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Supervised Transfer Learning Framework for Fault Diagnosis in Wind Turbines

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Introduction

Supervised learning enables fault diagnosis in wind turbines (WTs). Transfer learning allows knowledge transfer from a few source turbines to others, but many methods still require some labeled target data and result in non-interpretable features. We propose an end-to-end supervised learning framework in an *Anomaly-Space*. The *Anomaly-Space* is provided by our research partner, EnBW Energie Baden-Württemberg AG.

Contributions

- Fault diagnosis based on derived signals from SCADA data and vibration data, that are easily interpretable.
- Training and evaluation with stratified cross-validation on train data from different WTs.
- Showing transfer learning capabilities by applying the best performing classifier on a test set, that contains other types of WTs that were not part of the train set.

The Anomaly-Space

- Anomaly scores, that are derived signals from SCADA data and vibration data, available for each critical component where values greater than 1.0 are considered anomalous.
- The features (detectors) tuplet and **B**road-**B**and-**C**haracteristic-**V**alue (bbcv) are relevant for this work.
- Detector tuplet (Fig. 1) calculates the variance within each component group (e.g. all three voltage supply phases) and tests, if a statistically significant deviation from 0.0 is present.
- Detector bbcv (Fig. 2) extracts several features in the time and frequency domain, such as kurtosis and average. Calculate trendiness with hypothesis testing.

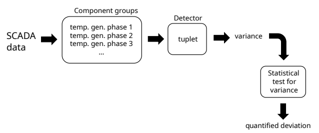

Figure 1.

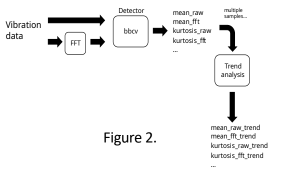

Figure 2.

Data

- *Anomaly-Space*, derived from **SCADA** data and **vibration** data.
- Train set: real data from 5 WTs across 4 wind parks.
- Test set: real data from 2 WTs across 2 wind parks.
- Two fault types: **bearing fault** and **sensor fault**.

Methodology

The proposed framework is depicted in Fig. 3.

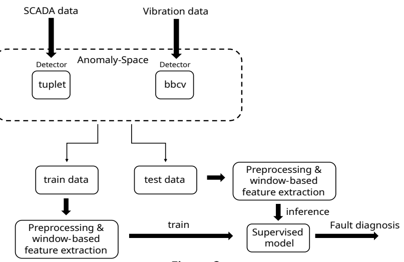

Figure 3.

Preprocessing: omit measurements not originating from normal operating-mode and forward fill for imputation. Calculate variance and p-values from trend tests for both detectors with a sliding window of size 144. The **Mann-Kendall test** is used for the trend test. Resulting data frame has 6 features.

Stratified 3-fold-cross-validation on train set to compare the following machine learning models:

- Above_One (baseline): Values above 1.0 from the bbcv detector are labeled as bearing fault, and values above 1.0 from the tuplet detector are labeled as sensor fault.
- Random Forest (RF).
- Light-Gradient-Boosting-Machines (LightGBM).
- Multilayer Perceptron (MLP).

Results

Results of model comparison are depicted in Fig. 4. The best model was the **MLP**, achieving an average $\boldsymbol{F_{0.5}}$ **score of 0.874**. This model has the ReLU activation function, the adam optimizer, a learning rate of 0.001 and 1 hidden layer with 5 neurons.

On the **test data**, a $\boldsymbol{F_{0.5}}$ **score of 0.937** has been achieved.

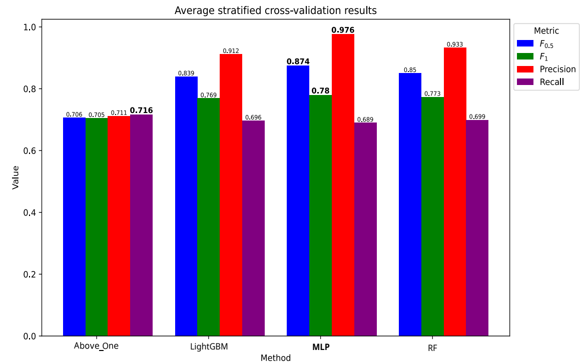

Figure 4.

Conclusion

- Supervised fault diagnosis framework based on the *Anomaly-Space* has been built.
- The *Anomaly-Space* encodes deviations from normal behavior for each WT component.
- Extracting variance and trend values with sliding windows.
- Our fault diagnosis framework using transfer learning delivers accurate prediction results.

Acknowledgements

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