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# Signature Investigation of Typical Faults on Francis Turbines

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**Abstract.** Hydropower is facing new operational strategies as the increasingly competitive power market demands for higher flexibility. Consequently, turbines are forced to handle tougher operation and are prone to more frequent degradation. By implementing a real-time monitoring system, a better understanding of the behavior of components may contribute to detect faults at an earlier stage, reducing potential downtime. This paper will present the work done in the preliminary work of the author's master thesis. The focus has been to characterize the normal behaviour of a Francis turbine through amplitude and frequency analysis. Steady-state measurements of pressure pulsations have been conducted on the Francis test-rig at the Waterpower laboratory at NTNU. Different hydraulic phenomena and respective frequencies were identified. In addition, the results revealed several unexpected frequencies and suspicious observations, and potential sources of these are discussed. Possible fault detection schemes based on peak-peak and frequency analysis are suggested. Alarm should be raised in case of mismatches in sensor relations, magnitude variations or if new harmonics or frequencies appears.

**Keywords:** Hydropower, Francis turbine, fault detection, pressure pulsations, sensors

## 1. Introduction

During the past decades, a situation has evolved that requires new strategies for the operation of hydropower plants. An increased amount of intermittent renewable energy sources, such as wind and solar, are being introduced to the European grid. As the production of these are strongly dependent on weather conditions, they are somewhat unpredictable. To compensate for the increasingly fluctuating contribution to the grid, the need for flexible energy sources that stabilize the grid frequency increases [1]. Hydropower is capable of providing both stability to the grid and a fast response to sudden changes in energy production. Furthermore, the deregulation of the energy market has resulted in a more market-driven operating strategy [2]. With significant variations in electrical prices, companies aim to maximize production when the prices are high, leading to an increased peak load production. Consequently, the turbines face higher dynamic loads, caused by more starts, stops, and operation outside their optimal operating point [1].

Hydraulic turbines are designed to operate around their best efficiency point (BEP), where the flow mainly follows the blade, resulting in a steady operation and high efficiency [3]. Operating at off-design conditions affects the dynamic stability of the turbine and can cause hydraulic phenomena such as pressure pulsations from the draft tube swirl and cavitation with associated noise, vibration and erosion [3]. These unwanted effects will create operating challenges as well as increase the risk of degradation and damages on the turbine. Thus, the demand for maintenance also increases.

To avoid failures and unscheduled downtime, plant operators have traditionally carried out regular inspections and maintenance based on experiences and scheduled actions. The turbines were typically



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operated around their BEP, and irregularities and deviations were detected at early stages [2]. However, due to the increased focus on cost reduction and new operational strategies challenges there are a huge potential for a real-time monitoring of the system condition, enabling better understanding of degradation of critical components [4]. Today, there is an extended use of digital systems in the hydropower industry that has increased focus on the implementation of models for fault detection and condition prediction [5]. By integrating such models in the maintenance strategy, the aim is to perform maintenance and other cost-related projects at the optimal time; thus, increase the availability and power production due to the prevention of failures and downtime.

The paper will present a brief literature review of methods used for fault detection in the hydropower industry to provide insight into state of the art. Further, relevant theory and methods necessary for identify the normal behaviour of a turbine will be presented. Steady-state measurements of pressure pulsations are carried out to obtain knowledge of how the turbine operates over the operating range without symptoms of failure. Peak-peak values and frequencies from the measurements are analysed and related to various hydraulic phenomena. Finally, possible fault detection schemes are suggested.

## 2. Background

When developing models used for fault detection, sufficient data from both normal and abnormal states are essential. Hydropower components are characterized by unique designs, high reliability and long lifetime, which results in a lack of historical fault data and knowledge of fault modes [5]. Hence, learning from historical faults are not feasible. Key findings from the literature shows that this limitation is usually dealt with by building models based on the normal behaviour of the system. Normal behaviour models aim to learn the typical relations and patterns for the operation of the system without symptoms of failure [6]. In this way, the real measured value from sensors can be compared with the estimated value from the normal model, where a deviation will indicate an abnormal situation that should be further investigated. When creating normal behaviour models, data from all possible states of operation are essential. This is crucial for a hydropower plant, due to the wide range of operating conditions. Also, external factors, such as seasonal changes in water, must be considered in context.

