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Author contact email: Roberto Lázaro (rlazaro@fcirce.es) Keywords: Wind Turbine, Gaussian Copula Mixture Models, Gearbox failures, Failure Index, Forecasting, Smoothing

Abstract. Wind turbine component's failure prognosis allows wind farm owners to apply predictive maintenance techniques to their fleets. This permits optimal scheduling of the maintenance actions considering the best time to stop the turbines and perform those actions. Determining the health status of a turbine's component typically requires verifying a wide number of variables that should be monitored simultaneously. The scope of this study is the investigation and the selection of an effective combination of variables and smoothing and forecasting methodologies for obtaining a wind turbine gearbox health status indicator, in order to interpret clearly the remaining lifetime of the gearbox. The proposed methodology is based on Gaussian Mixture Copula Model (GMCM) models combined with the smoothing treatment and the forecasting model to define the health index of the wind turbine gearbox. Then, the resulting index is tested using various warning and critical thresholds. These thresholds should be chosen adequately in order to indicate appropriate inspection visit and preventive maintenance intervention date. Then, the best combination found, for the studied cases, was 50% and 70% for warning and critical respectively. This combination ensures that the developed procedure is capable of providing long enough time window for maintenance decision making.

1 Introduction

Wind energy is a mature technology capable nowadays of providing 15% of the EU's electricity demand according to recent statistics [1]. However, European wind turbine fleets are facing with serious Operations & Maintenance (O&M) problems as they are getting older [2]. O&M strategies for wind farms are always focused on keeping the turbines in operation as much as possible in order to provide the demanded electricity maximising the revenue. This results in seeking the most reliable and effective strategy for planning the different maintenance actions including corrective and preventive tasks. Current developments focus on preventive tasks resulting from scheduled activities and condition based interventions. Condition monitoring methodologies have been classified as a high

priority task in the last European Technology & Innovation Platform on Wind Energy (ETIPWind) Roadmap [3].

Besides monitoring technologies, O&M engineers benefit from decision support systems (DSS) and asset health status summary indicators for effective decision making. They have to watch over a wide number of variables simultaneously for assessing the status of different wind turbine components. In order to anticipate asset failures and make timely interventions, which can slow failure propagation, O&M engineers need prognosis of the asset health status. Using an easy to interpret health status indicator, the failure propagation can be controlled (slowed or stopped) avoiding catastrophic failures. Such health status indicators can be considered as a decision criterion for intervention planning, component repair and asset remaining lifetime evaluations [4].

Nevertheless, as there are many wind turbine components, the critical ones have to be assessed profoundly in order to make the optimal O&M decision. The critical components of a wind turbine have been identified as the electric and control systems, generator, hub & blades and gearbox, due to their corresponding high failure rates and downtime duration [5, 6]. In the present study, the target is the early detection of gearbox failures.

Condition Monitoring System (CMS) and Supervisory Control and Data Acquisition (SCADA) data trends are used in decision-making on whether to inspect, repair or replace wind turbine components, particularly the gearbox [7]. There are also tools for remaining useful life time analysis of wind turbine gearboxes. These tools use maintenance and failure records of the gearbox. Nevertheless, many challenges exist in conveying data sets and deriving results from such analyses. On the one hand, existing methods, which use only CMS and SCADA data, are limited to aid only to short-term maintenance decisions. On the other hand, methods based on statistical distributions, which use only maintenance and failure records as input data, are not capable of providing fine temporal failure occurrence estimations. Moreover, these methods require to wait until a reasonable amount of failures has occurred before obtaining robust findings due to input failure data requirements of the models [8]. Therefore, new methods are needed in order to integrate all forms of maintenance, failure and operational data and aid in decision making for scheduling gearbox maintenance interventions.

