Example of temperature based diagnostic for offshore wind components

The temperature analysis can predict faults of mechanical and electrical drivetrain components a few weeks prior to their potential failure. Once an anomaly in a component's temperature is detected, a temperature based warning is triggered.

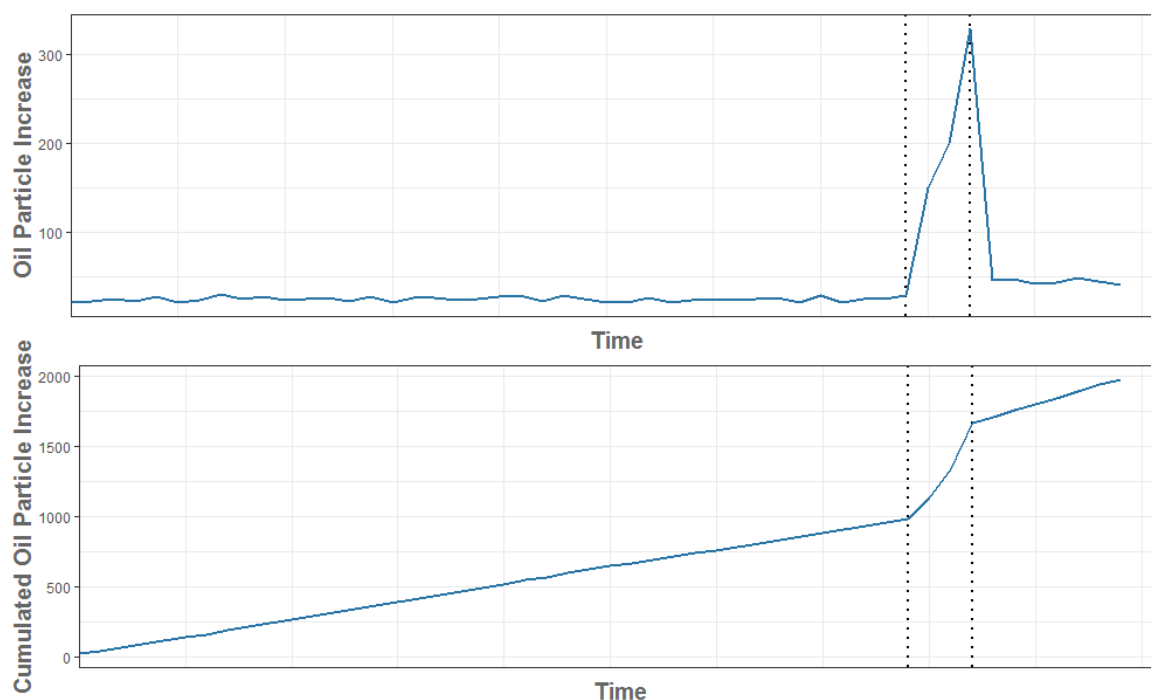
### 3.3. Oil based

The oil analysis is based on the lubrication system of the drivetrain components. The hydraulic oil analysis can be done using online oil sensors (such as oil pressure, temperature or particle counter) or offline oil samples (to check oil cleanliness or oxidation).

The offline oil samples and online oil pressure data can be used for fault detection of the lubrication system. However, the oil temperature and particle counter data can be used for fault detection of drivetrain components. Similar to temperature analysis, oil temperature anomaly detection can be triggered once the oil temperature deviates significantly from the oil temperature profile.

The oil particle counter data can be used to monitor sudden increase of particles (such as wear debris) created by degradation of drivetrain mechanical components. In an automated oil analysis, once the oil particle increase rises unexpectedly or once the slope of the cumulated oil particle increase in a given time period goes above a given threshold, an oil based warning is generated. In Figure 7 an example of oil particle increase and cumulated oil particle increase is given, in which abnormal increase of oil particles is highlighted with dotted lines.





**Figure 7.** Example of oil particle based diagnostic for offshore wind components

Similar to temperature signals, oil pressure, particle counting and temperature sensor data are collected by SCADA system. The oil particle counters can detect faults a few days prior to their potential failure and are typically very reliable. However, the oil particle results can't identify the exact location of the fault and the short time period between the diagnosis and potential failure doesn't allow proper preparation and planning for follow up condition based work orders.

