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Development of a Novel Cavitation Monitoring System for Hydro Turbines Based on Machine Learning Algorithms

Ali Amini[1], **Olivier Pacot**[2], **Dominique Voide**[2], **Vlad Hasmatuchi**[1], **Pierre Roduit**[2] **and Cécile Münch-Alligné**[1,2]

[1] Institute of Systems Engineering, University of Applied Sciences and Arts Western Switzerland Valais, 1950, Sion, Switzerland
[2] Institute of Sustainable Energy, University of Applied Sciences and Arts Western Switzerland Valais, 1950, Sion, Switzerland

Corresponding author: ali.amini@hevs.ch

Abstract. Operating hydro turbines in off-design conditions increases the risk of cavitation occurrence, which in turn, leads to numerous problems such as performance degradations, structural vibrations, and most importantly, mechanical damage due to erosion. It is therefore crucial to develop a monitoring system that detects the occurrence and severity of cavitation in real time. For this purpose, a cavitation detection methodology has been developed that is based on the analysis of acoustic emissions of a turbine with machine learning algorithms. In this method, a conventional microphone is used to record the airborne noise emitted from a turbine under different working conditions, and then, a supervised learning algorithm is trained to classify the recorded noise signals into cavitating and non-cavitating categories. The detection system was developed based on laboratory tests and was validated in Ernen hydropower plant located in Canton of Wallis in southeast of Switzerland. This power plant consists of two identical double-flux Francis turbines each having a maximum power of 16 MW and a net head of 270 mWC. The preliminary results obtained from a two-day experimental campaign in the Ernen powerplant are very promising in terms of cavitation detection with a classification accuracy of more than 90 %. The system could be implemented either for real-time monitoring of cavitation occurrence allowing the operators to avoid such a condition or as a post processing tool to evaluate the number of hours a turbine has worked under severe conditions. Work is still ongoing to deploy more complex learning algorithms for this task to minimize expert intervention and/or interpretation during the setup process.

Keywords: Hydro turbine, Cavitation, Machine learning, Acoustic emissions, Classification, Monitoring.

1 Introduction

With the massive integration of intermittent renewable energy sources such as wind and solar, higher flexibility in production is required from the hydropower sector [1]. This is translated into more frequent starts and stops, faster transition regimes, and more time spent in off-design conditions. Operating turbines far from their Best Efficiency Point (BEP) is accompanied with several concerns including hydrodynamic instabilities, fatigue and premature wear, and cavitation [2]. It is known that the occurrence of cavitation in a hydro turbine leads to numerous problems such as performance degradations, structural vibrations, and most importantly, mechanical damage due to erosion [3,4]. Mitigation of cavitation and its side effects has been a traditionally significant issue in the literature and many authors have contributed to this topic [5–8]. However, as the old saying goes, prevention is better than cure. It is, therefore, of utmost importance to develop a monitoring system that detects the occurrence and severity of cavitation in hydro turbines in real time. Being able to detect cavitation in a hydraulic machine opens the door to predictive instead of preventive maintenance.

Cavitation detection in pumps and turbines has been the topic of several works [9,10]. Most of the available techniques are based on classical signal processing methods applied to vibration, pressure, and acoustic signals measured at different locations close to the pump impeller or the turbine runner [11–15]. For instance, Bajic [16] implements 20 high-frequency vibro-acoustical sensors on the shaft of the guide vanes of a double-runner Francis turbine with a sampling frequency as high as 1 MHz to detect different types of cavitation occurring in the machine. In a similar study, Valentín et al. [17] deploy a total of 67 sensors, including pressure sensors, accelerometers, strain gauges, and several other sensors to detect cavitation in a large Francis turbine prototype with a rated power of 444 MW. Regarding cavitation detection methods in hydro turbines, Escaler et al. [10] present a comprehensive list of cavitation types and detection techniques. A few recent works have initiated the implementation of machine learning algorithms in cavitation detection tasks in different applications [18–20].

With the abundant amount of data that has become available in recent years, machine learning (ML) and deep learning (DL) methods could possibly be the new tool applied to detection of cavitation in hydraulic machines. In this regard, the present paper introduces a novel methodology for cavitation detection that has been developed based on the analysis of acoustic emissions with machine learning classification algorithms. The method has been developed through laboratory tests and been validated for the real case of a hydropower plant equipped with Francis turbines. The paper is organized as follows: Section 2 describes the adopted methodology as well as the experimental setups used in the project, the main results of the study are presented in Section 3, which is followed by a short conclusion in section 4.