The indicator proposed in this study, has been constructed on the basis of a Gaussian Mixture Copula Model (GMCM). These models have been used before in power curve modeling and outliers detection [9]. They were also applied to identify the health status of wind turbines [10]. The GMCM model is an advantageous alternative for characterising multivariate distributions, especially with non-Gaussian data and where unsupervised pattern recognition is needed [11]. Using the GMCM, it is possible to obtain a univariate index that allows monitoring the relationships between the critical variables of the component simultaneously.

The scope of this study is the investigation and selection of an effective combination of smoothing and forecasting methodologies for a wind turbine gearbox health status indicator. This indicator will allow to interpret clearly the remaining lifetime of a gearbox. Here, the first task is to generate a data-driven raw health status indicator, named as Failure Index (FI) using certain SCADA signals which are highly influenced by a wind turbine gearbox failure propagation. Nevertheless, as the resulting FI is a very noisy signal, it is not a good indicator for providing intuition to the O&M engineers. Therefore, signal smoothing solutions are implemented and applied to the FI to obtain an easy to interpret indicator.

In the final step, two forecasting approaches are considered (forecasting at scale algorithm [12] and linear regression [13]) for the smoothed FI time series with the purpose of generating good estimations of the gearbox remaining lifetime using pre-defined thresholds.

2   Data

2.1   Available Variables

Data were obtained from a Spanish wind farm with 12 wind turbines of 3000 kW each one. SCADA and CMS data together with failure and maintenance logbooks were compiled and used in the study. A thorough review of the available data revealed the existence of 2 gearbox failures whose parameters can be seen in Table 1 were the specific failure events found in the log book are showed.

Then, 4 data-sets were selected considering the turbines with failure, WT1 and WT2 and two more turbines without failure, WT3 and WT4, providing a total of 4 cases to be studied.

Taking into consideration the available data, failure propagation and recommendations that an optimal splitting of the data for supervised learning techniques would be around 60 to 80 % of data for training [14], the data have been splitted as shows table 1 for each case.

Each of the 4 data-sets was then splitted into two blocks, the first one for the generation of the GMCM Model (at least 6 months of data) and the derivation of the FI, and the second one for developing the forecasting models of the FI. This last block was also splitted into learning and testing periods (6 and 2 weeks respectively) in order to verify the goodness of the models.

Table 1: Considered periods in each data set and Gearbox failure events (from the maintenance log book)

Wind Turbine	Generation Period GMCM Model		Learning Period Forecasting Model		Test Period Forecasting Model		Reported Failure
	>6 months		6 weeks		2 weeks		
	Start Date	End Date	Start Date	End Date	Start Date	End Date	Start Date
WT1	01/09/2013	31/08/2014	23/09/2014	04/11/2014	04/11/2014	18/11/2014	18/11/2014
WT2	01/09/2013	28/02/2014	13/04/2014	25/05/2014	25/05/2014	08/06/2014	08/06/2014
WT3	01/04/2015	30/09/2015	05/10/2015	16/11/2015	16/11/2015	30/11/2015	No Failure
WT4	12/02/2015	08/10/2015	05/11/2015	17/12/2015	17/12/2015	31/12/2015	No Failure

In Table 1, the "Generation Period GMCM Model" covers the data used for the optimisation of the model coefficients and the defining parameters. Then, the GMCM output is obtained by using the model coefficients generated by "Generation Period GMCM Model". The resulting output is used as input for the forecasting process, which includes the "Learning Period Forecasting Model" and "Test Period Forecasting model".

SCADA and CMS data provide a total of 97 signals, whose time interval is 10 minutes.

These signals were reduced to only 7 using several feature selection and importance metrics[15].

The selected signals were Gearbox bearing temperature 3 (°C), Gearbox oil mechanical pressure (Bar), Gearbox oil electrical pressure (Bar), Rotor speed (rpm), Generator speed (rpm), Gearbox oil inlet temperature (°C) and Wind speed (m/s).

