Cavitation Damage Detection Through Acoustic Emissions

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Abstract. Cavitation in hydraulic machinery is a common phenomenon with high potential for causing damage. Often it is not known whether the machinery is damaged by cavitation or cavitation occurs at all. With regard to predictive maintenance it would be advantageous not only to detect cavitation, but also to determine the current condition or damage of the hydraulic machinery. Knowing the current condition of the machinery, maintenance could be planned properly ahead and unnecessary downtime could be avoided. Since visual inspection of the current status i.e. state of cavitation and possible damage of the machinery is usually not possible due to missing optical access, acoustic inspection offers an alternative. In order to determine whether and how damage results in changes in acoustics, experiments in a controlled environment were conducted using a hydrofoil. The hydrofoil was placed in a cavitation-channel and exposed to strong cavitation for a defined period of time. Afterwards measurements of acoustic signals at different flow conditions with different cavitation conditions including no cavitation were conducted. The measurement procedure was repeated for several hundreds of times. So various measured acoustic signals of different cavitation damage states on the hydrofoil were captured. Since it was not known in which frequency region changes may occur due to cavitation damage, a broad frequency region reaching from several Hz up to 1MHz was investigated. The experiment shows promising results, such that cavitation damage at the hydrofoil results in significant changes in acoustics. Further different behavior in different frequency ranges and flow conditions can be observed.

1. Introduction

Cavitation occurs in liquids when pressure locally drops below vapour pressure. When such created vapour bubbles enter regions of higher pressure, they will implode. This implosion can cause damage, if the implosion happens near solid surfaces. The process of nucleation, growth, and implosion is called cavitation [1].

In hydraulic turbines cavitation mostly occurs when operating close to the limits of the operating range. Often it is not clearly known whether the machinery is currently operating under cavitating conditions or not. Ideally cavitation should be avoided, if possible. For detecting such operating points with occurring cavitation several different approaches exist in literature. Most rely on acoustic emissions or vibration analysis [2–4].

Besides recognizing if cavitation occurs in the machinery or not, it is crucial to evaluate the current state of the machinery. In essence, how much damage is already caused at the machinery by cavitation? For this purpose no methods exist, which can be applied in real life power plants. Since acoustic emissions and vibration sensor already is state of the art for monitoring cavitation,
it is logical to evaluate how these sensors can be applied in order to estimate the current state. For evaluating the possible use of these sensors, experiments with a hydrofoil in a cavitation channel have been conducted. The hydrofoil was exposed to cavitation for a defined period of time and the changes in acoustics/ vibrations have been recorded. This paper focuses on data analysis of the experiments and shows how the acoustics/ vibrations change according to the cavitation damage.

2. Experiment
In this chapter, first the experimental setup is described, including the test rig and measuring hardware. In the second part the damage on the hydrofoil is presented and discussed.

2.1. Experimental Setup
In order to estimate the effects in the change of acoustics caused by cavitation erosion, a hydrofoil is damaged in a controlled environment. Therefore, a rectangle cavitation channel with height 75 mm and width 50 mm is constructed. An aluminum test body shaped as a hydrofoil and without any prior damage is placed in the middle of the cavitation channel (figure 1). It is made out of a semicircle (leading edge), a rectangular body, and a triangle (trailing edge). The angle of the test body is adjusted such that cavitation occurs on the leading edge.

Since the purpose of the cavitation channel is to create fast damage to the hydrofoil, the velocity of the fluid in the channel has to be large [5]. In the test rig a velocity of 40 ms\(^{-1}\) is realized. Corresponding to that velocity the selected pressure level is 6 bar at the outlet of the test section.

In order to determine the change in acoustics and also vibrations, different sensors are used. There is no prior knowledge in which frequency range a change (or not occurring at all) can be expected. Therefore three different sensors with different operating ranges are used:

- Acceleration Sensor (Acc): 3 – 10 kHz;
- Acoustic Emission Sensor (AE 1): 50 – 90 kHz;
- Acoustic Emission Sensor (AE 2): 0.1 – 1 MHz.

Using sensors, which operate in a high frequency range, comes with the advantage, that the signal is mostly free of inference from other mechanical parts. The sensors record a clean signal of the occurring cavitation. On the downside a very high sampling frequency (up to 2 MHz) is necessary and the analysis of the signals becomes increasingly complicated, since longer time signals have to be analyzed.

![Figure 1: Sketch of cavitation channel with three different sensors. Sensors are mounted on top plate with a distance of ca. 50 mm.](image-url)

Acceleration Sensor 3-10kHz AE Sensor 50-90kHz AE Sensor 0.1-1MHz

Inflow
The three sensors are mounted as close together as possible, while ensuring no contact between the sensors. Further, the sensors are mounted as near to the hydrofoil as possible. The distance between each sensor and the hydrofoil is approximately 50 mm. In order to ensure good acoustic and vibration signal transmissions a silicone gel is placed between the sensors and the top plate.

The measuring procedure is shown in figure 2. First, the hydrofoil is exposed to strong cavitation conditions for one hour. Afterwards the acoustic emissions and vibrations of three different operating points (cavitation free, cavitation low pressure, cavitation high pressure) are recorded. These procedure was repeated 290 times, which corresponds to an exposure of the hydrofoil to cavitation for 290 h. The first measurement was conducted without any prior damage. Additionally, the weight of the hydrofoil was recorded in irregular intervals.