In literature, models used for fault detection and condition prediction are divided into different categories. In this work, the type of models are classified as in Monitor X: physical models and data-driven models [5]. Physical models depend on the knowledge about the process and the underlying physical phenomena that results in faults [5]. It can typically be based on the first principle of the process, where the actual behaviour of the monitored process is compared with the behaviour estimated by physical equations from normal operations. Techniques involving physical models may be beneficial when detecting specific, local faults in a system or at component level, such as detection of different cavitation processes on the runner blade. Escaler, et al. [7] show how to detect four cavitation processes on a Francis turbine. By first identifying the frequency signatures of each process from vibration and pressure analysis, he demonstrates how the amplitude of each frequency changes when provoking the different cavitation types.

Data-driven models, on the other hand, aim to find the relation and patterns in large data-sets to identify unexpected trends and deviations [5]. Due to the complex structure of a hydropower system, with interacting components regarding mechanical, hydraulic and electrical equipment, the mapping between the different parameters at a system level may be challenging to describe with a physical model. Data-driven approaches allow for discovering non-linear dependencies in extensive data set based on machine learning algorithms. These methods are not widespread in the hydropower industry, but several attempts using Artificial Neural Network (ANN) and Support Vector Machine (SVM) have shown successful result [4, 6]. Sanz-Bobi et al. [6] illustrate how to predict the generated output power of a Kaplan turbine based on ANN. The model estimates the power output in normal behaviour and can constantly be compared with real-time data; thus deviations can be identified. Further on, Åsnes et al. [4] developed a model based on SVM for detecting wear in the servomotor in a Francis turbine. By

monitoring the friction forces in the guide vanes for different operational conditions over time, the model managed to accurately define a boundary for where measured forces located inside the boundary were classified as normal, and located outside as abnormal. In this way, real-time data can be compared with the boundary, and the system can signalize in case of faults in the servo system.

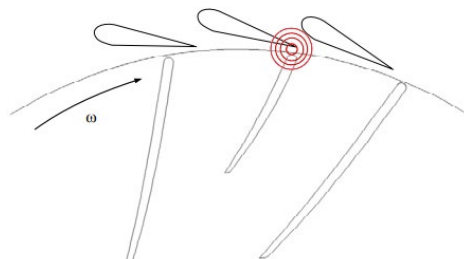
### 3. System identification

Even though hydraulic turbines are reliable, they are subjected to some modes of failure. According to the handbooks of EBL, standards used by Norwegian hydropower companies, the types of failures that occur on the runner blade can mainly be divided into crack propagation and regular wear [8]. These damages are caused by material defects and fatigue, in addition to cavitation problems and sand erosion [9]. They are essentially a consequence of vibration due to pressure pulsations and hydraulic instabilities in the fluid flow. These fault modes may not directly lead to breakdown; however, it may cause harmful and unstable operation, and if a turbine continues to operate under these conditions, the lifetime will be significantly reduced [10]. The appearance and intensity of the phenomena tend to increase when running outside the optimal operational point. A first step is, therefore, to identify the primary sources causing flow-induced vibrations, which are mainly associated with pressure pulsations.

Pressure pulsations are flow phenomena that occur inside the turbine and will always be present in the system. The pulsations can either be of stochastic or deterministic nature, appearing with different intensities from different sources over the operating range. A common source for deterministic pressure pulsations are the Rotor-Stator Interaction (RSI) and the part load vortex rope in the draft tube. Stochastic pulsations, on the other hand, can originate from boundary layer effects and secondary flows in the runner channel [10]. In addition, Von Karman Vortices, that typically alternate from the trailing edge of stay vanes, guide vanes or the runner blades, and elastic fluctuations, which are hydraulic instabilities in the waterway due to rapid load changes, can give rise to pulsations. If these frequencies coincided with natural frequencies, resonance may cause cracking of vanes or other damages on the turbine.

