

Prognosticating fault development rate in wind turbine generator bearings using local trend models

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ABSTRACT

Generator bearing defects, e.g. ball, inner and outer race defects, are ranked among the most frequent mechanical failures encountered in wind turbines. Diagnosis and prognosis of bearing faults can be successfully implemented using vibration based condition monitoring systems, where tracking and trending of specific condition indicators can be used to evaluate the former, current and potentially future condition of these components. The latter, i.e. evaluation of the fault progression rate and remaining useful lifetime (RUL), is of essential importance to owners and operators in regards to maintenance planning and component replacement. The above approach offers numerous benefits from financial and operational perspective, such as increased availability, up-tower repairs and minimization of secondary and catastrophic damages. In this work, a non-speed related condition indicator, measuring the signal energy between 10Hz to 1000Hz is utilized as feature to characterize the severity of developing bearing faults. Furthermore, local trend models are employed to predict the progression of bearing defects from a vibration standpoint in accordance with the limits suggested in ISO 10816. Predictions of vibration trends from multi-megawatt wind turbine generators are presented, showing the effectiveness of the suggested approach on the calculation of the RUL and fault progression rate.

1. INTRODUCTION

Condition monitoring has been gaining continuous attention in the wind energy sector over the past decade (Tchakoua et al., 2014). The increasing capacity of modern wind turbines

and high demands for time or energy availability has resulted in integration of condition-based maintenance strategies applied widely in other energy sectors. A small percentage increase in the availability of a park may not be appealing to certain original equipment manufacturers (OEMs) or owners and operators from a return on investment standpoint, especially in countries where labour is inexpensive. However, numerous supplementary benefits can be identified such as up-tower repairs which lead to minimum crane and crew mobilization, lead time to inspection, spare parts management, root cause analysis and minimization of secondary failures.

Vibration based condition monitoring is the main technique in large-scale wind applications focusing primarily on the drive train rotating components. Condition monitoring systems (CMS) are commonly semi-automated, where the system intelligence is combined with operator interaction in order to alert, diagnose and evaluate the severity of the potential defect, by evaluating numerous indicators describing the condition of the monitored subcomponent and employing advanced signal processing techniques. Although the above setup is sufficiently functional, estimation of the remaining useful lifetime is a crucial parameter towards the efficient consolidation of monitoring and maintenance.

Prognostics is one of the areas of increasing interest in academia and industry aiming at accurate prediction of the fault progression and finally evaluation of the component's RUL (Lee et al., 2014). Reuben *et al* have used exponential modelling to determine the time-to-failure of helicopter tail rotor gearbox bearings (Reuben & Mba, 2014). In (Li, Lei, Lin, & Ding, 2015), an improved exponential model is proposed for the RUL prediction of rolling element bearings. Weibull models are used in (Naganathan et al., 2013) for the prediction of the time for the occurrence of failure. Particle

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filtering is applied in (Hu, Baraldi, Di Maio, & Zio, 2014) and (Zio & Peloni, 2011) for the estimation of components' remaining useful lifetime. An interesting RUL estimation approach using information from warranty databases is presented in (Alam & Suzuki, 2009). Mixture of Gaussians Hidden Markov Models (MoG-HMMs) are employed as modelling tool of bearings' RUL in (Medjaher, Tobon-Mejia, & Zerhouni, 2012). In (Hussain & Gabbar, 2013), adaptive neuro fuzzy inference system and nonlinear autoregressive model with exogenous inputs are applied on the health monitoring and fault prognosis in wind turbines.

In this work, linear and quadratic local trend models are used towards the estimation of the fault progression rate in wind turbine generator bearings, based on vibration acceleration trends. The utilized condition indicator upon which the health of the bearing is evaluated reflects the energy between 10Hz and 100Hz as suggested in ISO 10816.

The paper is organized as follows: Section 2 presents the monitoring setup in the current application, including the used condition indicator, limit establishment and data classification based. The theoretical background of global and local trend models is discussed in Section 3. Section 4 shows the efficacy of linear and quadratic local trend models in the estimation of the fault progression rate based on real world data from a generator bearing inner race defect. Sections 5 and 6 present the discussion and conclusions respectively.

2. FAULT DETECTION

2.1. Data Collection

Vibration analysis is the most widely used monitoring technique in rotating machinery. The vast majority of high speed rotating wind turbine generators are supported by ball bearings on the drive-end – close to the coupling – and non-drive-end sides. Vibration signals are recorded by accelerometers installed on the bearing housing close to the load zone in order to ensure optimal vibration path, as shown in Figure 1. Accelerometers installed in the axial direction could also be part of the monitoring solution, although it is not frequent in wind turbines up to few megawatts due to cost savings and the already valuable indications from radially installed accelerometers.