![Figure 2: Measurement procedure](image)

### 2.2. Cavitation Damage

Figure 3 shows the damage on the suction side of the hydrofoil after 10 h and 266 h, respectively. There is no relevant damage on the pressure side of the hydrofoil. All of the damage mainly focuses on the bottom half (trailing edge) of the hydrofoil, although cavitation mainly develops on the leading edge. A close inspection after 10 h reveals little roughness on the left and right bottom corner of the hydrofoil (red circles). After 266 h there is a significant amount of cavitation damage across big parts of the trailing edge. The damaged surface is almost perfectly axisymmetric. Development of cracks can be seen on both sides (red circles). This position corresponds to the transition from the rectangular body to the trailing edge.

![Figure 3: Damage on hydrofoil](image)

Naturally increasing cavitation damage correlates with mass loss. The mass loss over time is shown in figure 4. The hydrofoil had a mass of 387.5 g at the beginning without any prior damage. In the first 50 h the mass loss is very little. Between 50 – 266 h the mass loss rate keeps mainly constant and shows a linear trend.

![Figure 4: Mass loss over time](image)
3. Analysis of Results

In this chapter the results of the experiment are analyzed. In the first part of this chapter the preprocessing is explained. In the second part the acquired data of the different sensors and operating points are analyzed.

3.1. Preprocessing

The data, which have to be analyzed, first come in the form time signals. A more information-rich representation of a time signal is its Fourier transformed. Thus for every sensor and operating point (OP) a Fourier transformation (FFT) is conducted. Since the dynamic range of the FFTs is naturally very high, the FFTs are transferred to the log-scale. This are typical processing steps found in many applications [6,7]. Afterwards, for each sensor and OP, a pseudo-spectrogram is build by stacking the corresponding FFTs together (figure 5a).

Since the dimensionality of the spectrogram is still very high, a dimensional reduction technique is applied. When dealing with high dimensions it is difficult to interpret global trends, caused by the curse of dimensionality [8]. It is assumed, that neighboring frequency bins behave similar, therefore it is justified to take their average. For higher frequency ranges of the sensors bigger average window sizes are applied (10, 100, and 1000). The result of taking the average is shown in figure 5b. Additionally, frequency ranges being not part of the operating range of the corresponding sensors, are cropped.

The last preprocessing step consists of scaling and centering each frequency bin. Finally, the corresponding bins are scaled to their quantile range (figure 5c). This scaling method makes different frequency bins more comparable and is additionally robust towards outliers. This step is crucial in order to apply dimensional reduction techniques for further inspections.
3.2. Results
Figure 6 shows the dimensional reduction for all operating points and sensors. For dimensional reduction the t-distributed Stochastic Neighbor Embedding (t-SNE) algorithm [9] is used. Using this algorithm it is possible to embed high dimensional data (like spectrograms or FFT) in a low dimensional space. The absolute position of each point is without any information and is random. Nevertheless it is possible to visualize the natural distribution of the data. Points which are close in the high dimensional space will also be close in the low dimensional space. In essence, the t-SNE dimensional reduction is a visualization of the natural distribution of the data. Each plot represents one pseudo spectrogram. Further, each point in a plot represents one horizontal line in the spectrogram, which is equivalent to one measurement. The color of each point represents its timestamp, e.g. a red point with $t = 290 \text{ h}$ represents a measurement after exposing the hydrofoil to cavitation for 290 h.

Both acoustic emission sensors ($50 - 90 \text{ kHz}$, $0.1 - 1 \text{ MHz}$) show relatively unstructured distributions for measurements without any cavitation (figures 6d and 6g). When having no cavitation these two sensors record very little signal and hence there is no or only little observable structure in the FFTs. The remaining OPs and sensors show smooth distributions/color transitions, which leads to the conclusion that there exist significant and time correlating changes in the pseudo spectrograms. In essence, changes in acoustics and vibrations correlating to cavitation damage on the hydrofoil can be observed across a broad frequency range. Further, these changes can be also observed in the presence and absence of cavitation.
Figure 7: Amplitude changes over time/damage. Operating point: Cavitation high pressure.

Figure 7 shows the amplitude change for one fixed and exemplary operating point over time. A higher time value naturally corresponds to higher damage. Each frequency range is represented by 20 lines representing one frequency bin. In the middle frequency range (figure 7a) the amplitude increases in defined frequency ranges. Since the cavitation damage causes a mixture of rough and porous surface, additional noise sources can be created. On contrast, the amplitude decreases in other frequency ranges, when inspecting the acoustic emission sensor with operating range $0.1 – 1 \text{ MHz}$ (figure 7b). A porous surface may function as an absorber for high frequencies and therefore decrease the amplitude.

4. Conclusion and Outline
In this paper the effect of cavitation damage on the acoustic emissions and vibration data has been shown. Cavitation damage affects the radiated emissions in a broad frequency range from several kHz up to at least 1 MHz. The effects of damage may result in different changes for different frequency ranges. Since further changes may be assumed for increasing damage, it is of interest to continue damaging the hydrofoil in the test rig. Additionally, it is not known whether such effects can also be observed for real life hydraulic machinery. This requires further investigations.

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