Health assessment of traction-motor blowers regarding their deformation degradation

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ABSTRACT

Traction motor blowers are essential components of electric trains. Their failure entails a complete disruption of the operational service, in addition to a safety hazard. Thus, maintaining them effectively is a must to guarantee the availability and reliability of the rolling-stock units. To this end, the predictive maintenance approach can add a lot of value because blowers display a complex behaviour, they seldom fail, but when they do the costs associated to their replacement and the subsequent time out of service of the train (not generating revenue) are prohibitively high and may challenge the viability of a business case. However, getting to deploy an adequate data-driven predictive approach is difficult because it entails collecting streams of useful information in order to generate bespoke diagnostics and prognostics in a timely manner. In this article, we have developed and deployed a network of intelligent wireless sensors that enable to capture vibration data easily on board, and to seamlessly integrate it into our data processing pipeline for a remote inspection of the blowers. In order to adapt the data analysis modules to the blower characteristics and test conditions, we have conducted a feature mapping with the complete fleet of blowers (288 component units) and a statistical analysis to detect anomalies. Then we have fitted a performing diagnostic function taking into account the criticality criteria from the ISO 10816 norm that is currently used as the only indicative reference for general rotational machine maintenance. Additionally, we have checked the validity of these analysis outputs with the dismantlement and visual inspection of some blowers. Our purpose is to develop a new schedule for the maintenance actions as we can now better determine the condition and predict the failure of a blower ahead of time, thus increasing the detection effectiveness of degraded blowers. We believe that an adequate maintenance of traction motor blowers with a remote predictive approach based on intelligent wireless sensors may increase the availability and reliability of the trains, and thus make the rail transport service more appealing.

1. INTRODUCTION

Electric trains rely heavily on the good operating condition of traction-motor blowers, which cool down the vast amount of heat generated by the power electronics that drive the traction unit. These blowers are rotational devices that incorporate a turbine that spins at various angular speeds according to the cooling demand. There are several issues that may compromise the correct operation of this device: the build-up of dirt may produce imbalance, the degraded coupling of the shaft may produce misalignment, the bearing that sets the turbine in place may experience cracks or spallings on its races, etc (S. J. Lacey,2008). At present, the maintenance team that is responsible for the reliability and availability of the traction-motor blowers makes use of the ISO 10816 standard (ISO,2009), which accounts for the root-mean-square value of the velocity signal to determine if the component is in good condition or not with a threshold. Also, they detect imbalances and correct them with counterweights along the surface of the turbine. However, these mechanical corrections eventually produce a fatigue that produces unexpected incidents which cause service-affecting failures, see Figure 1.

This paper presents the deployment of the Prognostic and Health Management (PHM) approach described in the ISO 13374 standard (ISO,2003) on the fleet of traction-motor blowers. This ISO standard defines a series of steps to be fol-

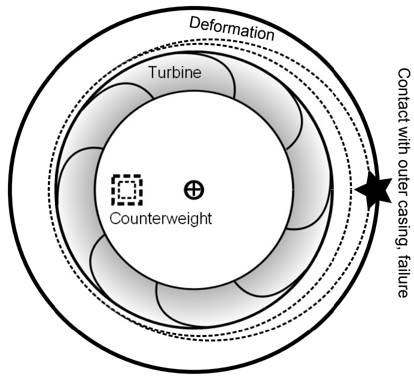


Figure 1. Fatigue of a traction-motor blower with counterweight imbalance corrections.