2 Methodology

The current study is based on experimental measurements, which include two distinct phases: the laboratory phase with controlled experiments in terms of flow conditions and background noise, and the powerplant phase where the real working conditions of a Francis turbine are tested. The laboratory tests were performed in the cavitation tunnel of the University of Applied Sciences and Arts Western Switzerland Valais (HES-SO), which has a test section of 40 × 80 × 500 mm. The maximum velocity at the narrow test section can reach 12 m/s and the facility bears a relative pressure range between -1 and 5 bars [21,22]. The model test is a NACA 0015 hydrofoil geometry with a chord length of 60 mm and a maximum thickness of 15 % of its chord length. A schematic of the cavitation tunnel highlighting its test section, downstream pressure tank, and the circulating pumps is illustrated in Figure 1 (left). A side-view image of the hydrofoil within the test section is shown in Figure 1 (right).

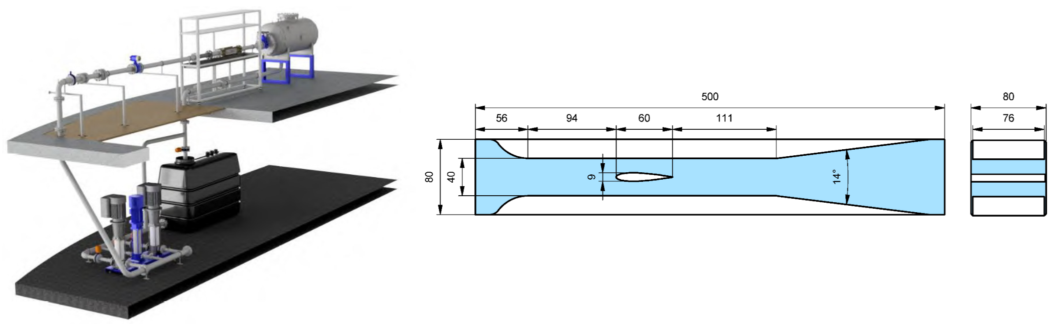

Figure 1: (left) schematic of the HES-SO Valais/Wallis cavitation tunnel, (right) cross section of the tested NACA 0015 stainless steel hydrofoil.

Thanks to previous measurements, the cavitation map of the described hydrofoil, which delimits the regions of different cavitation types for given values of incidence angle (α) and cavitation number (σ), was already in hand. This helped to prepare a comprehensive planning by targeting the zones of interests for the experimental campaigns. The laboratory experiments included static and dynamic regimes. For the static cases, the flow conditions including freestream velocity, incidence angle, and cavitation number were kept fixed and acoustic samples were acquired for one-second intervals. The airborne noise was recorded by means of a GRAS 46 AE microphone at a sampling frequency of 40 kHz. A summary of the tested flow conditions is available in Table 1.

Table 1: Summary of the tested flow conditions

Absolute pressure [bar]	**Inlet velocity [m/s]**	**Reynolds [-]**	$\boldsymbol{\sigma}$ **[-]**	$\boldsymbol{\alpha}$ **[°]**
0.1 – 4	0 – 10	0 – 600,000	0.2 – 10	0 – 15

To make the classification task more challenging, dynamic cases were introduced. In the latter, the flow velocity and angle of attack were fixed. The test rig pressure was initially set high enough to avoid any form of cavitation. Over a 150-second interval, the pressure was gradually decreased to induce cavitation on the hydrofoil and then pushed back to its initial value. The recorded signals were subsequently divided into samples of 1 second for further analysis.

The second phase of experiments was executed in Ernen powerplant located in Wallis, Switzerland. The main goal is to verify whether the developed methodology in the laboratory would be also practical in the case of a real hydropower plant with all the added background noise or not. A picture of one of the Francis turbines installed in this plant is shown in Figure 2. The Ernen run-of-river powerplant is built on the Rhône River and consists of two identical groups, each of which is equipped with a double-runner Francis turbine with BEP power of 13 MW, nominal head of 270 mWC and flow rate of 7 m^3/s. During the measurements, one of the two groups was mainly instrumented, and the second one only summary. In addition to the microphone used as the principal signal in the analysis, a wide range of mainly non-intrusive sensors (e.g., accelerometers, high- and low-frequency acoustic emission probes, etc.) as well as upstream and downstream static pressure probes were installed at various locations on the turbine casing. These signals were recorded as additional monitoring indices and may be used for further improvement of the analysis at later stages.