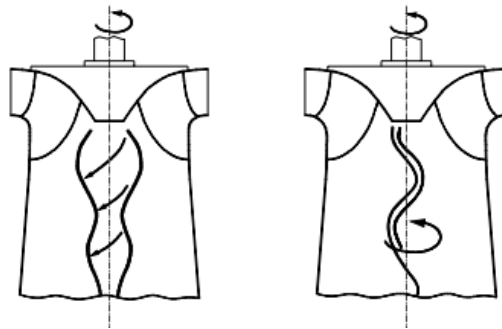
RSI refers to pulsations that occur as a result of the interaction between the rotational runner and the stationary parts [11], as illustrated in Figure 1. The frequency of this pulsation will depend on the rotational frequency and the reference system. Seen from the guide vane, the frequency experienced each time the runner blade pass, is called the blade passing frequency and is found by equation (1), where  $f_n$  is the runner frequency and  $z_r$  is the number of runner blades.

$$f_{bp} = z_r \cdot f_n \quad (1)$$



**Figure 1.** Illustration of RSI [12]

When a turbine operates outside its design point, a swirling component will occur in the draft tube. In case of a swirling flow that moves through a cylinder pipe, centrifugal forces will cause the fluid to move in the outer region, while a stagnation zone develops in the inner part [11]. If the swirl is severe enough, a reverse flow may develop in the stalled region, which is referred to as vortex breakdown [1]. At part load, the swirling component will move in the same direction as the runner, and a helical shaped vortex filament can be observed at the interface between the two flow fields, as seen right in Figure 2. This is referred to as the rotating vortex rope and induces pulsations in the range of  $\frac{1}{3}$  of the runner rotating frequency, recognized as the Rheingans frequency [13]. At over load the swirling component will rotate in the opposite direction of the runner and a pulsating cavitated vortex core can occur, as seen left in Figure 2.

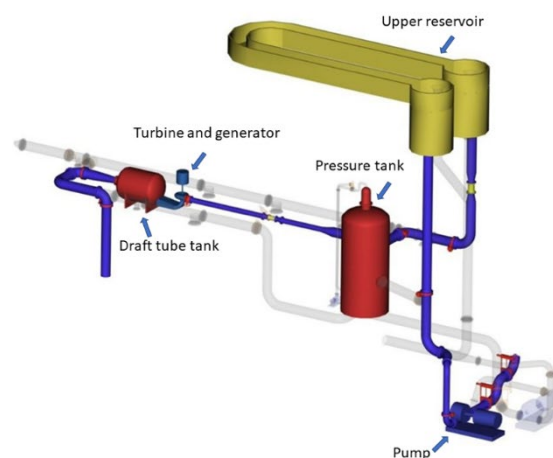


**Figure 2.** Left: full load vortex core. Right: part load vortex rope (2) [13]

#### 4. Experimental Setup and Method

##### 4.1. Francis Model Test Rig

The measurements were conducted on the Francis model test rig located at the Waterpower Laboratory at NTNU. The rig holds international standards according to IEC60193 and can be operated in an open or closed loop. Measurements were done for the open-loop configuration at a constant head of about 12 meters. Figure 3 shows an illustration of the open-loop circuit. The water is pumped from the lower water reservoir in the basement to the upper reservoir in the attic. From there, the water flows through a high-pressure tank, through the turbine, the draft tube, and the draft tube tank into the lower reservoir again. The purpose of the pressure and the draft tube tank is to stabilize the flow in case of flow variations. During the measurements, the pump-turbine runner, RPT, was installed, which consist of 6