Figure 2. TheMotes installed on the outer casing of the traction-motor blower.

lowed in order to approach the predictive maintenance in an ordered manner, first extracting the signal features, and then deploying models to conduct the diagnostics and the prognostics. We will particularly focus our efforts on the detection and management of the turbine deformation, because this is not being properly addressed by the current maintenance approach. In order to do so, the vibration of the blowers in operation will be acquired with a network of intelligent wireless sensors called TheMotes (A. Trilla and P. Gratacòs,2013), see Figure 2. Vibration is a very rich proxy variable that encodes lots of information and denotes the presence and condition state of rotating mechanical components. TheMotes were chosen because they are non-intrusive (magnetically attached to the outer casing), do not require cabling (data is forwarded wirelessly from device to device and finally collected with a tablet), do not interfere with the operation of the system and are ideal for retrofitting. They acquire a vibration signal with 3 axes, during 10 seconds, and with a sampling rate of 3.2kHz using an on-board Micro-Electro Mechanical System-based sensor.

This article is structured as follows: Section 2 shows the statistical analyses that have been conducted in order to model the fleet-wise behaviour of the traction-motor blowers. Then, Section 3 aggregates the results, makes some noteworthy remarks and proposes a model to conduct the health assessment procedure. Finally, Section 4 draws the conclusions and suggests future research lines.

Table 1. Frequencies of interest for understanding the vibration signature of the traction-motor blower. Note that the structural looseness refers to the harmonics of 55Hz greater than 3.

Frequency	Justification
55Hz	Imbalance (O1)
110Hz	Misalignment (O2)
272.061Hz	Bearing inner race (BPFI)
167.939Hz	Bearing outer race (BPFO)
20.992Hz	Bearing cage (FTF)
109.701Hz	Bearing rolling element (BSF)
219.403Hz	Turbine rolling element (RE)
770Hz	Turbine vanes (VA)
55Hz * [3..9]	Structural looseness (O3..O9)

2. METHOD

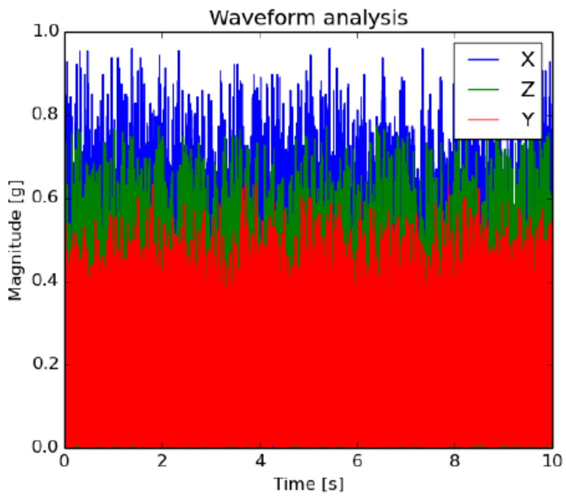
This section describes the vibration signature of the traction-motor blower component under analysis, and the statistical modelling approach that has been conducted in order to perform the analysis.

The tests have been designed so that the sensors capture the greatest amount of useful information. To this end, the trains need to be parked at the depot (zero speed avoids any noise effect from the wheel-track contact), the blowers need to operate at the highest speed so as to spread the frequency content without experiencing aliasing distortion with the acquisition system, and the ambient temperature needs to be not extreme (although this is regarded to have little impact on rotational machinery).

2.1. Traction-motor blower vibration signature

The traction-motor blowers considered in this article have a turbine with 14 vanes, which will be operated at a constant speed of 3300rpm (i.e., 55Hz). When such rotational devices are in good brand-new condition, they display a low vibration profile, with very little noise. However, as they accumulate hours in service and degrade, they develop a characteristic vibration signature. This signature will be used to locate the source of the problem, along with its severity. Figure 3 shows an example of such vibration signature. Note that over 800Hz (approx.) there is no vibration component of relevant interest.

In order to better understand the vibration signature displayed in Figure 3, Table 1 lists the frequencies of interest that can be directly related to the components that build the blower (B. Shannon,2008;M. DiGiovanni and T. R. Spearman,2008). These have been compiled from the parts datasheets.



