Finding Useful Features in Vibration Signals for Fault Diagnosis

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This contribution presents a selection of characteristic values derived from vibration signals that are useful for diagnosis of unbalance and coupling bend in hydropower rotors. The characteristic values are used with machine learning techniques for the estimation of fault type as well as fault intensity.

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1 Numerical Database of Unbalance and Bend Vibration for Fault Diagnosis

Imperfections like unbalance cause exciting forces on a rotating machine resulting in vibrational motion. When vibrations rise to a high level, the machine must be examined and in some cases even be switched off to prevent damages to components. The vibration measurements are then often analyzed by experienced experts to spot the cause. Automatic and permanent fault diagnosis with data driven techniques promises to improve this procedure. It might be possible to diagnose fault intensity, to observe trends in the data and to predict the date an action is necessary. This helps to avoid unscheduled downtimes and allows targeted and cost-effective maintenance.

To develop such data driven systems, a large database of exemplary vibration data together with cause information is helpful. However, this kind of information is quite rare and costly to produce experimentally for large turbo machinery like hydropower rotors. In this contribution, numerically calculated data is used to derive diagnostic methods. A total of 3500 numerical models of hydropower rotors is created and their vibration behavior resulting from mixed unbalance and coupling bend fault of different intensity is calculated. This research focuses on vertical large hydropower rotors with three guide bearings and only those have been modeled. The vibration is captured by twelve sensors measuring shaft displacement relative to the bearing housing and absolute bearing velocity at three bearings in the two radial directions x and y, respectively. The three bearings include the upper generator guide bearing (UGB), the lower generator guide bearing (LGB), and the turbine guide bearing (TGB). It is well known that unbalance and bend fault mainly cause speed synchronous vibration. Therefore, fast Fourier transform is applied and only the speed synchronous part of the vibration is relevant. Accordingly, the speed synchronous amplitude A and phase P for all twelve sensors on the rotor are stored in the database.

2 Meaningful Features Obtained from Vibration Data

The basic values of amplitude and phase do not allow to classify the type of fault or quantify its intensity directly. However, meaningful features might be calculated from those values. Here, two main ideas are presented.

Firstly, the measurements in x and y direction are combined to an elliptic orbit and the orbit’s characteristic values are calculated. The orbit is often described in a complex plane such that
\[ r(t) = x(t) + i y(t). \]

The minor and major semi-axis length of the elliptic orbit is then given as
\[ a_{maj/min} = ||\hat{r}_+|| \pm ||\hat{r}_-|| \quad \text{with} \quad \hat{r}_\pm = 0.5 \left( A_x e^{\pm i P_x} + i A_y e^{\pm i P_y} \right). \tag{1} \]

In Eq. 1 the terms \( \hat{r}_+ \) and \( \hat{r}_- \) result from a decomposition
\[ r(t) = \hat{r}_+ e^{i \omega t} + \hat{r}_- e^{-i \omega t} \]
and they allow the simple calculation of the ellipse characteristic values. While the semi-axis lengths give information about the vibration magnitude, the phase information of the vibration is another important aspect to consider. The forward whirl phase \( 1 \), given as \( \arg(\hat{r}_+) \), is a way to describe the phase of an orbit. For an unbalance-only rotor, a change of the unbalance circumferential position will result in an equally valued change of the forward whirl phase. This is not true for the signal phases \( P_x \) and \( P_y \), as they are distorted by the elliptic shape of an orbit.

Secondly, the sensor measurements of different bearings are combined to describe the operational deflection shape (ODS) of the rotor. Generally, the ODS describes a structure’s displacement resulting purely from internal excitation during nominal operation, somehow similar to a mode shape resulting from external excitation [2]. Inspired by this notion, ODS features are defined as amplitude ratio and the phase difference of two neighboring bearings. A single sensor, like relative vibration in x operation, somehow similar to a mode shape resulting from external excitation [2].

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been selected systematically with the sequential forward selection [4]. This method aims to efficiently select those features, for which a chosen machine learning model can achieve best results.

For the assessment of unbalance, the selected features include ODS features based on the absolute vibrations of the bearings and relative shaft vibrations, which are processed according to Eq. 1. Further, absolute vibration values at LGB are taken into account.

For the assessment of bend fault, the selected features include semi-axis of relative shaft and absolute bearing vibrations at LGB and TGB. For this fault, only absolute bearing vibrations at UGB and LGB are considered in terms of the ODS. The diagnosis is further improved by also including the model parameters bearing width, bearing diameter, and the axial position of the coupling on the shaft. The fact that the here defined orbit and ODS features have been selected automatically instead of the raw amplitudes and phases emphasizes their benefit for diagnosis of unbalance and coupling bend.

3 Results and Conclusion

The objective of this work is to diagnose unbalance share, i.e. the percentage of absolute vibration caused by unbalance rather than coupling bend, and the coupling bend angle. For those two tasks, the performance of different machine learning algorithms is analyzed, namely support vector regression (SVR), gradient boosting regression (GBR), and a simple artificial neural network (ANN) with one hidden layer. The algorithms are run with scikit-learn’s [5] standard hyper-parameter suggestions where they exist as well as with optimal hyper-parameters found for this special problem (“hyper-parameter tuning”). A first diagnosis is done based on the plain feature set including the amplitudes and phases from the twelve sensors. The second approach makes use of the more meaningful features calculated and selected as explained above. For all setups, the algorithm is trained on one part of the vibration database (“training data”) and its performance is evaluated on the second part of the database (“test data”) by analyzing the mean squared error of the prediction.

A naive diagnosis model could always give the same prediction of the mean of all target values in the database, regardless of any other information. This strategy would result in a mean squared error of 0.11 for unbalance share and $5 \times 10^{-4}$ for bend prediction. The presented machine learning models achieve results almost one order of magnitude better than this, see Fig. 1 and Fig. 2, indicating that an approximate prediction is indeed possible. Diagnosis results based on the selected feature set are improved compared to the plain set: looking at the best performing models for bend prediction, the diagnosis error is clearly reduced from $1.3 \times 10^{-4}$ (tuned SVR) down to $0.6 \times 10^{-4}$ (tuned GBR). Similarly, the error is slightly reduced for unbalance share prediction from 0.025 (tuned SVR) to 0.022 (tuned GBR). The results also indicate that the popular SVR algorithm is a solid choice for diagnosis from plain features. However, even better results are obtained by using the GBR algorithm on the selected feature set. In general, the standard settings for the hyper-parameters in scikit-learn seem to be a fine choice, but the models with tuned hyper-parameters achieve notably better results.

To conclude, a rough estimation of unbalance fault and bend fault in hydropower rotors is possible with a data-based diagnosis approach. The best results were obtained by calculating meaningful features from the raw vibration signals and feeding them into a gradient boosting regressor model. The meaningful features include orbit minor and major semi-axis, orbit forward whirl as well as amplitude ratios and phase differences from different bearings.

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