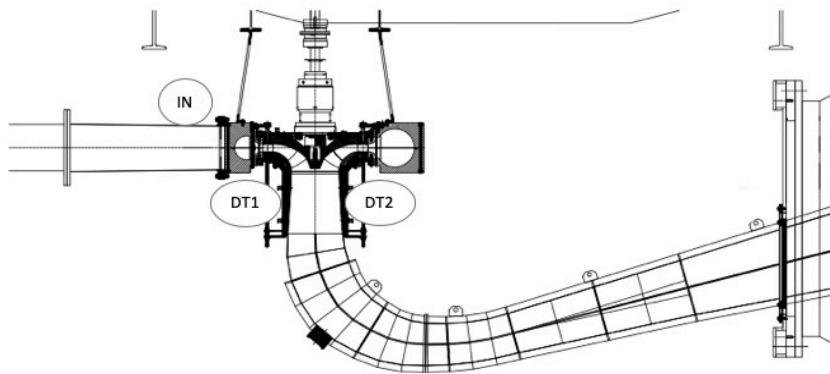


**Figure 3.** Illustration of the open loop configuration in the Water Power Laboratory.

runner blades. The number of guide vanes is 28, and the spiral casing consists of 10 stay vanes. The best efficiency point of the RPT runner corresponds to  $\alpha = 10^\circ$  and  $Q = 182 \text{ l/s}$ .

#### 4.2. Instrumentation

The pressure pulsations were measured by three pressure sensors, listed in Table 1. According to Figure 4, one was mounted at the inlet before the spiral casing and two on the upper draft tube cone,  $180^\circ$  from each other, to be able to identify the synchronous and asynchronous part of the vortex rope. The sensors were directly connected to a National Instrument data acquisition system through wires and further logged with a developed LabVIEW program in the laboratory. The sampling frequency was set to 5000 Hz to ensure reconstruction of all frequencies from the analog signal, with a recording time of 120 sec. This resulted in a TDMS-file with all the raw data that was further imported to Matlab.



**Figure 4.** Location of pressure sensors on the turbine test rig

**Table 1.** Sensors used for the pressure pulsations

Notation	Sensor	Range
IN	Kulite HKM-375M	0-1.7 bara
DT1	Kulite HEM-375M	0-1.7 bara
DT2	Kulite HEM-375M	0-1.7bara

#### 4.3. Measurement Procedure

Steady-state measurements were carried out for guide vane openings from  $\alpha = 4^\circ$ - $14^\circ$ , with an increment of  $\alpha = 1^\circ$ , at constant rotational speed. The rotational speed was set to  $n = 420 \text{ rpm}$ , according to the one obtained at BEP. Conventional turbines rotates at constant rotational speed as the synchronous generator is directly connected to the grid. Therefore the measured range will give a realistic picture of the actual working range for a full-scale turbine and produce results that can visualize the anticipated hydraulic phenomena. The pressure sensors mounted on the draft tube cone and at the inlet were calibrated with a dead weight manometer, which is considered to be the primary calibration method for pressure measurements according to IEC60193 [14].

#### 4.4. Analysis Method

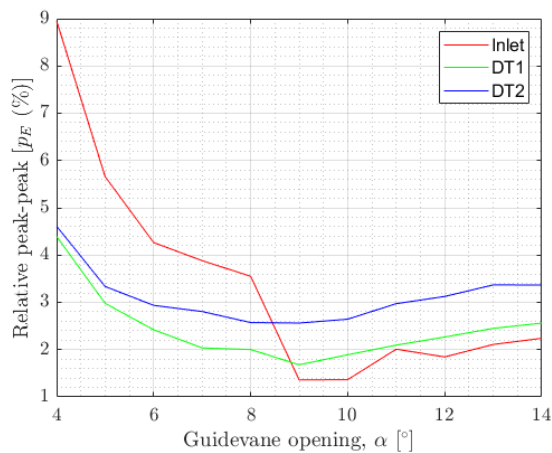
As the system degrades, characteristics of the signal in the time- and frequency domain may change. Matlab have been used for analyzing the measured data. Peak-peak values are calculated for each guide vane opening with the histogram method, containing 97 % of the sampled signals, recommended by [11, 14]. The peak-peak analysis only gives an impression of the intensities of the pressure pulsations independent of the frequencies. Hence, to investigate the origin of these the signals were decomposed. A spectral analysis of the acquired pressure values was conducted using the Power