In the current application, the recorded vibration signals are processed by the Wind Turbine Analysis System Type 3652 (WTAS Type 3652) from Brüel and Kjær Vibro, which calculates scalar values and streams them to central servers every one half to one hour for long time trending and alarming. These scalars are divided into two main groups, speed related, as for example running speed or gear mesh orders, and broadband filters, as described in the following subsection. Furthermore, 10.24 second vibration signals recorded by the accelerometers mounted on the generator bearings, gearbox and

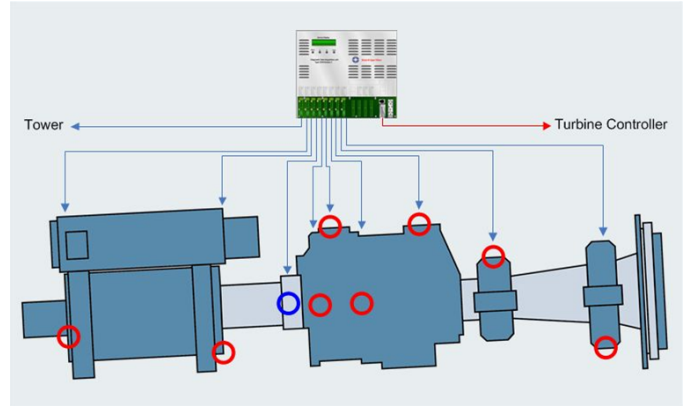


Figure 1. CMS sensor location. Positioning of accelerometers on generator bearings at the load zone.

main bearings sampled at 25.6kHz are delivered to the central servers every one or two days for detailed spectral analysis.

The detectable faults in generator bearings using vibration analysis range from typical bearing faults, such as defects on the inner and outer races (Marhadi & Hilmisson, 2013), rotor dynamics faults, e.g. imbalance, misalignment, looseness (Skrimpas et al., 2015) or unconventional failure modes present in special generator types, such as rotor circuit malfunction in DFIGs (Skrimpas, Sweeney, Jensen, Mijatovic, & Holboell, 2014).

2.2. Condition Indicators

Numerous condition indicators (CIs) are utilized on the characterization of bearing faults, such as broadband measurements, amplitude of running speed harmonics or statistical features in the time or frequency domains. Furthermore, features in the time–frequency domain using wavelet analysis, Wigner distribution or Short Time Fourier Transform (SFFT) have been suggested by researchers in order to overcome the issues introduced by speed and load variations in variable speed systems (Antoniadou, Manson, Staszewski, Barszcz, & Worden, 2015).

Focusing on the CIs employed on the evaluation of bearing defects, a rough division can be made between early and late stage fault indicators.

Generally, early stage defects contribute to increased vibration levels in the high bandwidth at the resonance frequency of the subcomponent (inner race, outer race, ball, cage). Figure 2 displays the frequency spectrum up to 10kHz, which is the cut-off frequency of the anti-aliasing in the current application, of a vibration signal recorded from a generator bearing suffering from early stage outer race defect. The latter commonly starts as subsurface fractures or early stage flaking. The resonance frequency of the defective subcomponent is visible between 3kHz and 5kHz, which may vary in other

bearing types or for different subcomponents. Therefore, by employing a broadband filter between 1kHz and 10kHz which will be referred as high frequency band pass (HFBP), a global condition indicator can be extracted, eliminating the necessity for special settings for each individual cases. However, it should be underlined that the offered information from this CI can serve merely as very early stage fault notification without the capability of providing any lead time to failure. The characteristic bearing frequency can be found using enveloping techniques as shown in Figure 3, and thus explicitly pinpointing the location of the fault.

At this point, it is of crucial importance to discuss the influence of the inverter switching frequencies and their sidebands on generator bearing vibration signals, present close to 8kHz in Figure 2. The presence of the aforementioned frequencies has not been correlated to any inverter malfunction as far as the authors are aware, hence they are treated purely as noise. However, in certain cases, they might contribute considerably to the vibration levels at specific frequency bands and thus indicate a generator as outlier if compared to neighbouring wind turbines or fleet. This phenomenon should be taken into consideration when diagnosing a bearing defect or performing trend park comparisons.

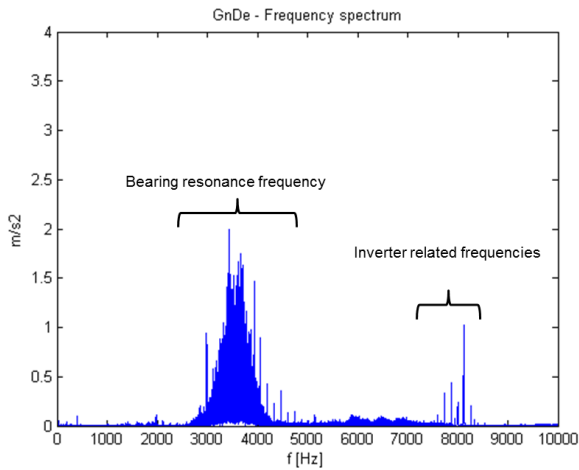


Figure 2. Early stage generator drive end bearing - Frequency spectrum illustrating the resonance frequency of outer race defect and inverter switching related frequencies.

Mid to late stage fault are directly observable in the low frequency range, typically below 1000Hz, as harmonics of the characteristic defect frequency. Based on ISO standard 10816, a broad band filter between 10Hz and 1kHz is used, abbreviated in this work as ISOA (ISO acceleration), which assists in facilitating consistent vibration limits, as shown in later section (ISO 10816, 2015). Figure 4 displays the frequency spectrum of a bearing diagnosed with late stage outer race defect. This condition indicates that the fault has esca-

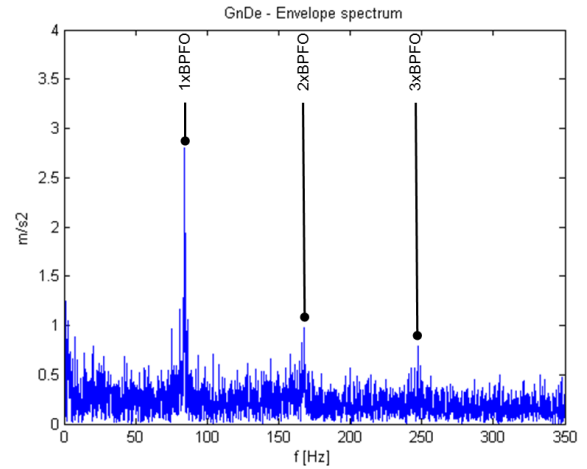


Figure 3. Early stage generator drive end bearing - Envelope spectrum demodulating the frequencies from 3kHz to 5kHz in Figure 2.

lated and bearing replacement should eventually take place depending on the fault progression rate.