2.2   Filtering Process

Selected SCADA signals are cleaned, NANs registers and duplicated were removed. Later, data were filtered using wind speed measurements and the manufacturer's power curve of the wind turbines. By mahalanobis distance [16], the recorded power is compared with the expected power according to the manufacturer's curve and the most significant outliers are detected and removed. In this way, the periods where wind turbine has a low performance or is stopped are identified and removed, which assures the operation in normal mode behaviour.

3   Methodology

The first step is the generation of the raw FI.

The goal is to ensure that the input data are fed into the Gaussian Mixture Copula Model (GMCM) and the resulting output (Log-likelihood density) is transformed as the inverse of the cumulative Log-Likelihood density [17] [18] in order to generate the failure index (FI). Here, the GMCM coefficients are saved and then used for evaluating the performance of the FI. All this process is performed in the initial GMCM block, coloured in green in Figure 1.
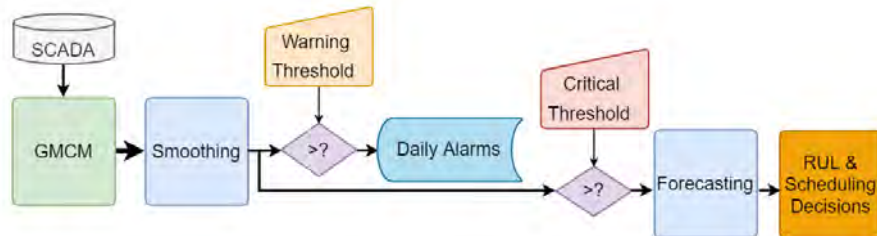

Figure 1: Flowchart of the proposed process

The raw FI time series (thick line in Figure 1) is then fed into the smoothing block which provides a clean FI signal.

Once smoothed, monitoring of the FI starts at the time, when it exceeds a pre-defined warning threshold, the DSS generates daily alarms for the decision maker in order to draw his attention to the component under consideration. These daily alarms are useful, when the decision maker would like to collect further inspection data from the gearbox and need to know the most suitable time for inspection data collection (such as deciding when to send a team for vibration analysis, non-destructive tests, etc.). Then, when the FI exceeds a pre-defined critical threshold, the historical FI series recorded during the last six weeks is fed to the forecasting phase to predict future values of the FI. The predicted FI values are then used to determine the remaining useful life (RUL) of the gearbox, which can be considered for scheduling the needed preventive maintenance intervention.

4 Tuning up of the models

In this section the methodology to convert the FI, obtained from the GMCM model, into a usable indicator providing information about the RUL of the gearbox is presented. The selected techniques are verified and justified here. Sub-section 4.1 covers the selection of an appropriate smoothing technique in order to obtain a clean FI signal. In sub-section 4.2, the selected warning threshold to start monitoring the smoothed FI is explained.

Finally, the forecasting methodology is presented in sub-section 4.3. Forecasting at scale (FS) [12] is first selected due to the possible seasonality present in the smoothed FI signal. Results are compared with linear regression (LR) [19] due to the apparent linear behaviour of the smoothed FI. Finally, in sub-section 4.4 trials with different critical thresholds are presented for choosing the appropriate limits to start generating the FI projections.

4.1 Smoothing method selection

The smoothing of the FI is evaluated in this sub-section. Simple moving average (SMA) [20] and cubic spline smoothing techniques (CS) [21] are tested in order to find which one adapts better to the FI evolution.