Figure 2: The double-runner Francis turbine at Ernen hydropower plant in Wallis, Switzerland.

The test schedule was organized in a way to cover most of the possible operating conditions. This was done by sweeping the power of the instrumented turbine incrementally from zero to its maximum while the other group is either off or is running at its maximum capacity (or instantaneously lower if not enough flow is available in the river) as well as performing a number of start and stop sequences. Being a determining factor in cavitation, these operations were repeated at various downstream levels. Special maneuvers such as activating the overhead crane or using a jackhammer close to the turbine casing were performed during the measurements to simulate background noise. More than 70 points were covered during the campaign. For each point, 180 seconds of measurements were recorded at 40 kHz, which were subsequently divided into subsamples of one second each. For further analysis, the acquired points were divided into two categories. About 30 % of the data were used as guidance points. These data were selected and labeled based on a hydraulic analysis of the powerplant. For these points, expert knowledge was used to determine the existence and severity of cavitation in the machine with a relatively high confidence. The remainder of the points were used as the test dataset to evaluate the functionality of the classification algorithm.

In this project, the cavitation detection task was defined as a classification problem with supervised learning approach, meaning that the dataset should be labeled beforehand. To this end, each sample is labeled as 'cavitating' or 'non-cavitating' manually at the first place. In the laboratory, this task is achieved via listening to the recorded signals and watching the corresponding high-speed videos. In the powerplant, live observation and expert knowledge were used to define the regions associated with high risk of severe or moderate cavitation. The acoustic signal recorded close to the cavitating element (hydrofoil or turbine) is first pre-processed and then fed to the ML process. Each sample is transformed into the frequency domain via FFT and further processed to create the input features of the ML structure. At this step, a k-Nearest Neighbors (k-NN) classification algorithm is trained with 30 % of the laboratory recorded data as the training set. The same methodology is applied to the case of the powerplant, with the only difference that the classifier is a Gaussian Mixture Model (GMM).

3 Results and Discussion

Being isolated from other phenomena, it is relatively easy to detect cavitation for the laboratory static cases. These cases are, thus, more of an exploratory nature and serve as a guidance for a better pre-processing of the signals and a wiser selection of the input features of the ML. In the time domain, the cavitation signature is visible through the augmented noise amplitude. In the frequency domain, the presence of cavitation is highlighted by an increase in the power of the higher frequencies. Therefore, the frequency content in the audible range is fed to the k-NN algorithm in this case as the input feature. Given the simplicity of the task and the correctness of the labels, the trained ML structure reached a 100% classification accuracy. This was no surprise as human ear could also easily distinguish the cavitating samples from non-cavitating ones.

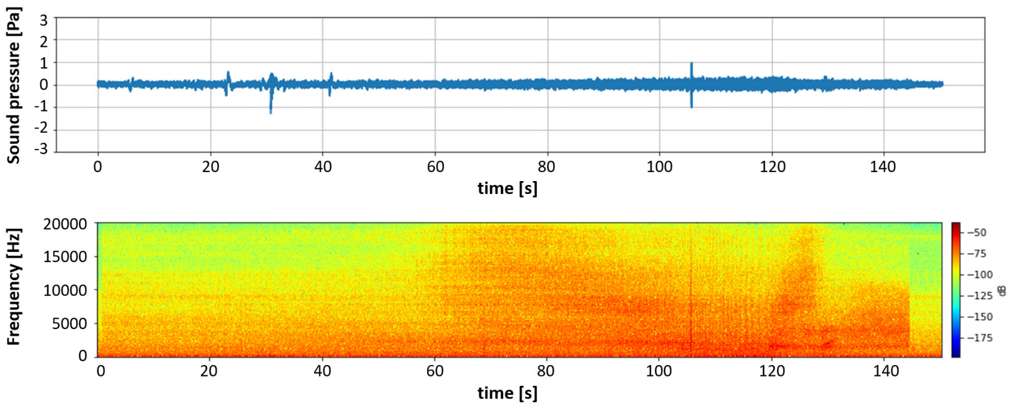

Figure 3: Acoustic signal of a dynamic test illustrated in time (up) and frequency (down) domains.