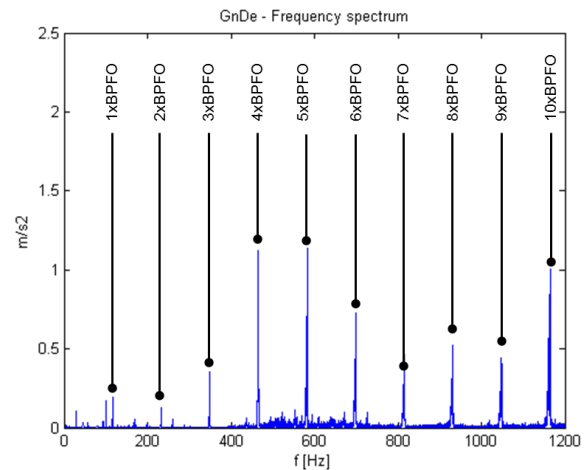


Figure 4. Late stage generator drive end bearing - Frequency spectrum from 0Hz to 1200Hz showing multiple harmonics of BPFO (ball pass frequency outer).

2.3. Limit Setting

Effective limit modification is a challenging task with two main contradictory requirements. In one hand, the limits must be set close to the actual vibration values in order to track any change on time, trigger an alarm and consequently notify the diagnosticians to proceed to further investigation. On the other hand, one of the main objectives in condition monitoring systems is to minimize the number of false positives, which is one of the most influential factors in the successful implementation of condition-based maintenance. Furthermore, it is important to underline that condition monitoring

systems are designed to track slow or moderately slow component deterioration over time, and thus should not be confused with safety systems.

It is common practise in vibration based monitoring systems to establish more than one limits so as to obtain the necessary flexibility and secure proper evaluation of the monitored component. In the current work, two limits are utilized referred to as alert and danger respectively. Bearing in mind the effectiveness of the condition indicators introduced in subsection 2.2 on the evaluation of the RUL of a generator bearing, a global danger limit is selected only for ISOA (10Hz–1000Hz) based on the limits included in ISO Standard 10816 Part 21 (ISO 10816, 2015), whereas individual alert limits for both ISOA and HFBP are computed statistically from the period where the generator runs fault free. A trivial statistical approach in limits setting is presented in Equation 1.

$$L = x \cdot \mu + y \cdot \sigma \quad (1)$$

where μ and σ are the mean and standard deviation of the vibration CI over a predefined time span and x and y are factors used for proper limit setting.

ISO Standard 10816 Part 21 defines maximum velocity limit for generator rolling element bearings between 10Hz–1000Hz equal to 10mm/s . The latter is applicable for geared wind turbines of nominal output below 3.0MW, which is consistent with the cases studied in this paper. In order to have a uniform setting of limits in acceleration term, the velocity limit (L_v) is converted to acceleration as shown in Equation 2.

$$L_a = 2 \cdot \pi \cdot f_c \cdot L_v \quad (2)$$

where the center frequency f_c is based on the lower and higher bandwidth values, shown as f_l and f_h respectively (Randall, 1987).

$$f_c = \sqrt{f_l \cdot f_h} \quad (3)$$

Using Equations 2 and 3, 10mm/s correspond to approximately 6.28m/s^2 . This limit can function as basis upon which slightly modified values can be established in cases where the vibration CIs are classified based on the power production, speed or torque.

2.4. Power Classification

Historical recording of CI is valuable for comparing and trending developing faults. For variable load applications, such as in wind turbines, it is advantageous to classify all vibration measurements according to the produced power at the time the measurement is recorded. This classification ensures that all extracted CIs can be compared and trended under the

same operating conditions. Furthermore, one of the main advantages in this approach is proper limit setting and therefore minimization of false positives. As example, the power output of a 1.5MW wind turbine can be divided into five equally spaced power bins with a tolerance of 10% error, as depicted in Figure 5.

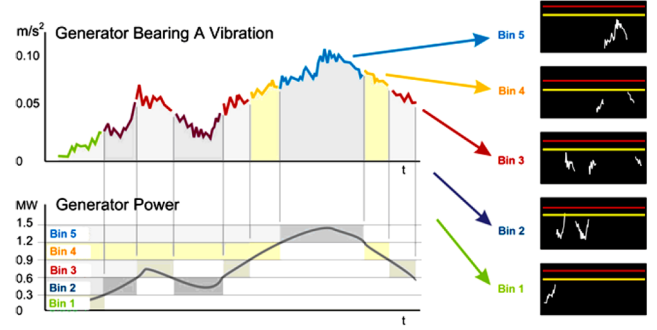


Figure 5. Power classification of vibration data in a 1.5MW wind turbine.

3. PREDICTIONS IN TREND MODELS

A trend model is a regression model of the following form (Madsen, 2008):

$$Y_{N+j} = \mathbf{f}^T(j) \cdot \theta + \varepsilon_{N+j} \quad (4)$$

where $\mathbf{f}(j)$ is a vector of known forecast functions and θ is a vector of parameters. The noise term ε is independent and identically distributed, i.e. $E[\varepsilon] = 0$ and $Var[\varepsilon] = \sigma^2$.

