Comparing vibration and acoustic signals for bolt loosening detection in a scale wind turbine drivetrain

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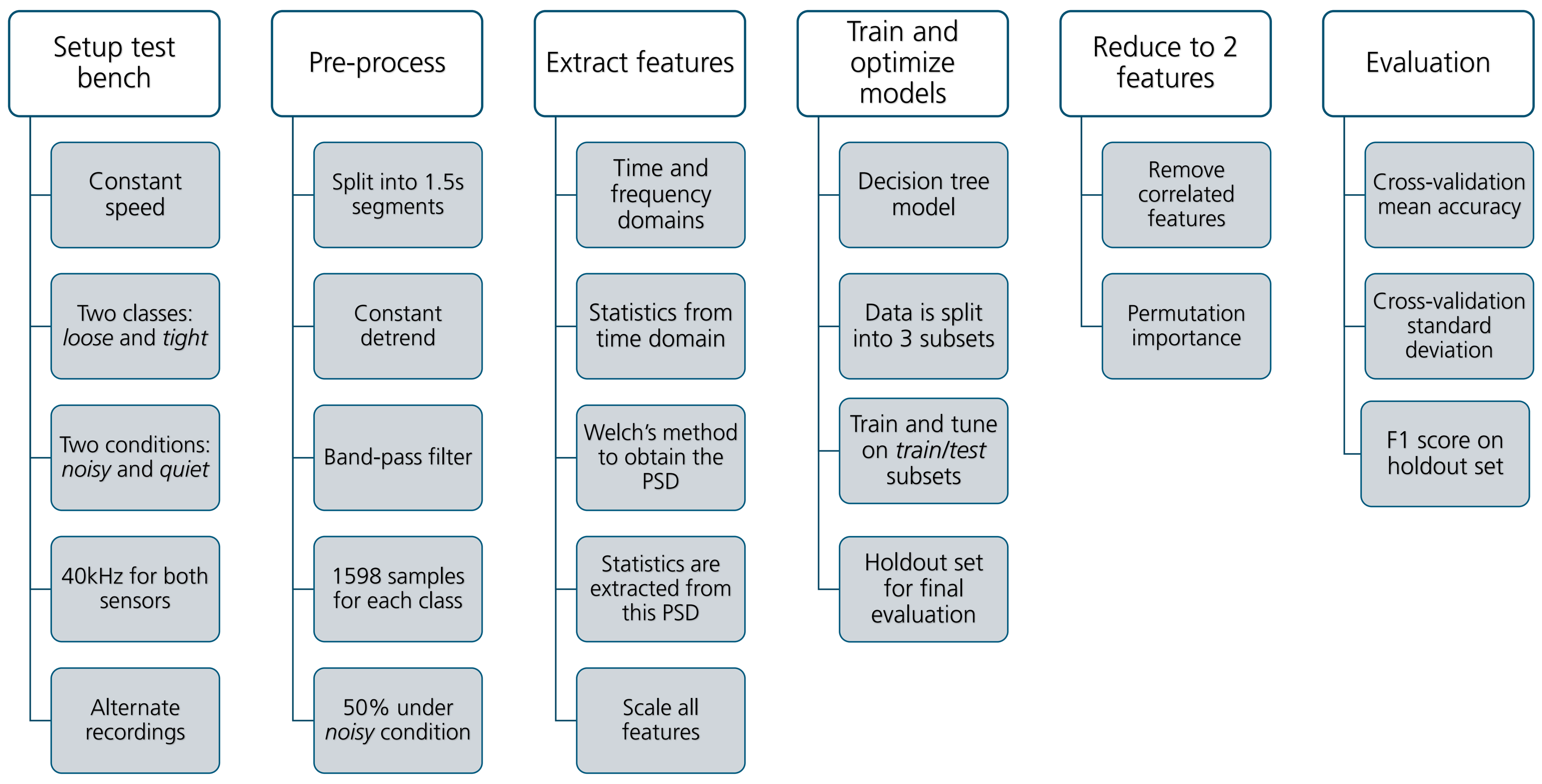
Introduction

This work investigates the feasibility of bolt loosening detection in a scale wind turbine drivetrain by using a microphone and an accelerometer. Signals for both sensors are collected with different levels of background noise and a two-features machine learning model is used to classify them.