(a) Raw FI & Smoothed FI: Failure Case 1

(b) Raw FI & Smoothed FI: Failure Case 2

(c) Raw FI & Smoothed FI: Healthy Case 1
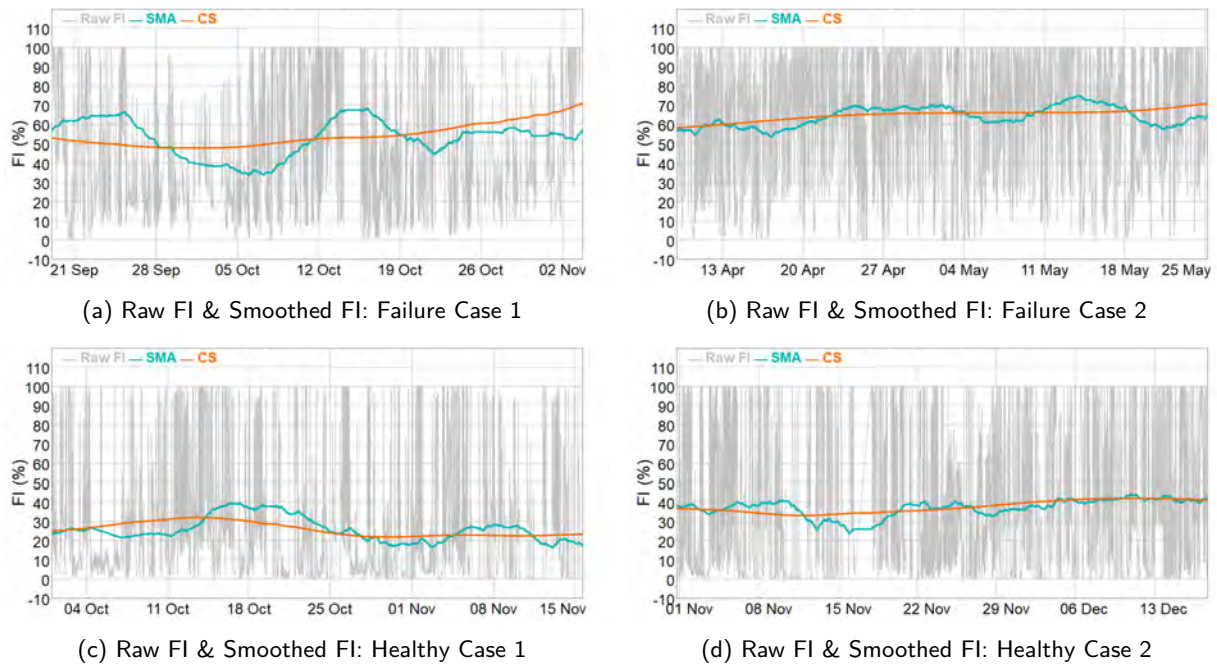
(d) Raw FI & Smoothed FI: Healthy Case 2

Figure 2: Smoothing for the FI

Figure 2 shows the raw FI and the comparison between both smoothing techniques for two failure cases (a and b) and two healthy cases (c and d). It can be seen that the raw FI output obtained from the GMCM is a very noisy signal which ranges from 0% to 100% values for both gearbox situations, healthy and faulty states.

The analysis of the faulty states reveals that the SMA smoothed FI fluctuates between 35% and 65% in (a) and between 55% and 75% in (b). Whereas, the CS generates less fluctuating FI series showing a clear increasing trend towards the failure date, as shown in sub-figures (a) and (b). Looking at the healthy cases, yet again, the SMA smoothed signal still shows fluctuations not present in the CS smoothed one, which looks more stationary as it should be in a healthy case.

All in all, the need for smoothing treatment for the FI is paramount in order to use the FI as an information provider. The CS performs better than the SMA. Therefore, it is concluded that the CS is selected as a smoothing technique to be used for the proposed FI.

4.2 Selection of the Warning Threshold

In practice, component health monitoring is a decision support tool, which provides health status assessments. In order to generate an informative alarm, two things are needed, a continuous health status signal and a fixed threshold value. With 10000 GMCM simulated FI estimations, the mean FI in the healthy cases is found to be lesser than 50%.

