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Fleet Monitoring

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Abstract

Distributed energy systems such as wind turbines share the properties of:

(1) having a rising number of similar installed system setups,

(2) being installed mostly in remote areas with limited access and

(3) needing high system reliability.

This makes fault diagnosis and identification (FDI) a crucial but challenging part for operation and maintenance (O&M) of these systems. Because of the large amount of wind turbines there is an increased need for monitoring the overall fleet, additional to individual wind turbines. This work focuses on using condition information of equal components in different machines and under different working conditions, to extract useful information for FDI of those components. Therefore, the focus of data analysis is the fleet information and not only individual systems information. It will be shown that properties of the introduced method can resolve common FDI drawbacks, e.g. setting up alarm thresholds.

Objectives

The problem that is researched in this paper is defined as supporting the monitoring effort of distributed energy system based on existing machine data. The focus is to detect unusual machine behavior on a fleet base. The definition of fleet monitoring is defined by the authors by [8]:

Monitoring a fleet of similar type or identical machines, operating under similar conditions, to detect unusual machine behavior of a single machine if compared to the fleet.

Additionally the introduced fleet monitoring method makes no use of design specific quantitative thresholds and no use of historical monitoring data. The thematic priority is not on machine individual FDI or prognosis of future machine conditions.

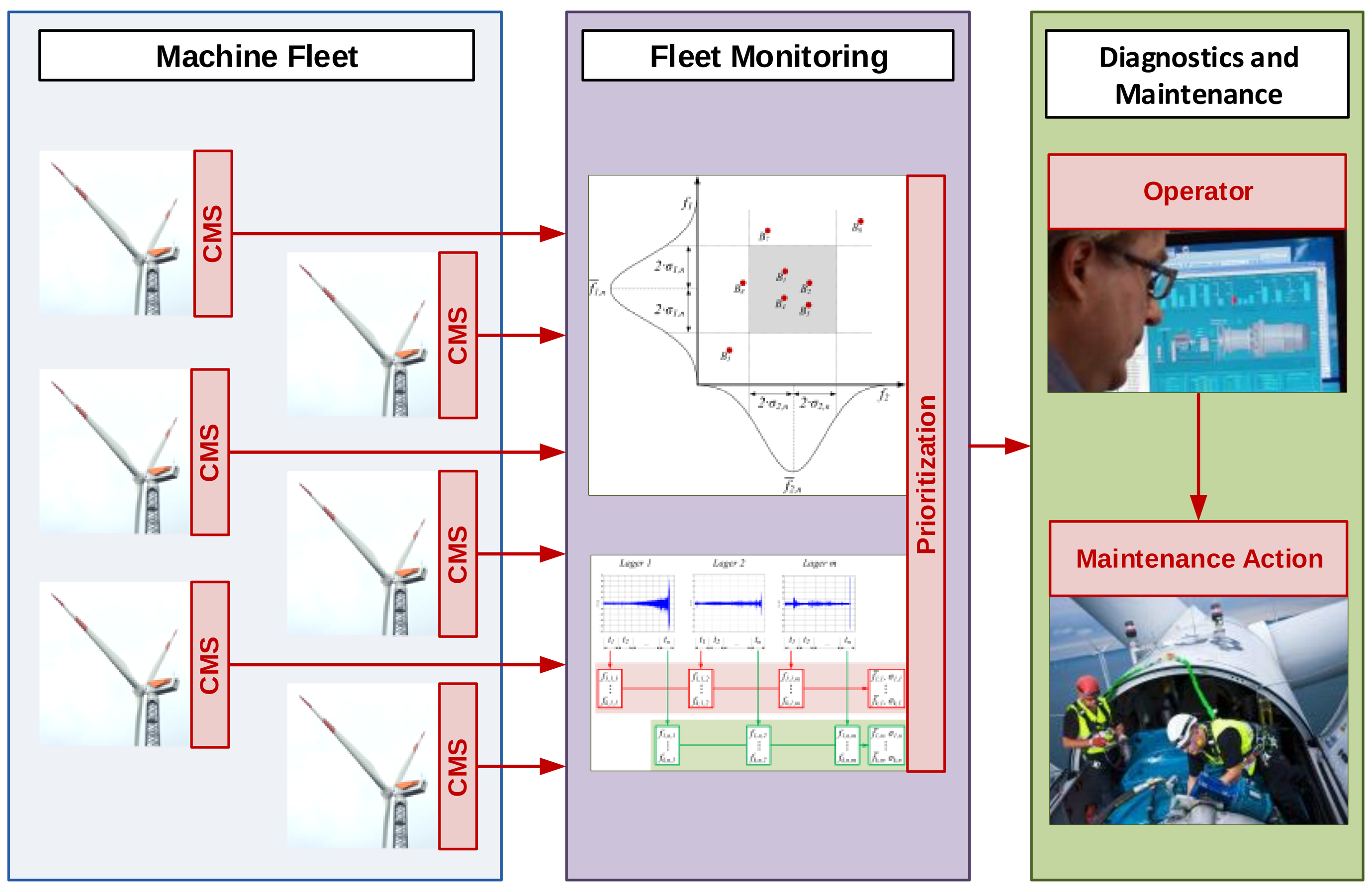

Figure 1 shows the aggregation of machine condition data from the machine fleet to provide a prioritization for O&M. Based on the prioritization the operator has additional information for further FDI and is able to react more efficient to faults. The operator triggers a maintenance action if needed so.