Welch Method. The method returns the estimated power spectrum by dividing the sampled data into overlapping segments. Each block is then multiplied with a suitable window to remove discontinuity in the signal, before the Fast Fourier Transform (FFT) is applied. Finally, the resulting periodogram are averaged over all windows to reduce the variance. The spectral analysis was performed in Matlab with the build-in function “pwelch”, with a Hann window and 50% overlap, recommended by [14].

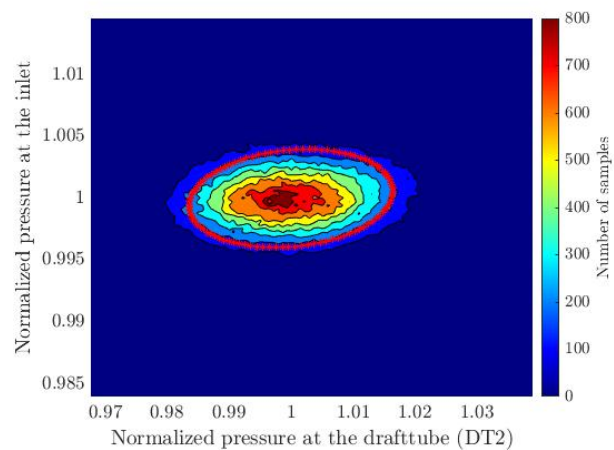
## 5. Results

### 5.1. Amplitude analysis

Figure 5 shows how the relative peak-peak varies with different guide vane angles for the three sensors. The values are normalized based on the total available hydraulic energy in the system. From the figure it is possible to identify how the intensity of the pulsations varies over the operating range in normal state. In Figure 6, the inlet and outlet (DT2) pressure values are plotted against each other at one operating point. This shows the pressure relation in normal state, and the red circle demonstrate a 94 % confidence interval which can be used as a boundary for detecting anomalies. A corresponding pressure relation between the inlet and DT1 sensor can be obtained, but is not included because it shows great similarity. The pressure values are normalized based on the mean value for each sensor.



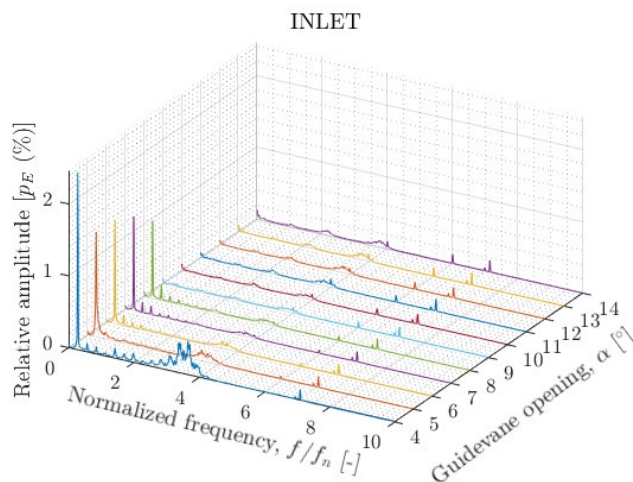
**Figure 5.** Relative peak-peak values for all guide vane openings