The warning threshold is important in order to know, when the decision maker should start monitoring the FI. It is worth to highlight that, the decision maker must monitor health status of various components for different turbines. Although, the FI is a single summary signal, continuous monitoring of the FI for a large wind farm consisting of many wind turbines is not feasible. Therefore, there is a need for an informative alarm. Here the rule is to generate an alarm, which summarises 24 hours prior the current time to be send as an information to the decision maker, when the FI exceeded at least once the warning threshold within the analysed 24 hours window. A low threshold value which provides early detection means having a long enough window to consider different maintenance options. Therefore, the FI 50% is used as warning threshold. In this paper, when the FI estimated

value reaches a warning threshold, it can be interpreted as a time for scheduling an inspection visit in order to gather more data and to assess profoundly the health status of the gearbox.

4.3   Forecasting method selection

When the FI exceeds a certain threshold, the decision maker needs to see the FI projections in order to schedule any needed maintenance intervention. This projections can be generated using various techniques. In the present study two of them, the forecasting at scale (FS) and the linear regression (LR) are considered. The FS technique is a recent forecasting method used for the social media user data statistics [12]. The advantage of this technique is its flexibility, when the nature of data has several seasonal patterns. To the authors knowledge, up until now, this technique has not been used in the wind turbine anomaly projection literature. Here, we will compare its results with a simple linear regression technique used as reference.

Figure 3 shows the forecasting trials applying FS to the failure (a) and healthy (c) cases and LR to the failure (b) and healthy (c) cases. The prediction results, shown in blue colour, have been calculated 2 weeks before the actual failure event (2 weeks before the end of the test period, in the healthy cases). The vertical red line indicates the separation point between the historical observations and the forecasts.

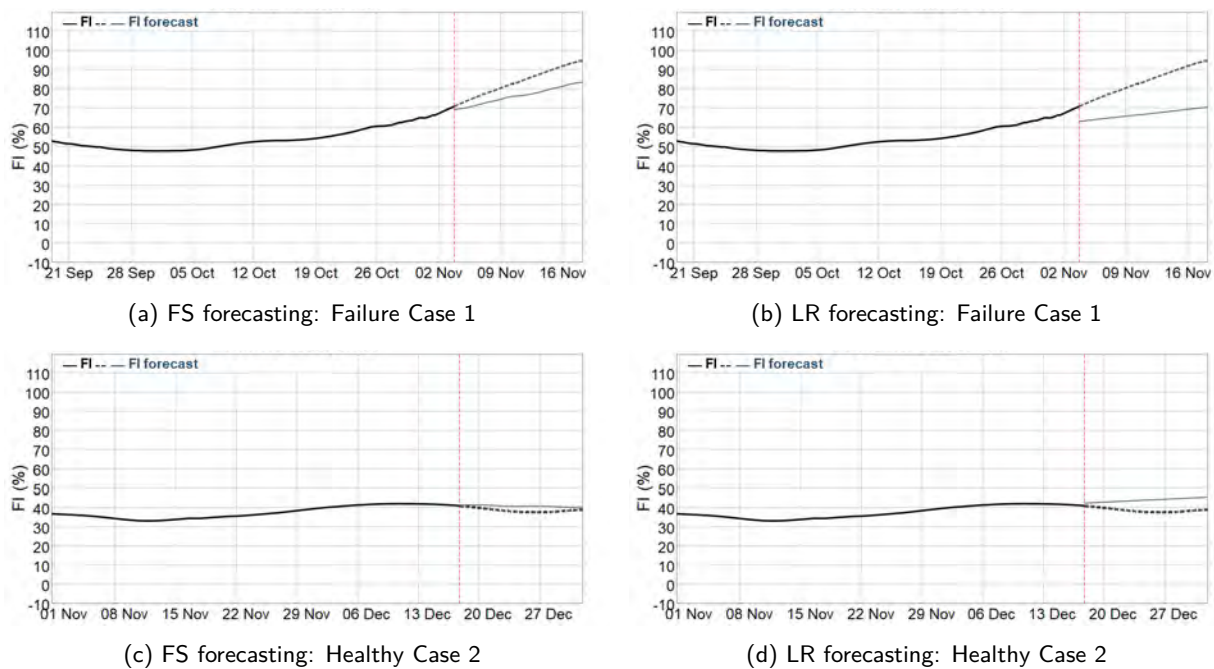| (a) FS forecasting: Failure Case 1 | (b) LR forecasting: Failure Case 1 |
| (c) FS forecasting: Healthy Case 2 | (d) LR forecasting: Healthy Case 2 |