The results of a dynamic test performed at the laboratory for $\alpha = 8°$ are shown in Figure 3. The upper plot is the signal amplitude presented in the time domain, while the lower plot depicts the signal in the time-frequency domain. Over 150 s, pressure is reduced to trigger cavitation and subsequently increased to make it disappear. It is clear in Figure 3 that this action is accompanied by a richer signal in the time domain with higher amplitudes mainly in the second half of the interval. The changes are more obvious in the frequency domain, and a clear increase is observed in the higher frequencies as cavitation appears and develops in the test section.

Shown in Figure 4 are the processed frequency content of all the cavitating (red) and non-cavitating (blue) cases of the static tests. The black curves correspond to 1-second cuts from the above presented dynamic test. Those depicted at left correspond to the interval of 10 to 20 s and are non-cavitating. The ones at right are taken from the 75 to 85 s interval and represent a cavitating flow. As it is clear, in this specific case, the non-cavitating flow falls right on the boundary, and thus, the predictions might be erroneous. This shows that the trained algorithm based on the static cases could not be directly used for the case of dynamic tests. Therefore, a new k-NN classifier is trained for the dynamic tests. This algorithm has a very good performance on the test dataset and achieves an accuracy of more than 95 % in cavitation detection. It should be noted that labeling the samples was more challenging for the dynamic tests. For some samples, it was very difficult to determine the state of cavitation by listening to the audio file. Therefore, there might also be some errors introduced due to mislabeling.

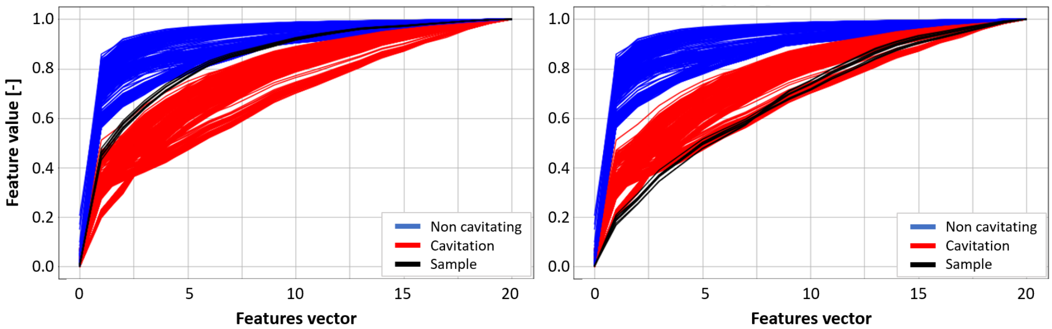

Figure 4: Distribution of the ML feature values of cavitating (red) and non-cavitating (blue) flows obtained from the static tests at $\alpha = 8°$. The black curve at left corresponds to non-cavitating state during a dynamic test at the same incidence angle, while the one at right represents cavitating conditions during the same test.

Based on the success of the proposed methodology in the laboratory tests, it was decided to test the technique in the real environment of a hydropower plant. Naturally, the measurements in the power plant are way more challenging. This is due to the huge background noise imposed by the generators and other machinery, as well as the limited access to the phenomenon compared to the laboratory. In particular, lack of visual access makes the labeling job more difficult and brings in an inevitable level of uncertainty. To minimize this effect, some of the points were acquired with extra care. These points were targeted based on the hydraulic analysis of the turbine to detect the zones with a high risk of cavitation and were later used as the labeled data to train the learning algorithm.

The experience gained with the simplified cases of the laboratory, however, facilitated the analysis and the same technique based on the frequency content was implemented to obtain the input features. Employing proper statistical tools, one could illustrate the results on a 2D plot based on the first two dimensions. This allows one to efficiently visualize the data and the classes, and thereby, facilitates the evaluation of the results. A distribution of a part of the tested points is plotted accordingly in Figure 5. The data shown in this figure are those subject to the hydraulic analysis, and thus, comprise the training set. The percentage shows the power rate compared to the BEP. The classes on Figure 5 are defined manually based on the expert knowledge. It is observed that the cavitating and non-cavitating flow conditions are effectively divided into two distinct regions on the left and right of this graph.