Methods

The core method for fleet monitoring is the multivariate normal distribution (also called multivariate Gaussian distribution). Therefore it is a multi-dimensional type of univariate normal distributions. It is important to note that the multivariate normal distribution is calculated for only a single time interval by using only the data of the machine fleet of this specific interval and without using any historical data. A main advantage is the absence of absolute measures for FDI and the use of relative measures between components/machines in the fleet. Besides the theoretical approaches, an example using vibration data of bearings is given. The runs of the bearings were performed with different speed and load and were only stopped by significant degradation. The dataset descends from the FEMTO-ST Institute (Besançon, France) from the "IEEE PHM 2012 Data Challenge" was used. During the experiments, one-tenth of a second of horizontal and vertical vibration signals were recorded each 10 seconds at a sample frequency of 25.6 kHz. [7] [8]

Mean value of a specific feature k in the time interval n:

$$\bar{f}_{k,n} = \frac{1}{m}\sum_{i=1}^{m} f_{k,n,i}$$

Standard deviation of a specific feature k in the time interval n:

$$\sigma_{k,n} = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(f_{k,n,i} - \bar{f}_{k,n}\right)^2}$$

Index:

m… Bearing, k… Feature, n… Time interval

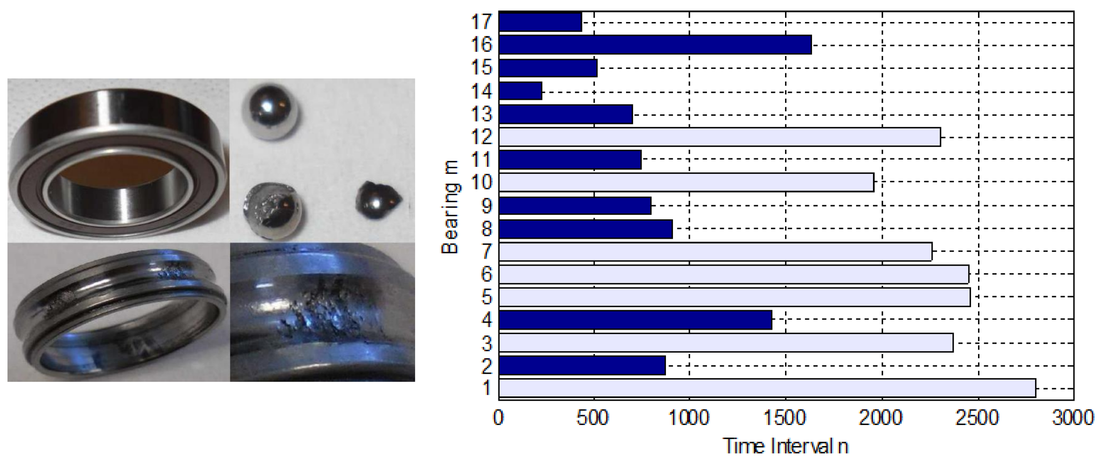

Figure 2 shows the available time intervals n for each bearing m. Because of a minimum of at least 8 required bearings, to assure test for normal distribution, the method will not deliver a result after the end of the life time of bearing $m=16$ at time interval n=1637 (assuming that all bearings started operating at n=1). [7]

For each time interval n all extracted features $f_{k,n,m}$ are tested if the features in that time interval are normal distributed. Therefore the Anderson–Darling test with a significant level of 5% is used. The test is valid until a sample size of at least 8.