Figure 3: Forecasting for the FI

As shown in Figure 3 the prediction with LR does not capture the final value of FI. Moreover, the Root Mean Square Error (RMSE) between the actual FI value and the predicted one has been calculated for both methods, see Table 2. The RMSE values are lower for the projections generated via the FS model.

Table 2: Forecasting comparison

WTG	RMSE: FS	RMSE: LR
Failure case 1	7.74	17.42
Failure case 2	5.96	9.05
Healthy case 1	2.19	2.24
Healthy case 2	2.3	5.52

Conclusively, the FS outperfoms the LR method, therefore as a forecasting technique the FS is selected for the proposed FI prediction.

4.4 Selection of the Critical Threshold

The low value chosen for the warning threshold allows distinguishing between healthy and faulty states and starting the specific monitoring of the corresponding FI. Then, last thing to be done is obtaining the value when the FI forecasting is launched in order to estimate the RUL of the gearbox. This FI value is named as critical threshold. Figure 4 shows the remaining useful lifetime (RUL), the duration between the failure date and the date at the first time when the critical threshold is exceeded, for the different critical FI thresholds.

When a critical threshold of 50 % is used, the gearbox shows a RUL bigger than 45 days. In contrast, if a threshold of 70 % is considered, the RUL estimations reduce to 23 days for failure case 1 and 18 days for failure case 2. Finally, the intermediate value of 60 % provides RUL values of 33 days for failure case 1 and 52 days for failure case 2.

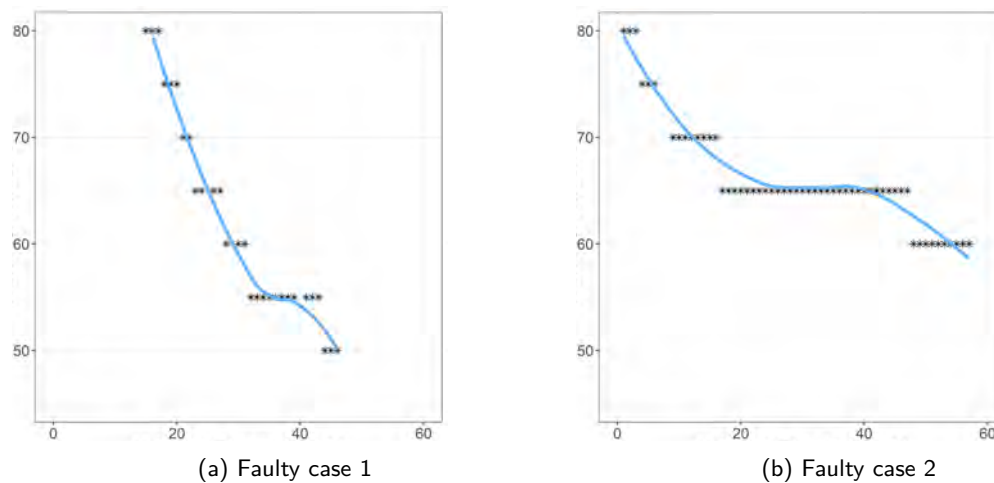(a) Faulty case 1   (b) Faulty case 2

Figure 4: Critical threshold sensitivity on lead time (or RUL) analysis

Proper selection of the critical threshold directly affects the remaining planning time for the needed intervention before the component failure. The resulting lead times show that it is possible to consider several thresholds. A value between 60 % and 75 % results in matching lead times obtained via other CMS techniques reported in the literature [22],[23]. The main difference is that our results achieved using only SCADA data without any extra investment in the turbine monitoring. It must be taken into account that the higher this threshold is, the less time of planning window is obtained. For a threshold of 70 %, the lead times are between between 14 and 21 days. These windows are appropriate for booking a maintenance team and generating a fine intervention plan. Consequently, the critical threshold is determined as 70%.