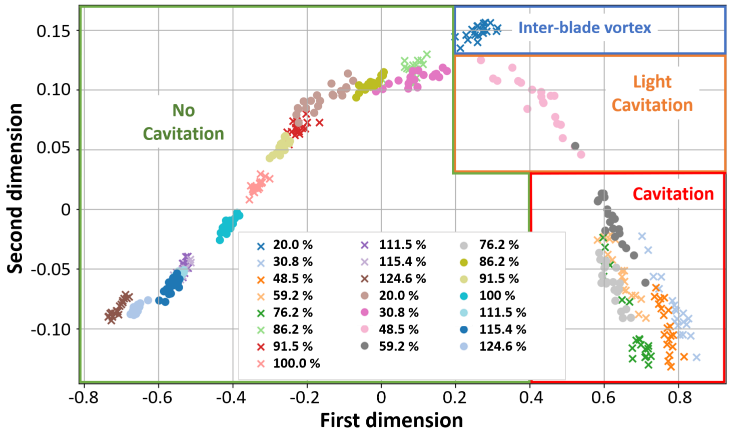

Figure 5: Distribution of the different operating points in the training set plotted on the first two feature dimensions. The classes are added manually based on the hydraulic analysis and expert knowledge. The crosses and circles correspond to tests with low and high downstream levels.

Considering a Gaussian distribution of data in each class presented in Figure 5, a GMM is trained based on the labeled points. In this technique, the classes correspond to a combination of best-fit ellipsoids that englobe the data holding the same label. In this case, the GMM is trained for four classes: 'no cavitation', 'light cavitation', 'inter-blade vortex cavitation', and 'cavitation'. Based on its input features, each datapoint is attributed to the class with the highest probability. The results of the classification algorithm for all the operating points are shown in Figure 6. As is clear, the different operating points are well distributed amongst the four classes with quite well-defined boundaries. It seems that even the first selected dimension could be safely used to distinguish between the two main categories of 'cavitating' and 'non-cavitating'. Concretely, it is observed that for values larger than 0.2, cavitation begins within the turbine, and for values higher than 0.5, the machine suffers from severe forms of cavitation. Such a condition could be directly employed as a health monitoring index. Besides, the three classes associated with different levels of cavitation are quite well shaped and delimited from the other classes. This is not, however, the case for the non-cavitating class. The data distribution in this class (green points) suggests that it should be comprised of some sub-classes. Notably, a cluster of datapoints is observable at the extreme left of the graph and two elongated less populated clusters are formed parallel to the main body of the data. Some of the corresponding points were looked up manually, and it was observed that each of these clusters corresponds to a distinct sub-category. The data accumulated at left reflect the tests where the instrumented turbine was not running, and the elongated clusters correspond to the points acquired during start and stop sequences. This observation puts in evidence that the acoustic signature of a turbine contains loads of useful information about its operating condition. It should be noted that including higher dimensions in the analysis may lead to more distinct separations between the classes and sub-classes.

It is noted that due to the large volume of the tested data, it was not possible to label all the datapoints manually; meaning that one could not precisely evaluate the classification accuracy. However, to have a rough estimate of the overall performance, a considerable number of points were selected randomly and verified whether they were attributed to the right class or not. For the large majority of the data, the classifier had led to the right result. In addition, the technique was applied to the measurements performed during the night with the operating points being set directly by the dispatcher. The results were promising; Similar patterns were observed in the distribution of the data as in Figure 6, which was further validated by random selection and verification of some of the datapoints.

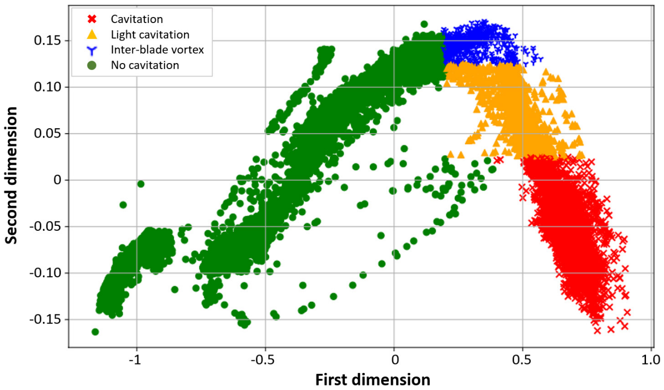

Figure 6: Distribution of the datapoints in the four classes plotted on the first two feature dimensions.