Besides the aforementioned diagnostic methods several other less well-known methods (such as visual, acoustic or ultrasonic) are available, which are not covered in this case study.

Now that diagnostic agents are briefly explained, the confidence and diagnosis matrices associated with these three diagnostic agents can be formulated. In the last section it was explained that the initial confidence matrix is defined based on the previous experience or expert's judgement. Equally, confidence matrices of similar components in similar operation offshore wind farms can be used as initial confidence matrix. In Table 1, the initial confidence matrix for three components and diagnostic agents discussed in this case study is given.

**Table 1.** Initial confidence matrix for three components and diagnostic agents discussed in this case study

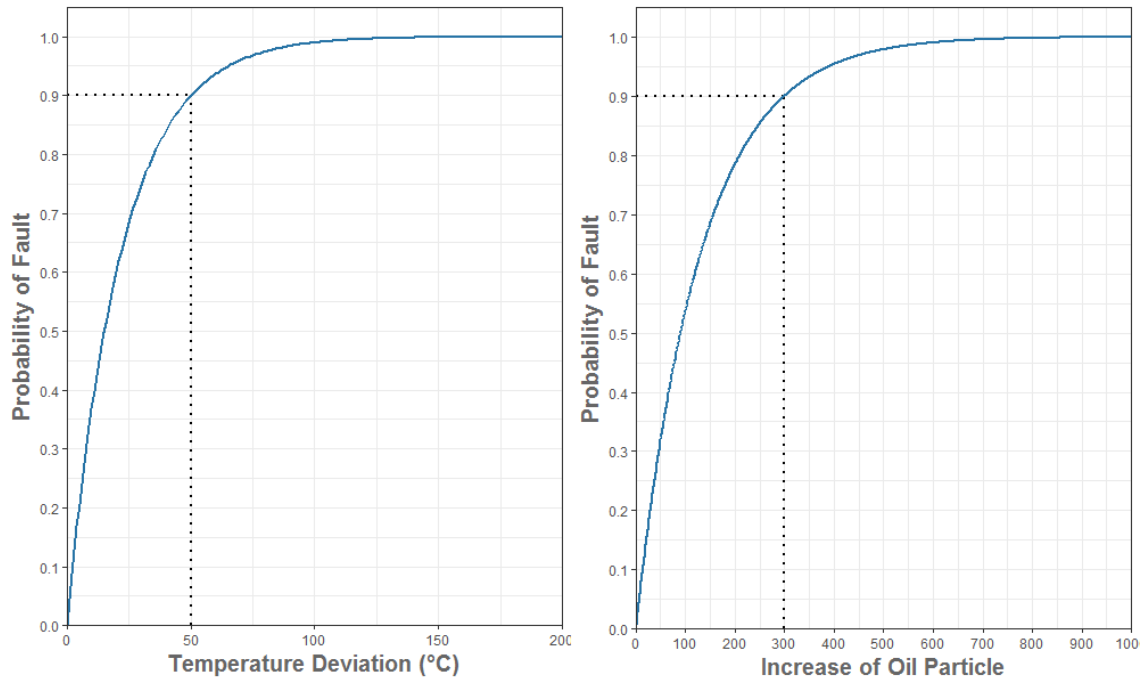
Component	Confidence of Diagnostic Agent - P(A)			
	Vibration based	Temperature based	Oil Particle based	Total
Bearing	0.3	0.2	0.5	0.1
Shaft	0.5	0.4	0.1	0.1
Gears	0.4	0.1	0.5	0.1

The next step is to define a diagnosis matrix for each diagnostic agent. In the previous section, an exponential model for anomaly based diagnostic agents such as temperature or oil particle was presented. Similar to exponential rate of a temperature agent discussed earlier, if due to experience it is known that once increase in oil particles is above 300 with 90% probability a component is in fault, then the exponential rate of an oil particle agent can be calculated as:



$$\lambda_{Ao} = \frac{-\ln(1 - 0.9)}{300} = 7.7E - 3 \quad (8)$$

In Figure 8 the probability of a component being in fault based on temperature and oil particle diagnostic agents is shown, in which 90% probability of fault in both graphs is highlighted.



