CAV2021
11th International Symposium on Cavitation
May 10-13, 2021, Daejon, Korea

Estimation of Cavitation Erosion Damage with Anomaly Detection Neural Networks

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Abstract: Being able to analyze the degree of cavitation erosion damage can ensure the long-term operation of the machine and reduce unnecessary downtimes. Due to limited optical access to the machine acoustic inspection can be used. In this work an anomaly detection neural network is used to process the acoustic emissions. After training, the network can detect changes in the signals resulting from changing damage states and quantify them. Experiments with two different hydrofoils inside a cavitation-channel are showing promising results, such that the neural network can estimate the state of erosion damage, while being robust to variations of the machine operation points.

Keywords: Cavitation Erosion; Acoustic Emission; Anomaly Detection

1. Introduction

Cavitation erosion in hydraulic machinery can lead to heavy degradation of the affected components. To avoid this, the cavitation limits are derived from model tests, which should not be exceeded during operation. Being able to analyze the degree of damage of a hydraulic machine due to cavitation erosion is of major importance in order to ensure the long-term operation of the machine. Thus, maintenance of the machine can be planned ahead to reduce unnecessary downtimes. Due to limited optical access to the machine while operating a visual inspection is in general not possible to get information about the current condition of the machine i.e., state of cavitation erosion.

An alternative way is acoustic inspection. Therefore, the acoustic emissions in the presence of cavitation are measured. There are a few approaches processing the raw signal of the acoustic emission using statistical methods to analyze the spectrum of these signals [1-3]. Also, data driven models can be used to detect cavitation or estimate the intensity based on acoustic emissions [4,5]. Moreover, a correlation of acoustic emissions and different states of erosion damage can be shown [6].

The proposed method extends these concepts by using a data driven model for processing the acoustic emissions to estimate the state of cavitation erosion damage. An anomaly detection neural network is trained to estimate the distribution of data measured during a state with constant cavitation damage (normal state) by compressing and reconstructing the input data. The quality of the reconstruction is evaluated with a distance function. In case of changing erosion damage the spectrum of the acoustic emissions changes. As a result, the reconstruction deteriorates and the values of the distance function become larger, which can be seen as a measure for the state of damage.

To proof the concept, two hydrofoils were placed inside a cavitation-channel and exposed to strong cavitation for certain time period obtaining erosion damage on the hydrofoil surface. Acoustic emissions were measured in constant time intervals for different flow conditions. The experiments show promising results, such that the neural network can estimate the state of erosion damage. It can be shown that this method can be applied to different hydrofoils and is robust to changes of the machine operation points.

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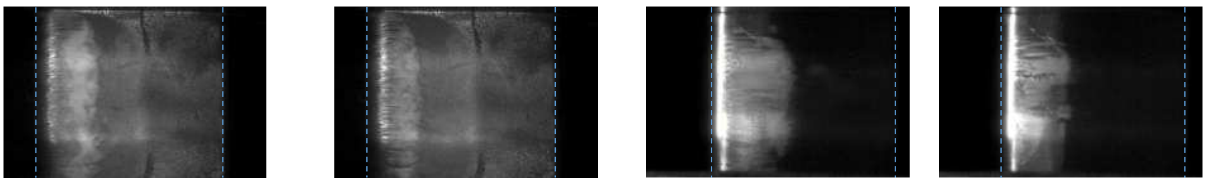
2. Experiments and Method

To develop the proposed method, experiments with two differently shaped hydrofoils inside a cavitation-channel were conducted to damage their surface in a controlled environment. The hydrofoils H1 and H2 are exposed to strong cavitation for 293h and 46h, respectively, to obtain a sufficient state of erosion damage, which is approximately the same level of damage for both hydrofoils. The acoustic emissions are measured from time to time for two different levels of cavitation (operation point OP1 and OP2). The sensor is mounted outside the channel on the top plate located above the hydrofoil, covering a frequency range of 50 – 90 kHz. The signals are measured after constant intervals of one hour. Examples of the cavitation at both hydrofoils H1 and H2 are shown in Figure 1, with the hydrofoil edges marked in blue.