Methodology



Test conditions

- The *noisy* condition refers to the measurements taken during normal working hours in the hall.
- Four main sources of noise are present: hydraulic pumps, an overhead crane, a forklift and workers handling tools.
- The condition named *quiet* refers to measurements taken outside working hours.

Testbench layout

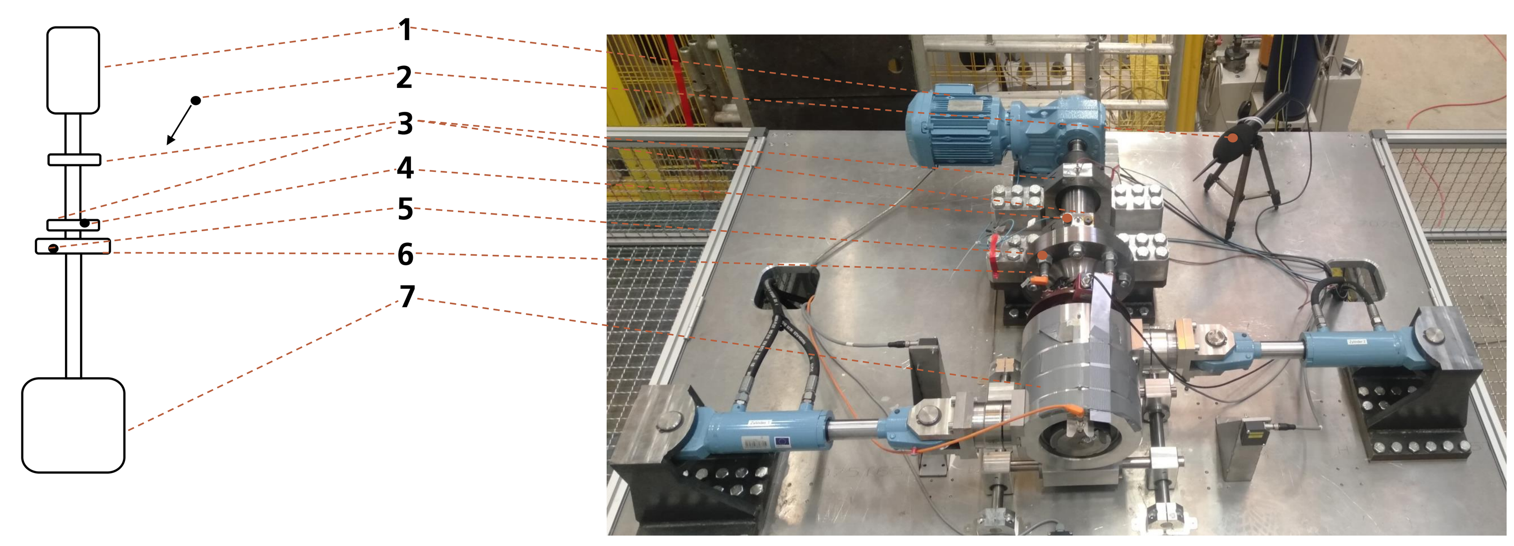


Figure 1: Test bench components. 1 – drive; 2 – microphone, 3 – bearings; 4 – accelerometer; 5 – bolt under investigation; 6 – bolted flange; 7 – load application point.