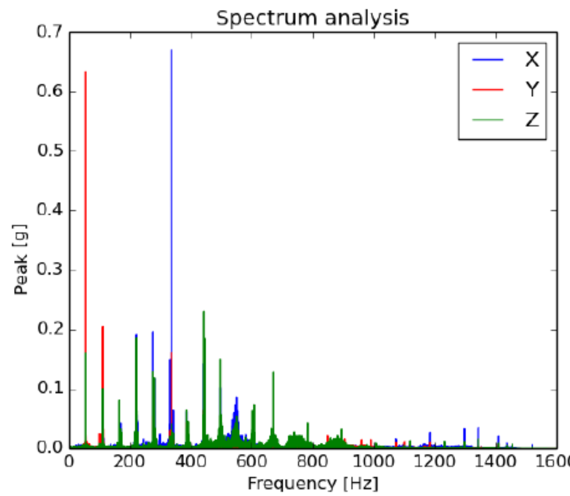


Figure 3. Example vibration signature of one traction-motor blower as it is acquired by TheMotes. Note the salient peaks on 55Hz and 330Hz. The axis with the greatest vibration amplitude (most severe fault) is selected for conducting the analysis.

In this study it is assumed that over order 10 (550Hz) the resulting high-frequency vibration is too attenuated and cannot be differentiated from the overall background noise level.

2.2. Statistical modelling method

After having monitored almost the complete fleet of traction-motor blowers (i.e., a “snapshot” sample size of 288 elements), a statistical analysis of the acquired vibration signature is conducted in order to model the usual behaviour of the component being studied, and to detect the presence of anomalous behaviours, i.e., values that lie out of the confidence interval of the observed distribution. In order to do so, the former list of relevant frequencies, see Table 1, is considered as possible useful indicators. Specifically, their peak amplitude vibration values is used. In theory, when an incipient failure is developing, a particular frequency increases its energy (i.e., its magnitude), and keeps doing so until the failure occurs. Additionally, the root-mean square (RMS) of the velocity signal is included, motivated by the ISO 10816 standard that is currently considered by the maintenance team.

Then, the distribution of each indicator is inspected through its histogram. First, a principal concentration of elements is identified, which denotes the usual behaviour of the traction-motor blower. Then, isolated events are spotted, which may denote the presence of a developing failure. It is assumed that the usual distribution of the fleet follows a Gaussian, and abnormal elements must lie out of a confidence interval of 99.7% (this article considers that a difference is statistically significant if it differs from the mean over 3 standard deviations). The appendix shows the results of the statistical analysis.

Note that the distribution for the O6 indicator, which is relative to a frequency of 330 Hz, is the only distribution which appears to be multimodal, and on which the Gaussian normality assumption is clearly mistaken.

3. DISCUSSION

This section elaborates on the statistical analysis and tries to establish links with actual service-affecting failures.

3.1. Statistical analysis

It can be observed that more than 40 units, out of the 288 under analysis, display indicators that lie out of the confidence interval with respect to the overall behaviour of the fleet. Table 2 shows a comparative ranking with this information.

Note that for the blowers leading the ranking it is usual to observe simultaneous outliers on different indicators.

3.2. Reported service-affecting failures

It is a matter of fact that the current maintenance plan has limitations because service-affecting failures do actually occur (validated through visual inspection). Table 3 shows the indicators for some of the failures reported so far.

Note that many of the indicator values for these failing traction-motor blowers have been masked by the overall behaviour of the fleet, i.e., they don’t show significantly anomalous values, except for blower 01-01-01. It is possible that the service-affecting failure develops so fast that its signature could not be acquired during the monitoring of the sample. Figure 4 shows an example of such catastrophic failures.

Also note that among the whole set of indicators, there are two of them that stand out from the rest in *all* cases due to

Table 2. Outlier indicator comparison ranking (top 10). The marks correspond to the presence of outlier indicators with respect to the fleet.