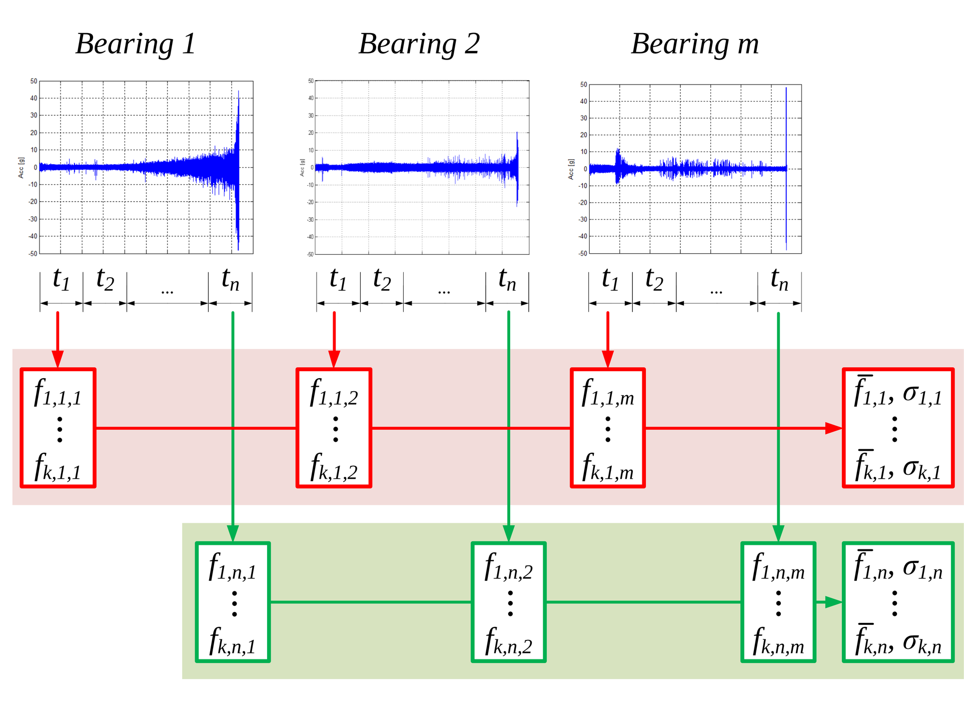

Figure 3 shows the approach for feature extraction. At first k features of m separate bearings B_m of m machines of the machine fleet for n time intervals (of equal length) are extracted resulting in values defined as $f_{k,n,m}$. Here the features root mean square (RMS), the peak magnitude to RMS ratio (Peak2RMS) and the maximum to minimum difference (Peak2Peak) are used [4]. [8]