Results

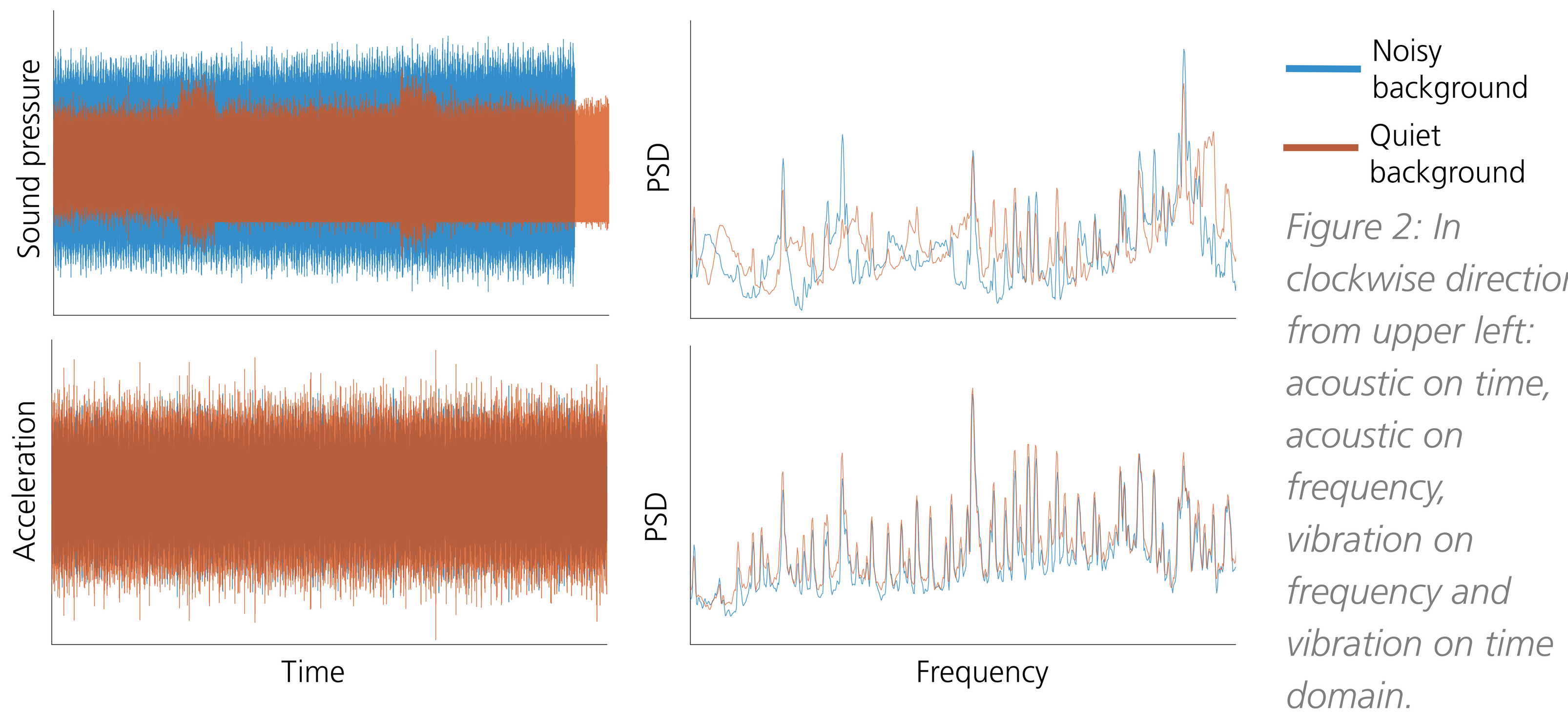


Figure 2: In clockwise direction from upper left: acoustic on time, acoustic on frequency, vibration on frequency and vibration on time domain.

Table 1: Classification scores for the model with two features

Sensor/background noise	CV mean accuracy	CV standard deviation	Holdout set F1 score
Accelerometer – quiet	81%	0.046	80%
Acccelerometer – noisy	78%	0.045	80%
Accelerometer – mixed	77%	0.039	78%
Microphone – quiet	87%	0.039	88%
Microphone – noisy	91%	0.050	86%
Microphone – mixed	88%	0.017	90%

In the presence of external activities, the acoustics signals are more impacted in both time and frequency domains (Figure 1). This seems to contradict the classification scores (Table 1), which are highest for this case. From there comes the motivation to reduce the model to two features and have a better understanding of the decision making. The process is done in two steps: first, correlated features are removed; second, permutation importance is evaluated and only the two features with highest score are left.