Blower Id	RMS	BPFI	BPFO	FTF	BSF	RE	VA	O1	O2	O3	O4	O5	O6	O7	O8	O9	Total
04-03-01	x		x		x	x	x	x	x	x	x						9
17-02-01	x	x						x			x	x		x	x		7
17-02-03					x	x	x		x		x					x	6
17-02-02	x					x					x				x		4
04-03-03		x				x					x	x					4
19-04-02		x				x					x	x					4
04-01-03					x		x		x								4
11-02-02					x		x		x								4
01-04-01					x		x		x								4
01-01-01	x												x				2

Table 3. Indicators for service-affecting failures.

Blower Id	RMS	BPFI	BPFO	FTF	BSF	RE	VA	O1	O2	O3	O4	O5	O6	O7	O8	O9
09-04-03	1.14	.01	.03	.00	.03	.02	.03	.23	.08	.03	.02	.01	1.46	.03	.11	.07
05-01-02	.75	.04	.06	.01	.10	.06	.10	.35	.10	.06	.06	.04	.48	.05	.46	.08
05-03-03	.62	.08	.15	.01	.03	.02	.03	.43	.03	.15	.02	.08	.34	.03	.05	.06
15-02-01	1.03	.01	.12	.01	.06	.03	.06	.30	.06	.13	.03	.01	1.20	.03	.90	.09
01-01-01	3.07	.03	.12	.00	.16	.05	.16	.04	.16	.12	.05	.03	3.64	.02	.09	.06
11-03-02	.82	.06	.09	.00	.17	.03	.17	.49	.17	.09	.03	.06	.62	.21	.10	.03

Figure 4. Service-affecting failure of a traction-motor blower. Note how the turbine has been heavily deformed before breaking.

their greater magnitude: RMS and O6. They are further discussed in the following section. Note that this work specifically focuses on the indicators related to actual failures. Other tails of anomalies from the statistical analysis that are not observed among the reported failures are not taken into account as they may be due to other issues that are out of the scope of this article.

3.3. RMS and O6 indicators

The RMS indicator operates directly on the velocity waveform of the signal and it is related to the energy of the noise that is perceived. It is considered by the ISO 10816 standard (current maintenance approach) to detect the presence of a failure and its corresponding level of alarm (usually when the peak goes over the threshold of 3mm/s, although this only happened for one single failure case, 01-01-01). According to the expert feedback received from the maintenance team with respect to the service-affecting failures, it seems reasonable to take it into account to note one particular condition state, and then relate it to the rest of the indicators more focused on the location of the source of the problem. However, the threshold values stated in the ISO standard may need to be revised because they don't seem to apply to this particular component or test characteristics.

The O6 indicator, which is related to a structural looseness problem, is the only one that displays a multimodal distribution. Because of this, it would appear to be the key indicator that denotes the presence of turbine deformation because this is arguably the most common issue that has been reported by the maintenance team. In addition, this distribution does not show a smooth degradation transition from a good condition to a bad one: the blowers either display it or not. It must also be noted that the O6 indicator currently gets smoothed when computing the velocities via numerical integration with the current maintenance process (it works like a low-pass filter), and that's maybe why it cannot be detected at present.

3.4. Predictive functions

In order to be compliant with the ISO 13374, which defines the way PHM systems should be implemented with respect to the data analysis pipeline, this section deals with the health

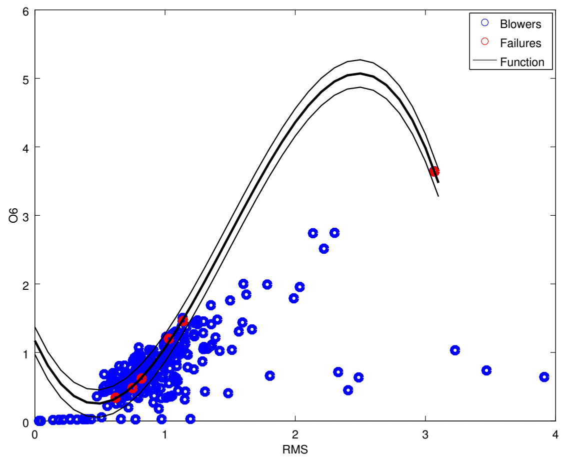


Figure 5. Indicator map and function learning.

assessment function that is to be produced in order to approach the deployment of this predictive approach.