A statistical analysis of the production history of the powerplant over a seven-year period is shown in Figure 7. It should be noted that each turbine has not run for 20 to 25 % of the time during this period and the corresponding columns at zero power are removed from Figure 7 for the better visibility of the other bins. Apparently, each of the two turbines has run close to its maximum nominal power for most of the time. Given the specific geometry of these double-flux Francis turbines with transversal shafts, no ordinary axisymmetric vortex could form in the draft tube, and thus, the full-load condition seems to be relatively harmless to the turbine. However, Figure 7 clearly shows that the distribution of the operating points of the turbine is not optimal regarding cavitation. In particular, there exists an outstanding peak at around 75 % of the nominal power for turbine number 2. Further analysis of the results presented in Figure 6 reveals that independent of the downstream level, the operating points between 45 % and 80 % of the nominal power (part-load regime) are prone to cavitation. The existence of this peak and distribution of the data in this interval shows that the turbine has been exploited in unfavorable conditions, which may have led to premature wear of certain components.

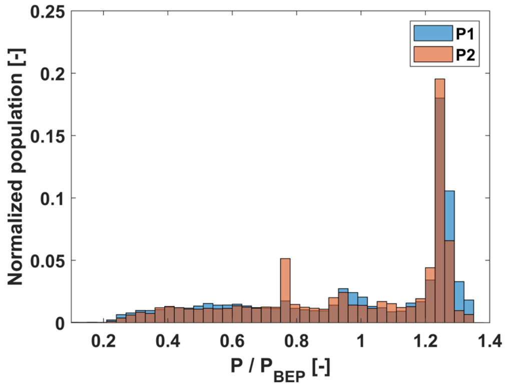

Figure 7: Normalized distribution of the power rate of the two identical turbines of the Ernen hydropower plant over a seven-year period.

Implementing such a cavitation detection system in hydropower plants could help the owners modify their schedules considering the machine health, or at least, make them aware of the number of hours that it has worked under severe conditions. The latter could serve as a building block for developing predictive maintenance in hydropower plants by providing the means to plan the next round of interventions before a serious damage occurs to a critical component.

4 Conclusion

In this paper, a novel cavitation detection technique based on the analysis of acoustic signals by means of machine learning algorithms was presented. The methodology is developed in the laboratory and further evaluated in a hydropower plant equipped with double-runner Francis turbines. The detection task is defined as a classification problem, requiring the input data to be labeled. Labeling the data was a challenging step in the study and was performed manually by expert interpretation. The acoustic signals are first transformed to the frequency domain via FFT, and then, fed to the ML structure as the input features. Depending on the cases, either a k-NN or a Gaussian mixture model is trained as the classifier. In order to visualize the classes more conveniently and verify the performance of the system, the powerplant data were reduced via proper statistical tools and were presented in two dimensions. This made it possible to plot the classes on a 2D plot and observe that the cavitating and non-cavitating point are efficiently distinguishable.

The presented approach allows one to detect cavitation, but not yet to separate the types of cavitation. The model is being improved to be capable of distinguishing between different levels of cavitation and attributing a severity index based on erosion risk. Developing such a system will help to minimize the number of hours spent in these regimes, increase the lifetime of the machines, and better plan the inspections. Nevertheless, the main objective of detecting cavitation in a non-intrusive way is proven feasible opening the door to predictive maintenance. Work is still ongoing to deploy more automized and complex ML algorithms such as clustering (unsupervised approach) for this detection task to minimize expert intervention and interpretation in labeling the samples. The outcome of this work will be a generic ML algorithm capable of detecting cavitation in a wide range of applications. This goal will be achieved via the '*Transfer of Learning*' technique; meaning that for each specific application, the main model will be fine-tuned through a standard calibration process. Concretely, the airborne noise of a given machine will be recorded over a relatively short period (a few hours) and will be used to calibrate the main model for this particular application.

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