**Figure 8.** Probability of fault for temperature and oil particle diagnostics

Now that exponential rates are known, the probability of fault based on temperature deviation or increase of oil particles can be calculated. For example if 30 degrees temperature deviation and increase of 100 oil particles is observed, then the probability of the component being faulty is:

$$P(D = Faulty|A_T) = 1 - e^{-\lambda_{AT}\Delta A_T} = 1 - \exp(-0.046 \times 30) = 0.75$$

$$P(D = Faulty|A_O) = 1 - e^{-\lambda_{Ao}\Delta A_o} = 1 - \exp(-0.0077 \times 100) = 0.54 \quad (9)$$

In Table 2, an example of the diagnosis matrix for three wind turbine drivetrain components discussed in this case study is given.

**Table 2.** Diagnosis matrix for three components and diagnostic agents discussed in this case study

Component	Diagnosis of Diagnostic Agent - P(D A)					
	Vibration based		Temperature based		Oil Particle based	
	Healthy	Faulty	Healthy	Faulty	Healthy	Faulty
<b>Bearing</b>	0.2	0.8	0.25	0.75	0.46	0.54
<b>Shaft</b>	0.7	0.3	0.8	0.2	0.9	0.1
<b>Gears</b>	0.3	0.7	0.5	0.5	0.5	0.5

Now that both probability confidence and diagnosis matrices are known, the probability of each component being in the faulty state based on the total probability theorem can be calculated. As instance, the probability of main bearing being in faulty state is:



$$\begin{aligned}
 P(D = Faulty)_{Bearing} &= P(D = Faulty|A_V)P(A_V) + P(D = Faulty|A_T)P(A_T) \\
 &+ P(D = Faulty|A_O)P(A_O) = 0.8 \times 0.3 + 0.75 \times 0.2 + 0.54 \times 0.5 = 0.66
 \end{aligned} \quad (10)$$

Similarly, the probability of shaft and gears being faulty can be calculated as 0.24 and 0.53 respectively.

In this case study it is assumed that once the probability of fault based on the holistic diagnostic model is constantly above 80% for more than one hour an inspection should be performed to validate the diagnosis. If an inspection confirms that the state of the component is faulty then, the prior estimations of the confidence matrix can be updated by Bayesian updating. As instance, the posterior confidence level of temperature based diagnostic agent for the main bearing given 0.66 as holistic probability of the bearing being in fault is:

$$P(A_T|D = Faulty) = \frac{P(D = Faulty|A_T) P(A_T)}{P(D = Faulty)} = \frac{0.75 \times 0.2}{0.66} = 0.23 \quad (11)$$

It should be noted that  $P(D=Faulty)$  is the holistic probability of a component being in fault based on diagnosis of all diagnostic agents and not the probability of fault given the inspection outcome.

In Table 3, the prior and posterior confidence levels of all diagnostic agents for the main bearing are shown. In Table 3 it can be seen that posterior confidence levels can be easily calculated by dividing the Bayes Numerator of each agent by total Bayes Numerator or  $P(D=Faulty)=0.66$  of the main bearing.

**Table 3.** Posterior confidence levels of diagnostic agents for the main bearing

Diagnostic Agent	Prior Confidence	Diagnosis	Bayes Numerator	Posterior Confidence
A	P(A)	$P(D=Faulty A)$	$P(A).P(D=Faulty A)$	$P(A D=Faulty)$
Vibration based	0.3	0.8	0.24	0.36
Temperature based	0.2	0.75	0.15	0.23
Oil particle based	0.5	0.54	0.27	0.41
<b>Total</b>	<b>1.0</b>	<b>NA</b>	<b>0.66</b>	<b>1.0</b>

The updated posterior confidence levels of diagnostic agents should be used for future diagnostics to enhance the fault detection made by this holistic diagnostic model.