Basic trend models are the constant mean, linear, quadratic, polynomial and harmonic models, listed below (Madsen, 2008).

$$\text{Constant : } Y_{N+j} = \theta_0 + \varepsilon_{N+j}$$

$$\text{Linear : } Y_{N+j} = \theta_0 + \theta_1 j + \varepsilon_{N+j}$$

$$\text{Quadratic : } Y_{N+j} = \theta_0 + \theta_1 j + \theta_2 j^2 / 2 + \varepsilon_{N+j}$$

$$\text{Polynomial : } Y_{N+j} = \theta_0 + \theta_1 j + \theta_2 j^2 / 2 + \dots + \theta_k j^k / k! + \varepsilon_{N+j}$$

$$\text{Harmonic : } Y_{N+j} = \theta_0 + \theta_1 \sin(2\pi/p) + \theta_2 \cos(2\pi/p) + \varepsilon_{N+j}$$

3.1. Global Trend Model

In the global trend models, all Y_1, \dots, Y_N observations can be represented in matrix format as shown in Equation 5.

$$\mathbf{Y} = \mathbf{x}_N \cdot \theta + \varepsilon \quad (5)$$

where $\mathbf{Y} = [Y_1, \dots, Y_N]^T$, $\mathbf{x}_N = [\mathbf{f}^T(-N+1), \dots, \mathbf{f}^T(0)]^T$, $\theta = [\theta_1, \dots, \theta_N]^T$ and $\varepsilon = [\varepsilon_1, \dots, \varepsilon_N]^T$.

The estimated model parameters, $\hat{\theta}_N$, can be computed applying the least-square method, yielding (Madsen, 2008)

$$\hat{\theta}_N = (\mathbf{x}_N^T \mathbf{x}_N)^{-1} \mathbf{x}_N^T \mathbf{Y} = \mathbf{F}_N^{-1} \mathbf{h}_N \quad (6)$$

where $\mathbf{F}_N = \mathbf{x}_N^T \mathbf{x}_N$ and $\mathbf{h}_N = \mathbf{x}_N^T \mathbf{Y}$.

The prediction \hat{Y}_{N+l} at step l , given the observations Y_1, \dots, Y_N at time N , is

$$\hat{Y}_{N+l|N} = \mathbf{f}^T(l) \cdot \hat{\theta}_N \quad (7)$$

The variance of the prediction error $e_N(l) = Y_{N+l} - \hat{Y}_{N+l|N}$ is equal to

$$\text{Var}[e_N(l)] = \hat{\sigma}^2 [1 + \mathbf{f}^T(l) \mathbf{F}_N^{-1} \mathbf{f}(l)] \quad (8)$$

where the estimated variance is

$$\hat{\sigma}^2 = \frac{[\mathbf{Y} - \mathbf{x}_N \hat{\theta}_N]^T [\mathbf{Y} - \mathbf{x}_N \hat{\theta}_N]}{N - p} \quad (9)$$

and p stands for the number of parameters.

The $100(1 - \alpha)\%$ prediction interval for the future value is calculated as

$$\hat{Y}_{N+l|N} \pm t_{\alpha/2}(N - p) \sqrt{\text{Var}[e_N(l)]} \quad (10)$$

where $t_{\alpha/2}(N - p)$ is the $\alpha/2$ quantile in the t -distribution with $N - p$ degrees of freedom.

3.2. Local Trend Model

In global trend models, the parameter θ is constant in time and each observation has the same weight. This approach imposes a number of limitations especially when dealing with trends changing behavior over time. Local trend models overcome the latter challenge by assigning less weight on past observations and higher weight on more recent, introducing a forgetting factor λ in the calculating of the parameter θ . In local trend models, the variance of noise ε in Equation 5 becomes (Madsen, 2008) :

$$\text{Var}[\varepsilon] = \sigma^2 \Sigma \quad (11)$$

where

$$\Sigma = \text{diag}[1/\lambda^{N-1}, \dots, 1/\lambda, 1] \quad (12)$$

In this case, the estimated model parameters are calculated using the weighted least-square method,

$$\hat{\theta}_{Nw} = (\mathbf{x}_N^T \Sigma^{-1} \mathbf{x}_N)^{-1} \mathbf{x}_N^T \Sigma^{-1} \mathbf{Y} = \mathbf{F}_{Nw}^{-1} \mathbf{h}_{Nw} \quad (13)$$

It can be shown that

$$\mathbf{F}_{Nw} = \sum_{j=0}^{N-1} \lambda^j \mathbf{f}(-j) \mathbf{f}^T(-j) \quad (14)$$

and

$$\mathbf{h}_{Nw} = \sum_{j=0}^{N-1} \lambda^j \mathbf{f}(-j) Y_{N-j} \quad (15)$$

The prediction values and prediction intervals are calculated using Equations 7 and 10 respectively.

In local trend models, the variance σ^2 can be alternatively estimated as

$$\hat{\sigma}^2 = \frac{[\mathbf{Y} - \mathbf{x}_N \hat{\theta}_{Nw}]^T \Sigma^{-1} [\mathbf{Y} - \mathbf{x}_N \hat{\theta}_{Nw}]}{T - p} \quad (16)$$

where T is referred to as total memory and is a measure of how many observations, the estimation is essentially based upon.

$$T = \sum_{j=0}^{N-1} \lambda^j \approx \frac{1 - \lambda^N}{1 - \lambda} \quad (17)$$

Finally, if $\lambda = 1$ then the resulting local trend model is identical to the global un-weighted trend model.