5 Results

The results of the combined smoothing and signal prediction models with the recommended warning and critical thresholds are presented and discussed in this section.

Figure 5 shows the results for the Failure case 1, where a major gearbox failure is reported on November the 18th.
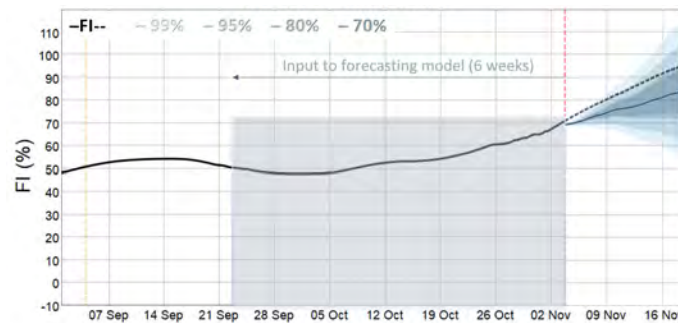
Figure 5: Smoothing and forecasting for the FI: Failure Case 1, orange dashed line stands for the date, when the FI reaches the warning threshold (50%), whereas red dashed line stands for the date, when the FI reaches the critical threshold (70%).

The smoothed FI resulting from the GMCM and the CS shows a growing trend starting at approximately 50% on September the 5th and reaching a value of 95% on November the 18th, the day when the failure occurred. 24 days prior to the gearbox failure occurrence, the FI reaches 60%. Then, the FI enters in a special surveillance mode Monitoring the FI, an apparent increase in the index is observed between 26 October and 5 November, when the FI reaches 70%, which is illustrated via vertical dashed red line. In this point, the historical FI series are sent to the FS in order to generate projections for the FI growth and the failure propagation. The FS generates prediction intervals, which are able to cover the FI estimations. As a result, in this case an early failure detection could be achieved by tracking the FI.

In Figure 6, Failure case 2 is analysed. In this case, a major gearbox failure is reported on 8 June 2014.
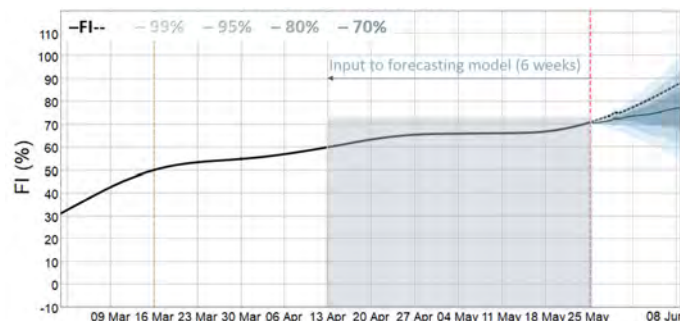

Figure 6: Smoothing and forecasting for the FI: Failure Case 2, orange dashed line stands for the date, when the FI reaches the warning threshold (50%), whereas red dashed line stands for the date, when the FI reaches the critical threshold (70%).

The smoothed FI resulting from the GMCM and the CS ranges from 59% to 89% between 13 April and 8 June. In 16 March, 84 days prior to the gearbox failure occurrence, the FI reaches 50%, which is the pre-determined warning threshold. Next, the FI reaches to 70 % at 25 May. In this point, the historical FI series are sent to the FS in order to generate projections for the FI growth and the failure propagation. Being consistent with the previous findings, the FS generates prediction intervals, which are able to cover the FI estimations. In this case also failure detection for gearbox could be achieved by tracking the FI.