It should be noted that the statistical outlier indicators hardly match the service-affecting failure indicators: they overlap and don't display a clear differentiating feature. Figure 5 displays a scatter plot of the RMS indicator vs the O6 indicator.

Additionally, a multilayer neural network is employed to fit a function to discriminate the failing traction-motor blowers, with a moving margin (bias) to allow for measurement uncertainty. Its performance is rather good, showing an overall sample accuracy of 99.31%, with a precision of 75.00% using a small margin, as recall easily gets to the maximum. However, we admit the the shape of this learnt function is too tight to be generalised with confidence so as to clearly explain the failures (note that to this end the model has been trained with all failure cases).

The fitting function depicted above may be used as a diagnostic function if the distance of a new sample point to the function is computed and normalised, as it would be done with a *soft* classification approach, but this is hard to interpret.

4. CONCLUSIONS

The degradation analysis of the traction-motor blowers is complex and unclear. The ISO 10816 norm that has been used by the maintenance team to establish the threshold alarm levels has resulted to be inefficient to detect developing failures ahead of time. Thus, this criterion is necessary but not sufficient to attain spotting the incipient points of failure, which is the main goal of the predictive maintenance approach.

With the study presented in this article it has been observed that the joint analysis of a set of indicators extracted from the vibration signal may be of help when their values are significantly different from the behaviour of the fleet, especially with respect to the structural looseness of 6th order, which is supposed to be indicative of a turbine deformation degradation. Nevertheless, the relationship between the indicator and the state condition of the degradation is not clear today.

In order to progress with the addition of value to the know-how of the traction-motor blower maintenance process, we suggest collecting more diverse data, including the mileage, which is also necessary for conducting the prognosis. Additionally, delving into the machine learning approach focused on the recognition of patterns may be of great help to gain insight into the nature of this degradation function.

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BIOGRAPHIES

Alexandre Trilla is a Data Scientist working on R&D projects that add value to the predictive maintenance approach of railway systems. He has a background in electronics and telecommunications engineering, and his development mainly focuses on the deployment of PHM to rolling-stock components with vibration analysis and machine learning.

Pau Gratacòs is a R&D Maintenance Manager working on the development of maintenance optimisation projects based on predictive maintenance. He has a background in industrial mechanical engineering, and his development mainly focuses on test benches, and on on-board and off-board sensing solutions.

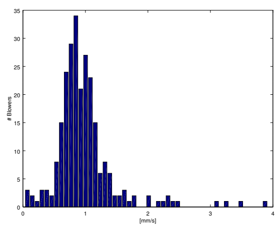
David Guinart is a R&D Project Engineer working on the design, management, planning and research of intelligent wireless sensor networks. He has a background in industrial engineering, and his development mainly focuses on the deployment of the predictive maintenance approach to railways.

Allegra Alessi is a Data Scientist currently involved in the Prognostic branch of the Alstom Predictive Maintenance Centre of Excellence, within Alstom's HealthHub. She has a background in Safety and Prevention Engineering, and her research interest focus on PHM, health assessment and monitoring of railway components and artificial neural networks. She is co-author of 2 works accepted for publication on PHM.

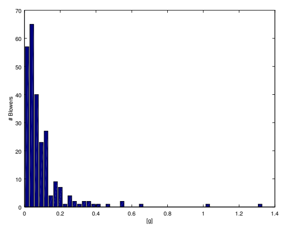
Benjamin Lamoureux is a Data Scientist/PHM Engineer currently involved in the Prognostic branch of the Alstom Predictive Maintenance Centre of Excellence. He has a background in industrial engineering, and holds a PhD degree in PHM for aeronautics.