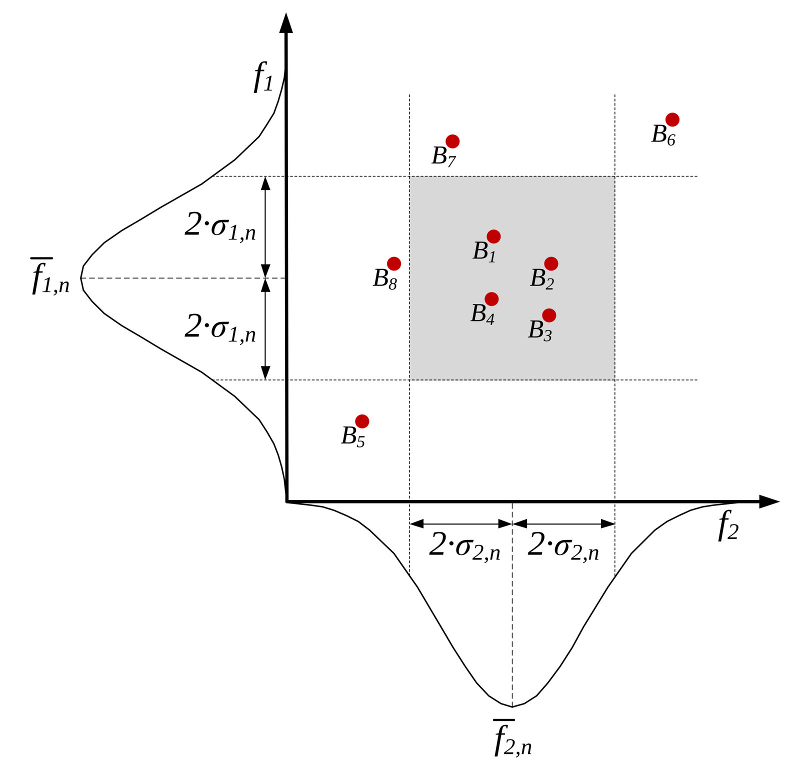

Figure 4, illustrates a two-dimensional normal distribution for a time interval n. The axis display two features (f_1, f_2), mean values ($\bar{f}_{1,n}$, $\bar{f}_{2,n}$) and standard deviations ($\sigma_{1,n}$, $\sigma_{2,n}$). It is important to note that the representation is valid for only a single time interval. [8]

Results

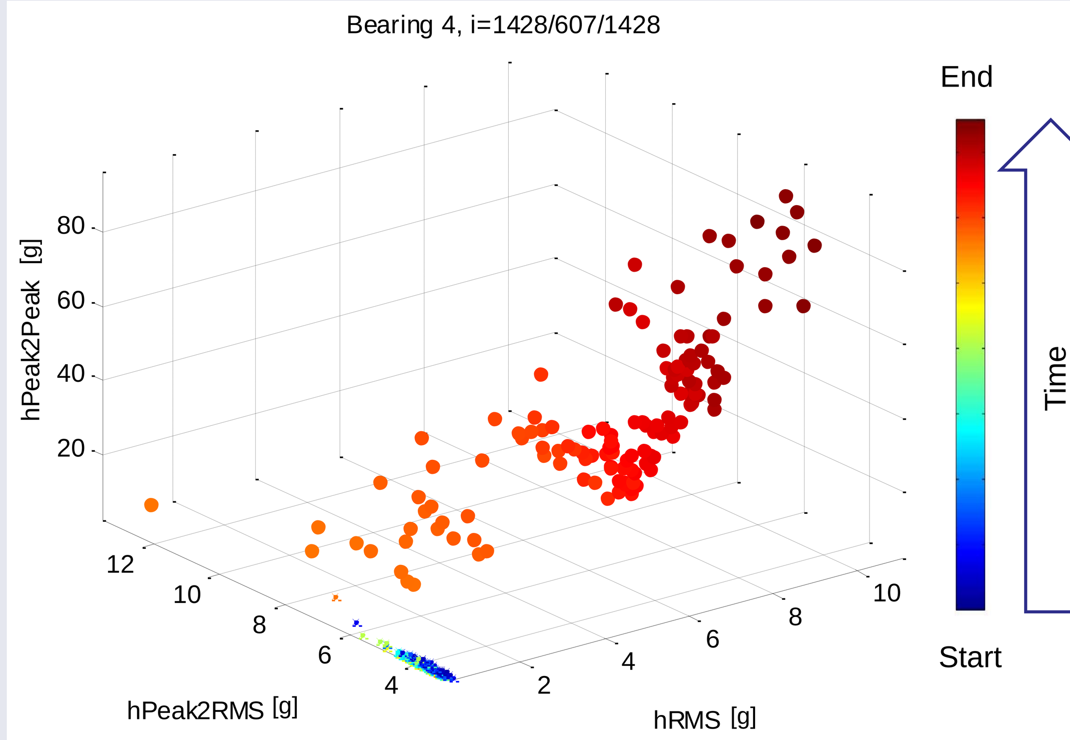

Figure 5, shows the results of bearing $m=4$. The color indicates the life time of the bearing. Crosses classify healthy behavior, circles classify unusual behavior (depending on the $\sigma_{k,n}$ threshold).

It can be seen that for all normal distributed bearings an unusual behavior before the end of life time could be classified using no design specific quantitative thresholds. The results show the detectability depending on fleet size and feature selection. Further research is needed regarding sensitivity analyses, feature extraction and feature interconnectivity.