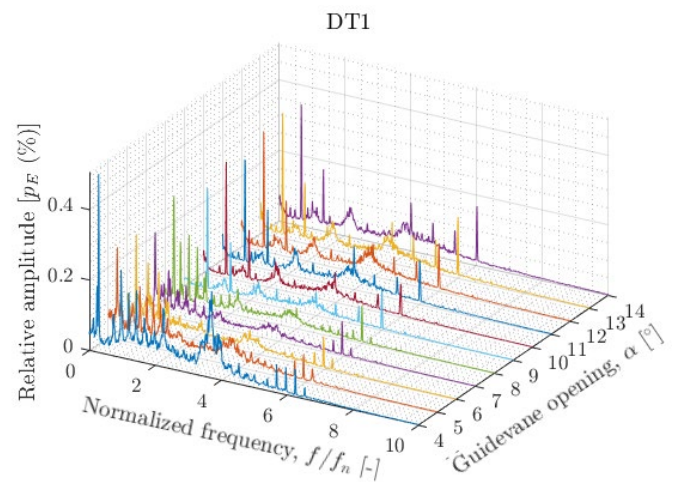
**Figure 6.** 2D histogram contour plot of the pressure values at the inlet and outlet (DT2) for one operating point ( $\alpha = 10^\circ$ ). A 94 % confidence interval is illustrated with a red circle.

### 5.2. Frequency Analysis

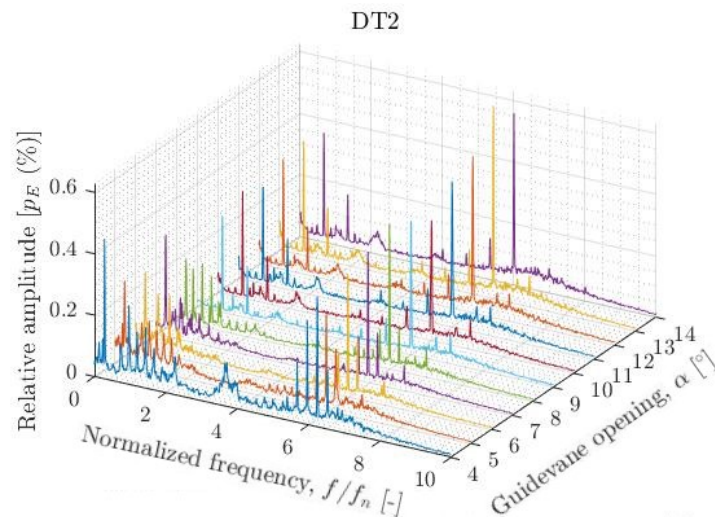
Frequency analysis was performed to investigate which hydraulic phenomena that occurred for the different operating conditions and which contributed the most. Because most of the hydraulic phenomena that occur in hydraulic turbines are periodic and related to the rotating frequency, the graphs are plotted with the normalized frequency. Due to the varying rotational speed over the operating range, the frequencies are normalized with the mean runner frequency at each guide vane openings. The amplitudes are normalized with the available hydraulic energy in the system. The results from the frequency analysis are presented in Figure 7-9.



**Figure 7.** Frequency analysis of the inlet sensor for all guide vane openings



**Figure 8.** Frequency analysis of the draft tube sensor DT1 for all guide vane openings



**Figure 9.** Frequency analysis of the draft tube sensor DT2 for all guide vane openings

## 6. Discussion

From Figure 5, the highest peak-peak value for all sensors are found at deep part loads, where the negative gradient is largest. In this operating range, the flow entering the draft tube is characterized by irregularities and swirling components inducing pulsations with high amplitudes. The peak-peak values for all sensors further decrease with increasing guide vane opening, with a more ideal flow leaving the runner blades, and reach minimum around BEP. As the guide vane further opens, the peak-peak values for all the sensors increases with a similar relative growth. For the inlet sensor, this can be explained by a smaller volume in the vane-less space causing more pronounced pulsations with higher amplitudes. This relative growth would probably have been more distinct with a sensor installed in the vaneless space. In addition, there will be a growing swirling flow component in the draft tube that adds to the pressure amplitude seen by the draft tube sensor.