Additionally, the proposed FI can be used in order to make projections for verifying the health status of the wind turbine gearbox. Therefore, next two healthy cases are analysed. In Figure 7, Healthy case 1 (a) in Turbine 3 is analysed.
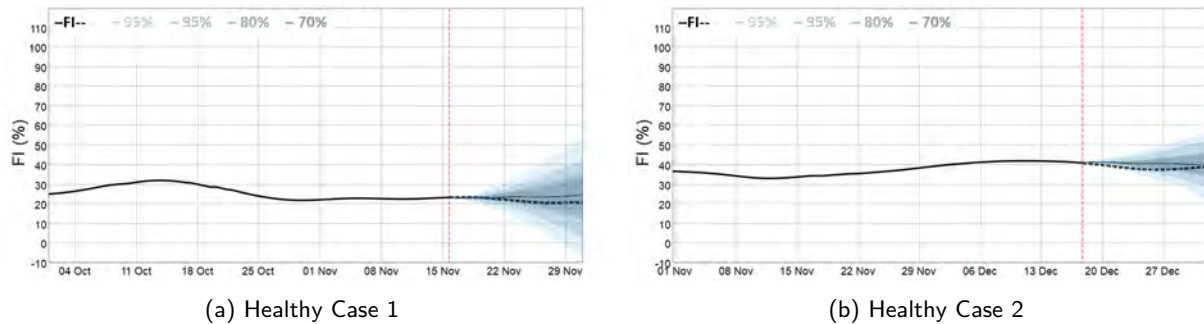
(a) Healthy Case 1

(b) Healthy Case 2

Figure 7: Smoothing and forecasting for the FI: Healthy Cases

In this case a flat and clear signal is obtained. The FI values do not exceed 50 % warning threshold during the investigated analysis period. If the decision maker would like to generate forecasts for a healthy case, only the upper 99 % prediction interval reaches to 50 % for the end of 14 days projection. The mean forecasts are found to be very close to the FI estimation.

In Figure 7, Healthy case 2 (b) in Turbine 4 is analysed. In this case, no failure is reported in the gearbox.

The second healthy case displays higher FI values in comparison to the previous case. Yet, the FI is under the warning threshold 50%. If the decision maker would like to generate forecasts for this healthy case, the upper 99 % prediction interval reaches to 50 % at the end of 10th forecast day. The mean forecasts are found to be very close to the FI estimation.

6 Conclusions

Main aspects of multivariable component health status estimation models are addressed and improved for wind turbine gearboxes. A functional and practical FI definition is provided, which is validated via real healthy and faulty case studies. First the raw FI is generated using the certain SCADA signals which have a high influence on gearbox failure propagation. However, the resulting raw signal is found to be very noisy and impractical to derive conclusions. Therefore, as a treatment procedure, two smoothing techniques are considered in order to have a clear FI signal. The Cubic Spline Smoothing is selected as the treatment technique. It is found that, if the FI signal exceeds 50%, the gearbox under consideration displays an anomalous working. This finding is sent to the decision maker in a form of a daily alarm. When, the decision maker starts to monitor the FI, it is a recommendable time to collect more inspection data from the gearbox under consideration in order to decide, which action should be carried out for preventing the anticipated failure. If there is no intervention, eventually the FI reaches to the critical threshold, 70%. From this point backwards to 6 weeks (42 days), the historical FI series is used as an input for generating the FI predictions of the coming 14 days. Here, two different forecasting methods are considered. It is found that the Forecasting at Scale algorithm, which is not used for the RUL estimations up until this study, performs better in comparison to the Linear Regression. When the RUL estimations and the literature are considered, the proposed FI, which uses only the SCADA data, is as much as successful in early detection of failures in comparison to the advanced frequency domain analysis, which uses the CMS data.

The proposed methodology can indicate failure propagation and the remaining intervention planning time a reasonable time in advance to failure.

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