APPENDIX

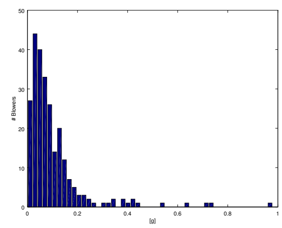
Statistical analysis of the indicators through the histogram:



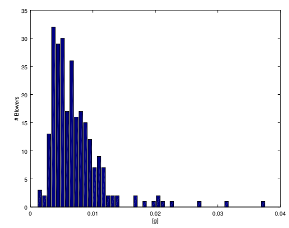
(a) RMS



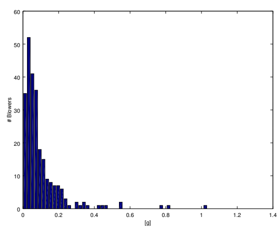
(b) BPFI



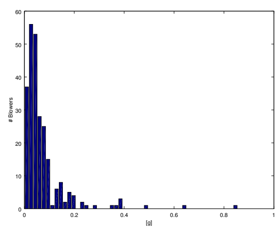
(c) BPFO



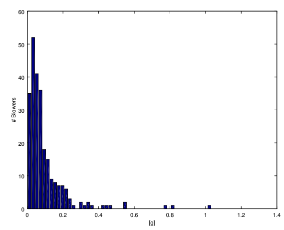
(d) FTF



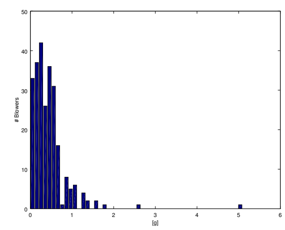
(e) BSF



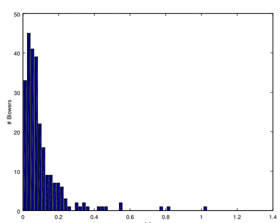
(f) RE



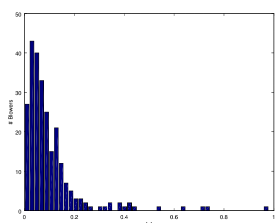
(g) VA



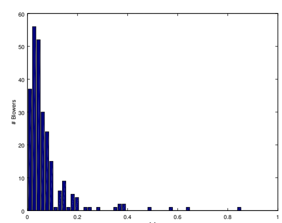
(h) O1



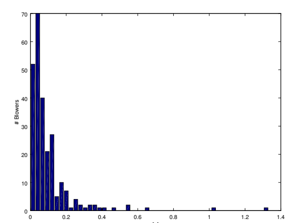
(i) O2



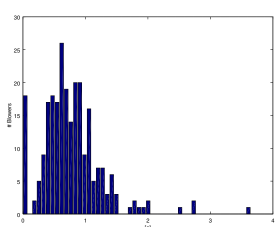
(j) O3



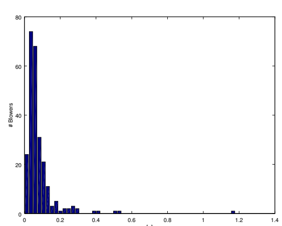
(k) O4



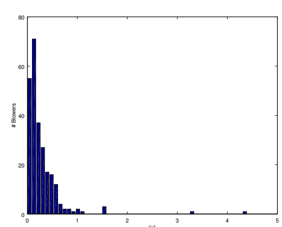
(l) O5



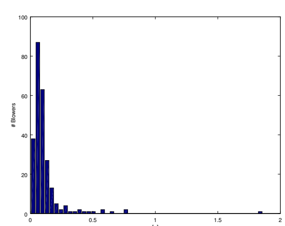
(m) O6



(n) O7



(o) O8



(p) O9