4. PROGNOSIS OF FAULT DEVELOPMENT EMPLOYING LOCAL MODELS

Figure 6 illustrates the vibration trends of a generator bearing subjected to an outer race defect. The displayed condition indicator is ISOA, which is the energy between 10Hz and 1000Hz. The monitoring strategy incorporates classification of data in five power classes as elaborated in section 2.4. Although the analysis will be based only in one set of data from one power class in this case study, the same method is applicable in all remaining four classes. An ensemble approach combining the outcomes of all five power bins has not been followed in the present work based on the overall front-end and back-end design of WTAS Type 3652 from Brüel and Kjær Vibro. Vibration scalar values are generated by the CMS unit every one hour in each power class, given that the turbine has operated at the corresponding power production level for a predefined period of time. In the proposed prognostic scheme, the hourly data are averaged per day based on

the argument that the level of predictive accuracy is not in the order of hours but rather in days or even weeks, where a side benefit of this approach is data de-noising. The erratic behaviour encountered in the actual ISOA trends is directly linked to the consolidation of vibration data into five discrete power bins, whose range is in the order of $600kW$. In addition, any speed variations of data within the same power bin are not taken into account or compensated, resulting in relatively large deviation. Finally, the green points in Figure 6 are interpolated points in missing days using spline function in order to account for no production in this power bin at a specific day.

A point of interest in the below figure is the establishment of the two limits, where the alert limit is set very close to the actual trend and the danger limit is equal to $7m/s^2$, which is roughly 10% higher compared to the limit in the ISO standard.

The following prediction approaches do not depend on physical models of bearing fault development, such as exponential models, but treat the available vibration data as time series, offering unbiased estimations of the bearing condition.

4.1. Linear Model

The first step in prediction systems is to determine the parameters influencing the model. In local trend models, these are the past time, forgetting factor and the model. Figure 7 shows the normalized logarithmic model error for varying λ and past time, of a linear model. Two main conclusions can be made: 1) the model error is minimized using longer past interval, 2) the forgetting factor influence the error heavily. Based on the above, a reasonable model parameter selection is 70 to 100 days as past values and high λ above 0.95.

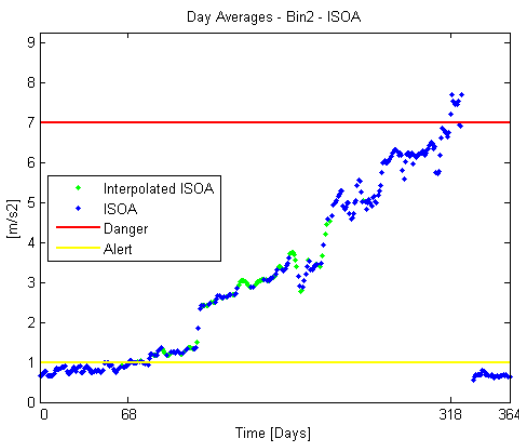


Figure 6. Generator bearing daily averaged ISOA trend and limits in power bin 2 (low-mid power production).

Figure 8 illustrates the prediction of the last 30 days of a late stage bearing defect based on 70 days of past values and λ

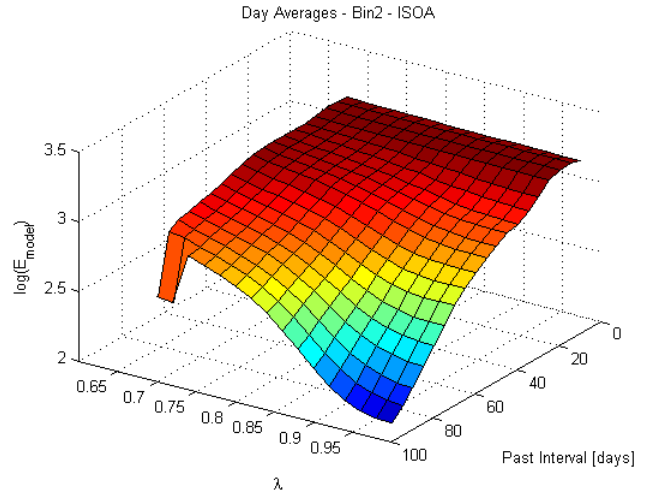


Figure 7. Relationship of past interval and forgetting factor λ for local linear trend model given 30 days of prediction time for linear model.

equal to 0.95. Zooming in the prediction period, it is observed that the forecast is representative of the actual overall development rate of the fault. The progression is equal to $0.0255m/s^2$ per day, which is time independent. Furthermore, the 95% confidence intervals are presented which incorporate the necessary uncertainty level of the prediction. Naturally, it is not expected that the trend will settle down without any intervention, such as replacement of the defective bearing, but it covers the probability of erratic behaviour. The upper confidence level functions as the worst case scenario in case of sudden change of the component condition. From an operational standpoint, the upper confidence level represents the least available time which all the necessary procedures for ordering of components, crane mobilization and recourse allocation, before the condition of the bearing becomes critical.

An investigation of high interest regarding the broad use of the model is the estimation of the prediction error as function of the past and forecast intervals, given a specific forgetting factor. Figure 9 shows the aforementioned error for λ equal to 0.95. It can be seen that if the prediction time exceeds 40 to 50 days, the prediction error increased significantly for limited period of past values, and it gets its highest values for future predictions of 100 days while the past time is limited to less than 15 days.