The frequency plots are analysed manually and revealed dominating phenomena for different operating conditions. Several of the expected frequencies were identified, and the RSI and the Rheingans frequency turned out to be most prominent. The blade-passing frequency ( $6 \cdot f_n$ ) appear for all operational points with an increasing amplitude for increasing guide vane angle. The Rheingans frequency ( $\sim 0.27 \cdot f_n$ ) are most dominating at part load in the draft tube and decreases with increasing guide vane angle towards BEP ( $\alpha = 10^\circ$ ). In addition, several unexpected frequencies appear from the results. The most dominating ones are observed in the draft tube at  $0.67 \cdot f_n$ , with slightly constant intensity from  $\alpha = 9^\circ$  to  $\alpha = 14^\circ$ , and one around  $0.2 \cdot f_n$  that appears at deep part load. No clear sources of these have been identified, but possible sources could be system frequencies or external influencing elements which can distort the signal. Stochastic pulsations may occur at deep part load in the low frequency range but will rarely give rise to such high amplitudes. To further investigate their sources, additional measurements at different rotational speeds would be beneficial in order to divide the rotational speed-dependent frequencies from the independent ones.

When a runner is damaged, either through cavitation, erosion, or cracks, this will affect the water downstream the turbine and may increase the intensity of the pulsations in the draft tube. One way to detect such local degradation can be to identify the difference between the peak-peak values of the inlet and outlet sensors for different operational points. When the difference reaches a given threshold, an alarm should be raised. However, measurements over a considerable time scale combined with a wide range of seasonal conditions are necessary to ensure repeatably and to avoid randomness when estimating a threshold. Another way to detect local faults can be with multivariate indicators, as illustrated in Figure 6. Fault modes appearing on the runner or changes in the system prior to the inlet will change the pressure relation and induce corresponding mismatches. The red circle may demonstrate an alarm bound of which deviations from normal behaviour can be detected. Further, this can be expanded to include more sensors and all operational points. With advanced machine learning algorithms mismatches may be detected more immediately.

Accordingly, by continuously monitoring the intensity of the expected frequencies, alarms should be raised if amplitudes increase or new harmonies appear, that deviates from the normal characterization. Mechanical or hydraulic instabilities in the system can result in hydraulic fluctuations, seen in the runner frequency [12]. For example, in case of cracks on parts of the runner blades or detached parts, this will induce vorticities and pulsations in the waterway, rotating with the same frequency as the runner blade. As a result, the amplitude of the runner frequency may increase. Therefore, magnitudes of the expected frequencies can be trended over time and compared with predefined limits set based on the normal fingerprint. In addition, increased roughness on the runner blades or obstacles in the guide vanes will increase the formation of eddy swirls in the turbine passages, thus increase the stochastic pulsations seen as noise in the frequency analysis. Based on knowledge of the observed frequencies in normal state, such noise can be filtered out and continuously monitored to detect local, slow growing faults. However, the strength of these will vary with the operational point, therefore, it will be challenging to set thresholds.

The analysis revealed several suspicious observations. First of all, the relative peak-peak values for the inlet sensor at part loads are considerable higher compared with the draft tube sensors. There is also a domination of the magnitude of the Rheingans frequency for the inlet sensor compared with the magnitudes with the other sensors at part load. During the measurements it was challenging to keep the rotational speed constant, and a low-frequency sound was observed until  $\alpha = 9^\circ$ . If the rotating frequency coincides with the pulsating vortex rope, this could be a reason for the observed domination. Another suspicious observation is the difference in the amplitudes of the blade passing frequency ( $6 \cdot f_n$ ) between the two sensors in the draft tube, where the amplitudes of DT2 are considerable higher than DT1. The geometry of the spiral casing may be a possible reason. Kobro [12] addressed in his PhD thesis the consequence of a heart-valve on the spiral housing, causing a slightly non-uniform velocity distribution in the stay vane outlet. Due to the location of the DT2 sensor with respect to the heart-valve, the sensor may capture a local pressure rise. An alternative

explanation could be mounting differences between the two sensors that may have dampened the pulsations captured by DT1 to a greater extent.