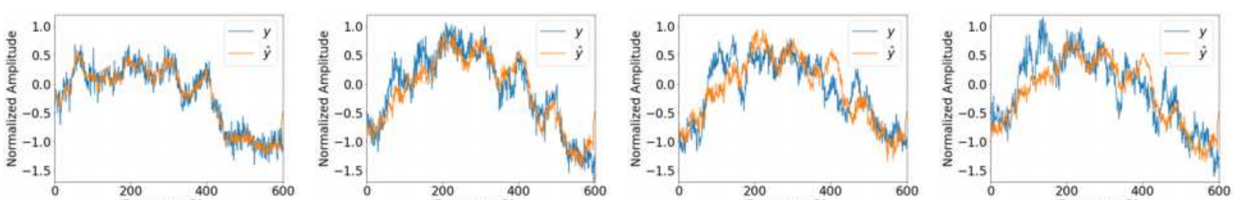
(**a**) H1 – OP1 (**b**) H1 – OP2 (**c**) H2 – OP1 (**d**) H2 – OP2

Figure 1. Cavitation at hydrofoil H1 and H2 (OP1 – Strong cavitation; OP2 – Medium cavitation).

The recorded raw time signals have to be preprocessed before they can be used as input for the neural network. First the fast Fourier transformation (FFT) is applied to get the spectrum, which is then transferred to log-scale. A triangular filter bank is used to reduce the dimensionality of the spectrum. The amplitudes of the spectrum are further centered by removing the median and scaled to the quantile range to match the expected range of the input values for a neural network. All these steps are common preprocessing techniques for processing acoustic signals with neural networks [7].

The main idea of this work is to use an anomaly detection neural network (ADNN) to estimate the distribution of a normal state and detecting out-of-distribution samples. Measurements recorded during a condition without erosion damage are representing the normal state. The hydrofoils H1 and H2 are free of erosion damage for the first 10h and 5h, respectively. So, there are $N = 10$ and $N = 5$ measurements used as training dataset $D \epsilon \mathbb{R}^{N \times M}$, with $M = 600$ denoting the length of the FFT.

The ADNN is following an encoder-decoder architecture. In the encoder path, the input spectrum $y \epsilon \mathbb{R}^{1 \times 600}$ is compressed stepwise to a latent space $l \epsilon \mathbb{R}^{1 \times 20}$, have only a fraction of the dimension of the input data. In the decoder path, the network learns to output a reconstruction of the input data $\hat{y} \epsilon \mathbb{R}^{1 \times 600}$ from the latent space. By compressing and reconstructing the input spectrum, the network is learning the features of the input data and is learning the underlying distribution of the normal state data to successfully restore the input. Figure 2(a) is showing an example of an input spectrum from the normal state with its corresponding reconstruction.



(**a**) 1h (**b**) 15h (**c**) 65h (**d**) 175h

Figure 2. Spectra of H1 (blue) used as input for the ADNN at different time steps and their corresponding reconstructed spectra (orange).

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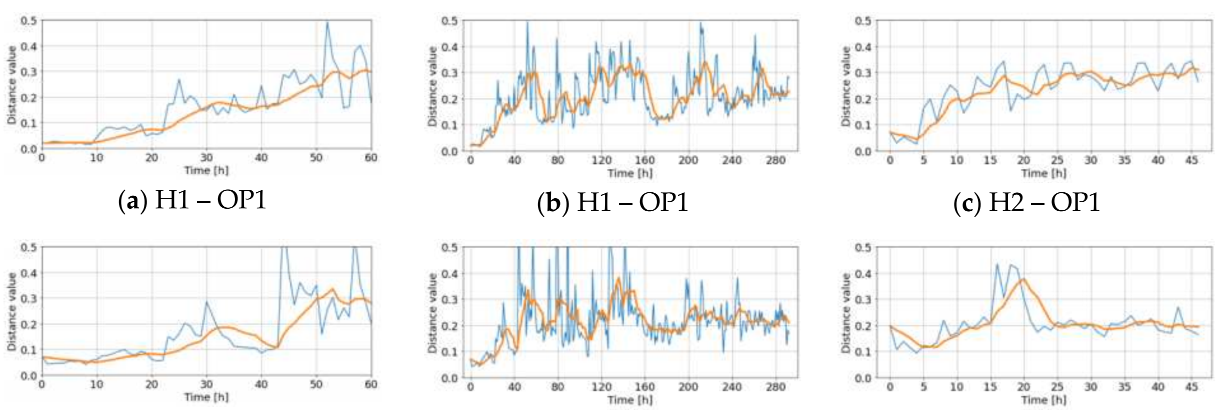
The ADNN is trained with the mean squared error (MSE) $\mathcal{L}_{MSE} = \sum(\hat{y} - y)^2$ as loss function to minimize the difference between the reconstructed spectrum $\hat{y}$ and the input spectrum y. So, the quality of the reconstruction is rated with the MSE as distance function. During test time new unseen measurements are feed to the network. In case of no erosion damage the signals are remaining similar to those from the normal state. They are of the same distribution as the training data and thus can still be reconstructed well by the ADNN. An example is displayed in Figure 2 (b) where the reconstruction still matches the input spectrum. In case the erosion damage state changes, the acoustic emissions and hence their spectra are changing. These samples are lying outside of the distribution of the train data and can be seen as anomalies. For these out-of-distribution samples the reconstruction deteriorates and the distance values become larger. So, the distance function can be seen as a measure of how close new samples are lying to the distribution of the normal state. This gives an indication for the level of erosion damage. Figure 2 (c) is showing an out-of-distribution samples at 65h which cannot be reconstructed successfully. A more detailed description of the ADNN can be found in [8,9].