4.2. Quadratic Model

Quadratic models can be also employed to predict future vibration trends, development rate and ultimately the component's RUL. Detailed analysis on the model parameters is a requisite in order to define the most suitable for the current trend. Figure 10 displays the logarithmic model error as function of λ and the past interval. The graph shows that the error

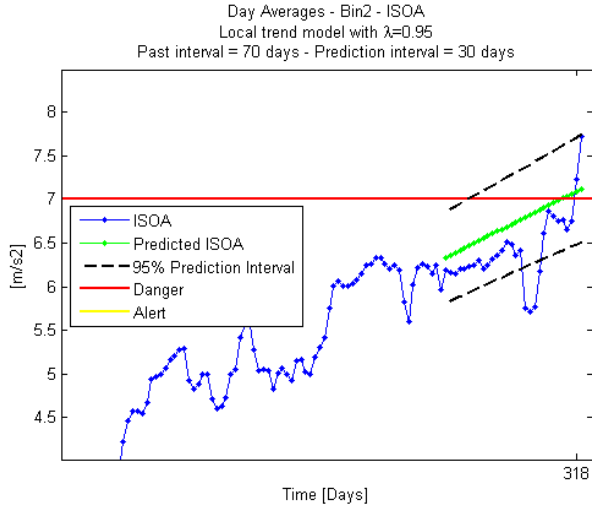


Figure 8. Estimation of fault progression rate using local linear model. The fault development rate is $0.0255m/s^2$.

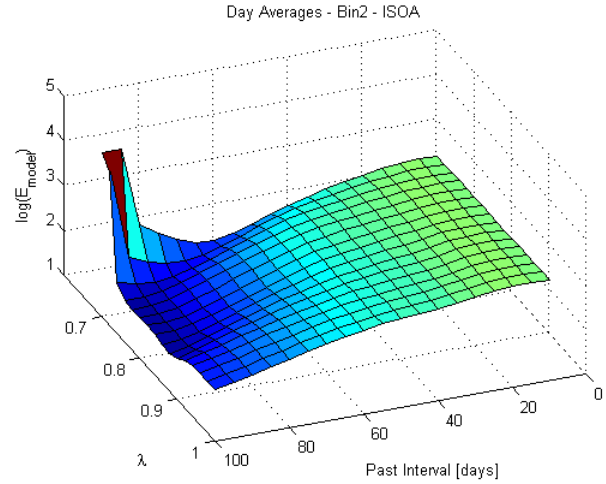


Figure 10. Relationship of past interval and forgetting factor λ for local linear trend model given 30 days of prediction time for quadratic model.

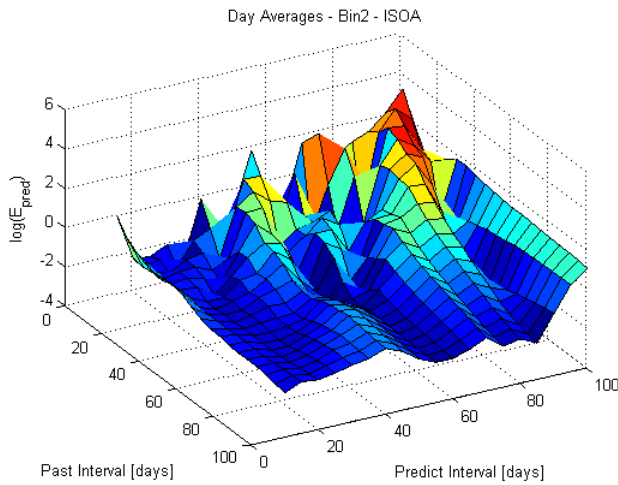


Figure 9. Relationship of past predict intervals for $\lambda = 0.95$ for local linear trend model.

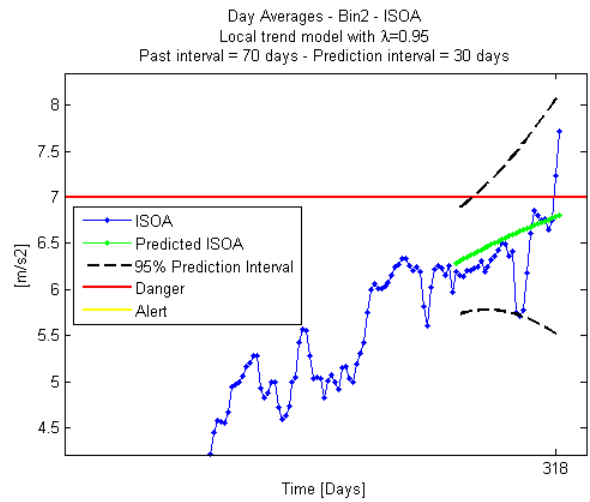


Figure 11. Estimation of fault progression rate using local quadratic model.

is low for long past values and it is relatively insensitive for λ 's above 0.8. In order to compare the linear and quadratic models, the same models settings are applied in this case as well. The predictions follow a very smooth second order function along with the confidence intervals whose quadratic behaviour is more pronounced, as shown in Figure 11.

The fault development rate is shown in Figure 12, where the progression is not constant as in the linear model, but "decelerates" with increasing prediction interval. Although this decelerating pattern might be contradictory with the expected development rate in any faults, it could be justified if a wind turbine does not operate at high power bins for a certain time period and hence the average stress on the bearing is reduced.

This condition can manifest in the trend as decay of the fault progression rate, as shown in Figure 12.

As in the case linear models, the prediction error in quadratic models is low for long past values and short prediction intervals, as displayed in Figure 13.