#### 4. Discussion

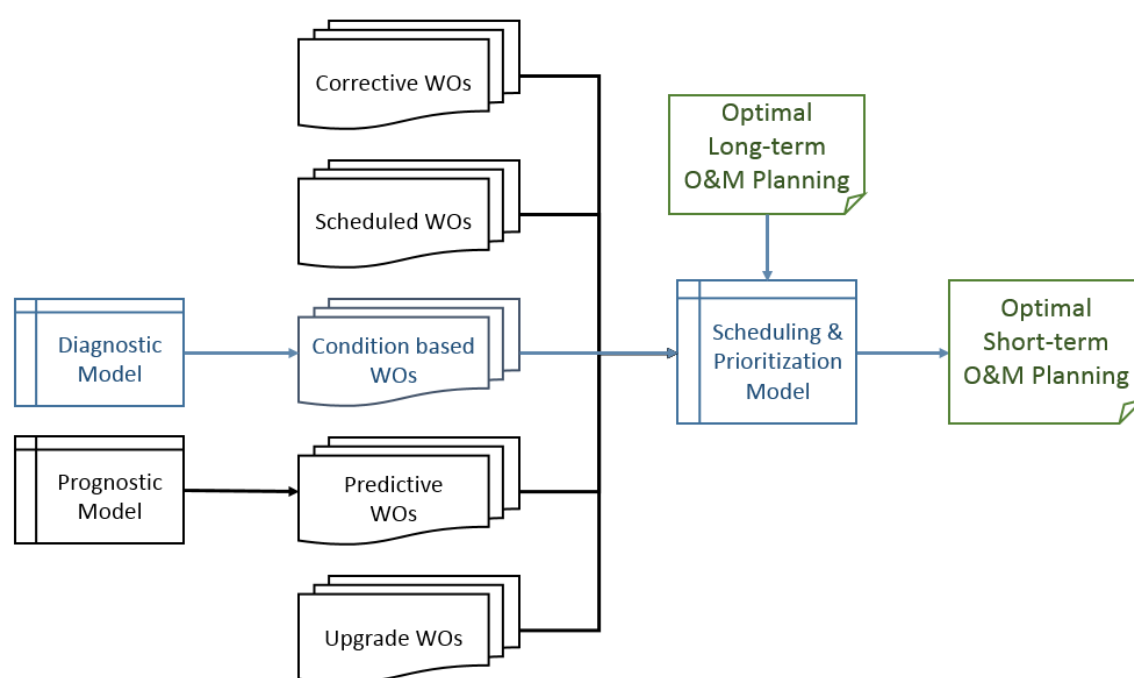
The diagnostic model introduced in this paper is a holistic model, in which results of multiple diagnostic agents can be incorporated into each other to detect faults of a single wind farm component. This holistic diagnostic model is based on the assumption that no diagnostic agent single-handedly can optimally detect faults in a wind farm component. The relevance or contribution of each diagnostic agent is defined within an initial confidence matrix. Once the diagnosis of such a diagnostic model is verified by inspections, the initial confidence matrix can be updated based on the Bayes' rule.

The case study presented in this paper is based on three diagnostic agents and the probability of each diagnosis is modelled using an exponential distribution. In future studies the application of further diagnostic agents and more accurate probabilistic diagnosis models can be explored. Furthermore, in future studies the confidence model of such a holistic diagnostic model can be based on failure modes of each single component to increase the accuracy of the model results.

Last but not least, in the case study presented in this paper only two component states (healthy or faulty) is assumed as the diagnosis of diagnostic agents. In future studies, diagnosis of diagnostic agents can be presented as multiple component states or deterioration levels (such as healthy, minor



damaged, damaged, server damaged). Additionally, instead of using only one threshold to initiate an inspection and/or a condition based maintenance work order, application of multiple thresholds associated with different deterioration levels and condition based maintenance strategies can be investigated.

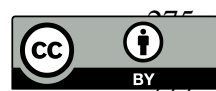


**Figure 9.** Framework for optimal short-term O&M planning of offshore wind farms

Once based on the holistic diagnostic model defined in this paper optimal condition based work orders are created, a work order scheduling and prioritization model such as the one shown in Figure 9 should be used to determine optimal short-term O&M planning for all outstanding work orders in a working shift, including corrective, scheduled, predictive and upgrade work orders. In [4] scheduling and prioritization model is further discussed.

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