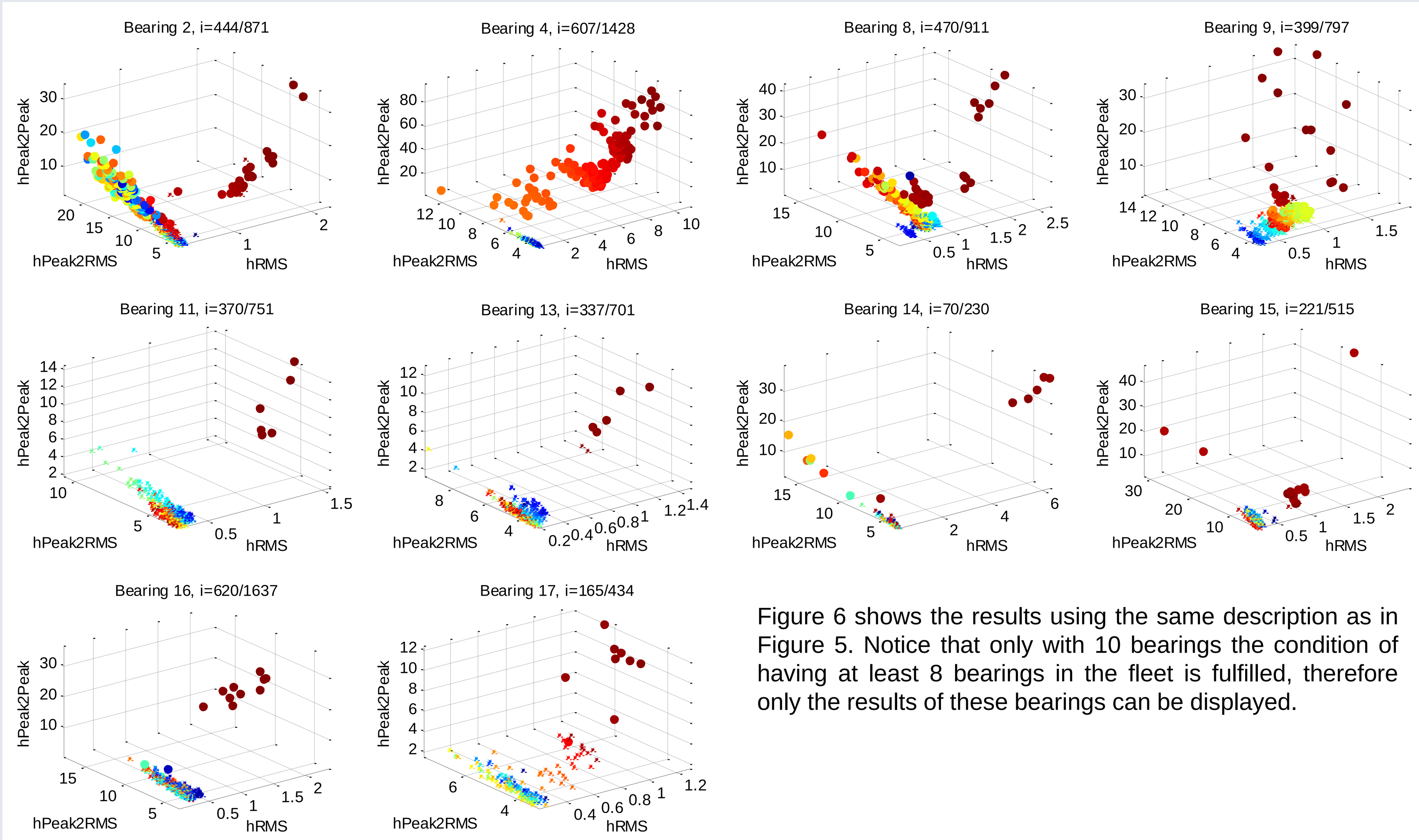

Figure 6 shows the results using the same description as in Figure 5. Notice that only with 10 bearings the condition of having at least 8 bearings in the fleet is fulfilled, therefore only the results of these bearings can be displayed.

Conclusions

A method for fleet monitoring is given to detect unusual machine behavior of a single machine if compared to the fleet. The method is applied to vibration data of 17 bearings. For a fleet size of at least 8 bearings, for every bearing in this fleet unusual behavior could be detected before the end of the bearing life time.

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