4.3. Long Term Predictions

The former sections present the forecasts of the two models aiming at prediction time of 30 days, which is relatively long from a prognostics perspective, but could be considered limited in certain occasions, as for example in offshore installations. In order to cover the latter, long term prediction of 120 days (four months) are presented using both linear and

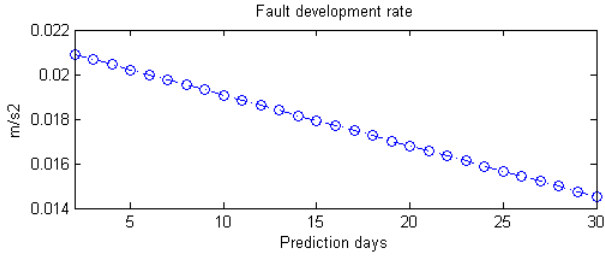


Figure 12. Fault development rate as function of prediction time in quadratic model.

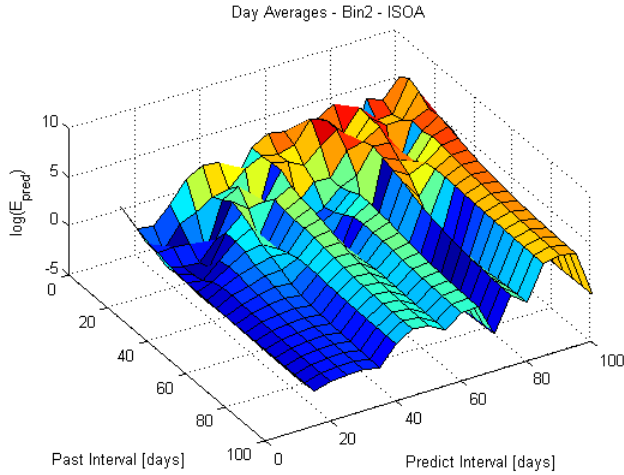


Figure 13. Relationship of past predict intervals for $\lambda = 0.95$ for local quadratic trend model.

quadratic model in Figures 14 and 15 respectively. It can be seen that the linear model underestimates the progression of the fault by inherently establishing a constant development rate, whereas the quadratic model offers a more coherent prediction. It should be emphasized that the selection of past values is of essential importance in the model building in both cases. Furthermore, it is important to re-estimate the model when new data is available in order to update the current fault condition continuously. The necessity of constant model updating is reflected if one compares the fault development rates in two different time periods as shown in Figures 12 and 16.

5. DISCUSSION

Deployment of prognostic systems has inherent limitations in trend analysis of CMS data mainly due to the varying load and running speed conditions of modern wind turbines. This operational frame complicates the predictions considerably both regarding the past values based on which the model is designed and the forecast time.

From an operation and maintenance standpoint, the main question is the added value of these systems in the decision making process of the maintenance and component replace-

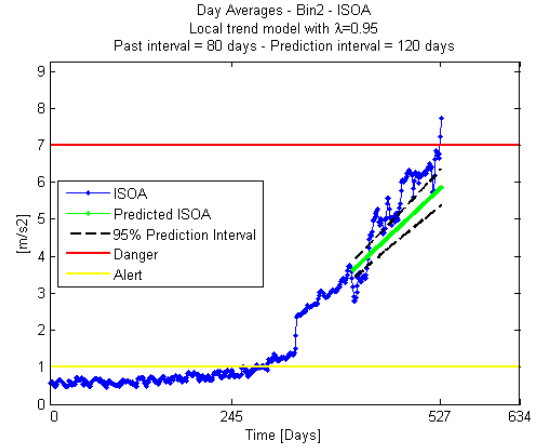


Figure 14. Estimation of fault progression rate using local linear model for long term prediction.

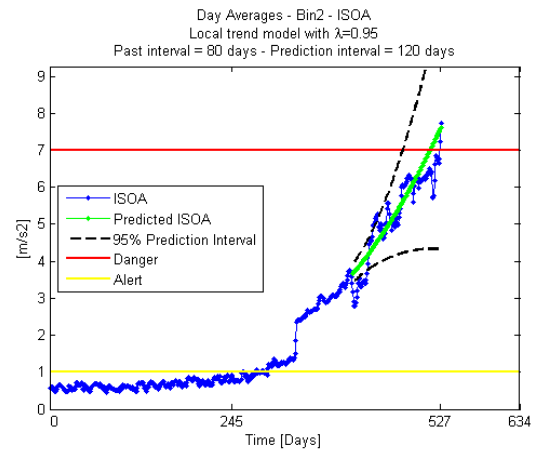


Figure 15. Estimation of fault progression rate using local quadratic model for long term prediction.

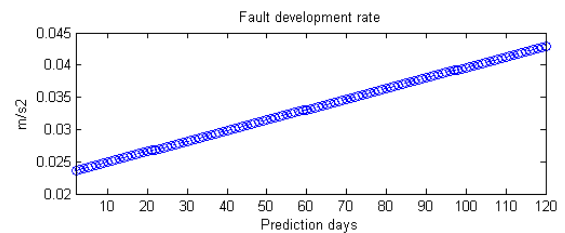


Figure 16. Fault development rate as function of prediction time in quadratic model for long term prediction.

ment planning. Quantification of the expected RUL based on the history of the fault minimizes the uncertainty of too early or too late actions, but it basically provides the proper lead time to order spare parts, mobilize cranes if needed, allocate the required human resources, etc.