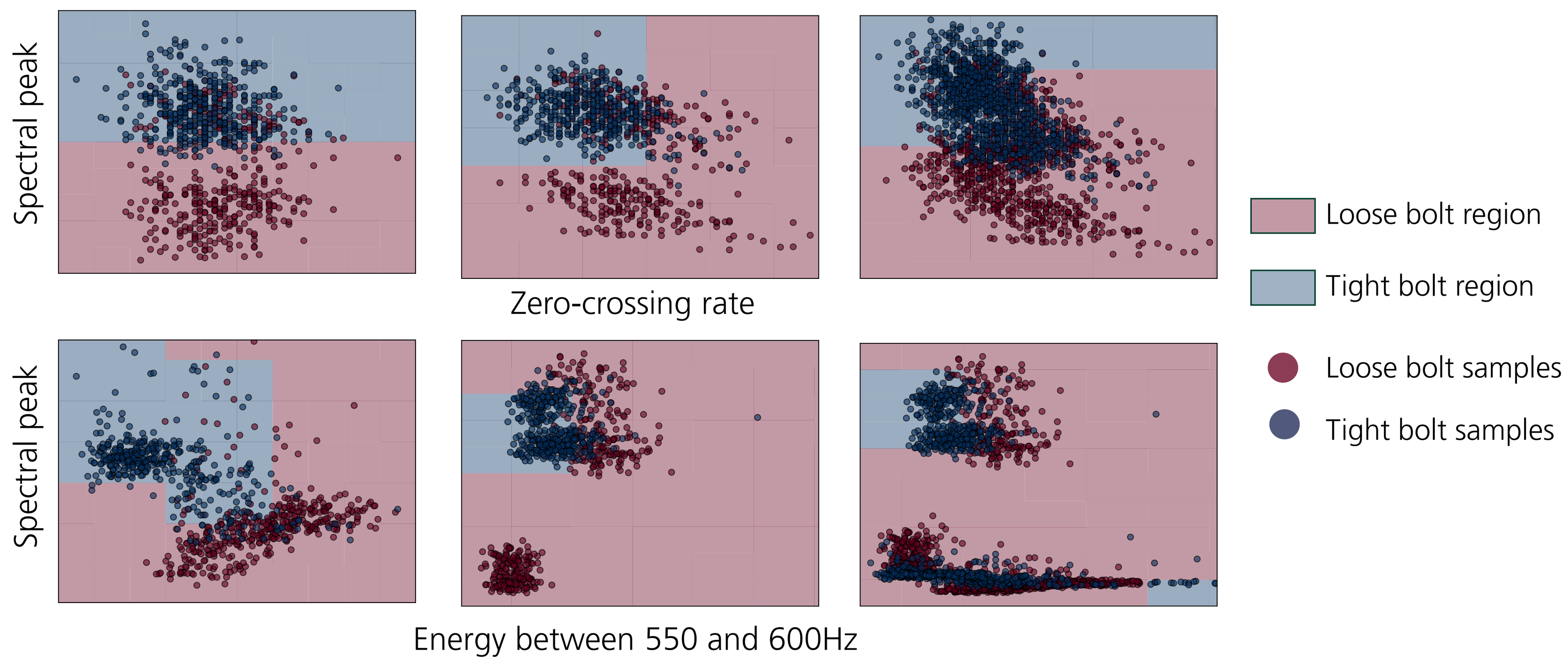


Figure 3: On the top row, from left to right: decision boundaries and scatter plots from vibration signals in the quiet scenario only, noisy only and mixed. On the lower row, decision boundaries and scatter plots from acoustics signals in the quiet scenario only, noisy only and mixed.

The scatter plots show that the microphone data becomes sparser, i.e., the clusters are formed far away from each other when high levels of background noise are present. While this results in high classification scores, it is unlikely that new data with different sources of noise would be correctly classified. In the absence of background noise, however, the figures are consistent with the classification, indicating the microphone's ability of identifying the fault. As for the vibration data, both the formation of clusters and the scores do not change significantly within both scenarios.

Conclusion

- Background noise causes the microphone data to be sparser, but class separability is maintained. To quantify and qualify the formation of these extra clusters more data is required.
- Generalization will not be good in the presence of background noise if the model is not trained with it, as small variations of noise could make the data behave differently.

Contact

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