The ongoing erosion damage only results in a variation of a sub-frequency band but does not change the whole spectrum. This is highlighted in Figure 2 (d). At some point in time the variation does not further increase the distance value e.g., the signal at 65h and 175h have the same distance to the normal state. Thus, no progressing damage state can be detected. At this point, a new normal state has to be defined to continue the estimation of the erosion damage level.

3. Results

The distribution of the normal state is learned from the first 10h and 5h of OP2, respectively. Then the whole measuring period of OP2 is used for evaluation. The distance values (blue) for H1 are displayed in Figure 3 (b). It is visible that the running mean (orange) is increasing over 50h befor reaching a plateau. Thus, a smooth increase of the erosion damage can be detected in this time period. Afterwards, the variation in the spectra does not increase the distance value. At this point a new normal state has to be defined from the measurements at the plateau i.e., 50h – 60h. To explain the results more detailed Figure 3 (a) is showing the time horizon of H1 from 0h to 60h. The first 10h are used for training, so the distance value is close to zero. Until 22h the distance value is staying low, which indicates that only negligible erosion damage is present. From visual references this can be confirmed until 20h. The visual reference at 31h is then showing noticeable erosion damage which comes together with an increasing distance value. Thus, the results match the true behavior of the airfoil surface.



(**a**) H1 – OP1 (**b**) H1 – OP1 (**c**) H2 – OP1

(**d**) H1 – OP2 (**e**) H1 – OP2 (**f**) H2 – OP2

Figure 3. Distance values (blue) and the running mean (orange) for H1, H2 at OP1, OP2 over the whole measuring period. (a), (b), (d), (e) Training with 10h of H1 – OP1. (c), (f) Training with 5h of H2 – OP1.

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So far only measurements from OP1 are used for training and evaluation the model. It can be shown that the model is able to handle strong variations of the operation points. Therefore, the same model trained on 10h of OP1 is evaluated with the data from OP2, thus the model has never seen data from OP2 during training. From Figure 3 (d) and (e) it is visible that for OP2 the behavior of the distance value is only slightly worse than for OP1. Therefore, the proposed method is not limited to the operation points used for training.

In general, the same results can be achieved for H2, which is shown in Figure 3 (c). However, the distance value is increasing very fast after the first 5h used for training. From visual reference it appears that an erosion damage is already present at 10h. Thus, a strong increase of the distance value is valid. The erosion damage of H2 arises faster compared to H1 so the point at which no more variations of the signals can be detected is reached much earlier after 17h. The application from OP1 to OP2 is also given for H2 as displayed in Figure 3 (f). From Figure 3 (c) and (f) it is visible that different operation points can be handled but at different levels of the distance values.

Further, using data from more than a single operation point by training the normal state with slight variations speed and pressure level for OP1 and OP2 is leading to a proper estimation of the cavitation erosion damage even for new unseen variations of the operation point. Thus, the proposed method is in general independent to variations of operation points, but different levels of cavitation intensity for training are improving the robustness of estimating the erosion damage in varying operation conditions.

4. Conclusions

This work shows that using an anomaly detection neural network can estimate the state of erosion damage based on acoustic emissions for a certain time horizon. The benefit of this method is that it can be applied to different hydrofoils and is robust to changes of the machine operation points. In a next step another distance function has to be found to predict the damage state for a longer time horizon. Also, the application of this method to rotating turbomachinery needs to be investigated.

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