On the contrary, the major pitfall in prediction systems is the loss of trust not only in the prognosis part but also in the diag-

nosis of a fault in case of inaccurate forecast. Hence, it is of essential importance to provide predictions only in the cases of developing faults and not under sudden events. Undoubtedly, confidence intervals facilitate part of the uncertainty and should always be part of any forecasting system in order to stress the outlook and level of trust of the future estimations.

An important part of discussion is the required skills of the analyst employing prognostics in order to formulate more advanced severity estimation of the defective component. The method of local trend modelling is a function of four main parameters, the forgetting factor λ , the prediction time, the past time and the model itself, i.e. linear, quadratic or higher order polynomial. Unrealistic predictions for example due to improper past time selection should be identified and discarded, and modification of the above mentioned factors should be considered in order to obtain an updated estimation of the future condition. The latter, i.e. update of forecast, is important as the fault severity might escalate rapidly which cannot be predicted based on the past progression rate. The model update frequency should ideally be equal to the data import rate or at least at daily basis.

6. CONCLUSIONS

Modern condition monitoring systems incorporate diagnostics and prognostics services for fault detection, severity estimation and prediction of the component remaining useful lifetime. Two different trend models are applied for predicting the fault progression rate of wind turbine defective generator bearings, based on the energy of vibration signals from 10Hz to 1000Hz, as suggested by ISO 10816. It is shown that both linear and quadratic local trend models can be employed successfully for relatively short prediction interval in the range of one month, offering useful information to the service provider. In both models, it is concluded that high forgetting factors and relatively long past intervals produce the most accurate predictions of the fault development. On the contrary, for long term forecasting, it is observed that quadratic models have more coherent behaviour. In the model configuration part, one of the most important factors is the selection of appropriate past values in order to obtain representative forecasts. It is concluded that updated estimations are necessary when new data are available so as to systematically specify the current fault condition.

REFERENCES

- Alam, M. M., & Suzuki, K. (2009). Lifetime estimation using only failure information from warranty database. *IEEE Transactions on Reliability*, 58, 573–582.
- Antoniadou, I., Manson, G., Staszewski, W., Barszcz, T., & Worden, K. (2015). A time–frequency analysis approach for condition monitoring of a wind turbine gearbox under varying load conditions. *Mechanical Systems and Signal Processing*, 64, 188–216.
- Hu, Y., Baraldi, P., Di Maio, F., & Zio, E. (2014). A prognostic approach based on particle filtering and optimized tuning kernel smoothing. In *European Conference of the Prognostics and Health Management Society 2014*.
- Hussain, S., & Gabbar, H. A. (2013). Vibration analysis and time series prediction for wind turbine gearbox prognostics. *IJPHM Special Issue on Wind Turbine PHM*, 1, 69–80.
- ISO 10816. (2015). *Mechanical vibration - evaluation of machine vibration by measurements on non-rotating parts - part 21: Horizontal axis wind turbine with gearbox* (Vol. 10816).
- Lee, J., Wu, F., Zhao, W., Ghaffari, M., Liao, L., & Siegel, D. (2014). Prognostics and health management design for rotary machinery systems reviews, methodology and applications. *Mechanical Systems and Signal Processing*, 42, 314–334.
- Li, N., Lei, Y., Lin, J., & Ding, S. X. (2015). An improved exponential model for predicting remaining useful life of rolling element bearings. *IEEE Transactions on Industrial Electronics*, 62, 7762–7773.
- Madsen, H. (2008). *Time series analysis*. Chapman & Hall / CRC.
- Marhadi, K., & Hilmisson, R. (2013). Simple and effective technique for early detection of rolling element bearing fault: A case study in wind turbine application. In *International congress of condition monitoring and diagnostic engineering management*.
- Medjaher, K., Tobon-Mejia, D. A., & Zerhouni, N. (2012). Remaining useful life estimation of critical components with application to bearings. *IEEE Transactions on Reliability*, 61, 292–302.
- Naganathan, A., Er, M. J., Li, X., Chan, H. L., Li, H., Li, J., & Vachtsevanos, G. J. (2013). Complete parametric estimation of the weibull model with an optimized inspection interval. In *2013 IEEE Conference on Prognostics and Health Management (PHM)*.
- Randall, R. B. (1987). *Frequency analysis*. Brüel and Kjær.
- Reuben, L. C. K., & Mba, D. (2014). Bearing time-to-failure estimation using spectral analysis features. *Structural Health Monitoring*, 13, 219–230.
- Skrimpas, G. A., Dragiev, I. G., Hilmisson, R., Sweeney, C. W., Jensen, B. B., Mijatovic, N., & Holboll, J. (2015). Detection of generator bearing inner race creep by means of vibration and temperature analysis. In *10th International Symposium on Diagnostics for Electrical Machines, Power Electronics and Drives (SDEMPED)*.
- Skrimpas, G. A., Sweeney, C. W., Jensen, B., Mijatovic, N., & Holboell, J. (2014). Analysis of generator bearing vibration data for diagnosing rotor circuit malfunction in dfigs. In *21st International Conference on Electrical Machines (ICEM)*.

- Tchakoua, P., Wamkeue, R., Ouhrouche, M., Slaoui-Hasnaoui, F., Tameghe, T. A., & Ekemb, G. (2014). Wind turbine condition monitoring: State-of-the-art review, new trends, and future challenges. *Energies*, 7, 2595–2630.
- Zio, E., & Peloni, G. (2011). Particle filtering prognostic estimation of the remaining useful life of nonlinear components. *Reliability Engineering & System Safety*, 96, 403–409.

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