## 7. Conclusion

To identify the normal behaviour of the turbine, the main focus has been to detect different hydraulic phenomena occurring over the operating range at constant speed. Measurements of pressure pulsations were conducted and have been analysed in time- and frequency domain. The variation in peak-peak values shows how the intensity of the pulsations independent of frequency varies with guide vane angle, where the highest amplitudes occur at low and high loads, away from BEP. From the frequency plots, several expected frequencies were classified, with the Rheingans and RSI as most prominent. In addition, several unexpected frequencies appear from the results. From the normal classification, alarms should be raised in case of mismatches in sensor-relations, changes in the magnitude of expected frequencies, or if new harmonics or unexpected frequencies that deviates from the normal condition arises. However, due to a lack of sensors and low accuracy in the conducted measurements, the results should be treated with caution due to considerable uncertainties.

The results presented in this work highlight the importance of preparation and awareness concerning the measured system prior to testing. First of all there are several limitations from the measurements that may have limited the accuracy of a complete normal identification. Examples are the varying rotational speed, a lack of sensor on adequate positions and problems during the manual calibration. Thus, careful planning of the number, types and locations of sensors is crucial and should be done according to the standards. A sensor in the vaneless space and on the runner blades would have improved the detection of RSI. Also, several sensors along the draft tube cone would improve the detection of the complete vortex rope. It is essential to be aware of system frequencies and other disturbing elements that may affect the measurements. Finally, proper calibration and evaluation of the uncertainty according to the standards, are vital. As the main goal of the preliminary work was to learn how to operate the laboratory rig and how to perform measurements, accuracy was not the main priority. However, these experiences have given valuable knowledge for future measurements which will be carried in the master thesis during the autumn 2020.

## 8. Further Work

The main focus of the work has been to identify the condition of the turbine based on data from the normal state. The new variable speed optimized runner designed by Igor Iliev allows for changeable runner blades. By 3D-printing blades, one can simulate various types of faults, such as cracks or erosion. The master thesis will investigate how to identify such errors with extended measurements and comparative analyses.

The focus when discussing fault modes has been locally on the runner. This is a narrow scope, as other components will naturally affect the unit. Therefore, for further work, it would be interesting to consider the influence on other parts and components, such as an asymmetric rotation due to faults in bearings, or speed variation due to frequency variation in the grid. Also, to provide enough data for building sufficient models for fault detection and condition prediction, several measurements from a long time-span should be carried out to obtain representative data that captures a representative range of operational and seasonal conditions.

## References:

- [1] Gogstad, P J 2017 Experimental investigation and mitigation of pressure pulsations in Francis turbines. Doctoral thesis NTNU
- [2] Welte T 2008 Deterioration and maintenance models for components in hydropower plants Doctoral thesis NTNU.
- [3] Chirag T and Cervantes M J 2017 Fluid-structure interactions in Francis turbines: A perspective review *Renewable and Sustainable Energy Reviews* **68** 87-101
- [4] Åsnes A, Willersrud F and Imsland L 2018 Predictive maintenance and life cycle estimation for

hydro power plants with real-time analytics.

- [5] Welte W and Foros J 2019 MonitorX-Final Report *Technical Report* Energi Norge AS
- [6] Sanz-Bobi M A, Welte T and Eilertsen L 2018 Anomaly indicators for Kaplan turbines components based on patterns of normal behavior DOI: [10.1201/9781351174664126](https://doi.org/10.1201/9781351174664126)
- [7] Escaler X, Eduard E, et al. 2006 Detection of cavitation in hydraulic turbines *Mechanical Systems and Signal Processing* **20** 983-1007
- [8] EBL Tilstandskontroll av Vannkraftkontroll *Energibedriftenes landsforening* Accessed: 2019 11-16
- [9] Kjølle A. 2010 Hydropower in Norway – Mechanical Equipment. NTNU. Compendium
- [10] Iliev I, Trivedi C, Agnalt E and Dahlhaug O 2019 Variable-speed operation and pressure pulsation in a Francis turbine and a pump-turbine *IOP Conf. Ser.: Earth Environ. Sci.* **240** 072034
- [11] Döfler P, Sick M and Coutu A 2013 Flow-induced pulsation and vibration in hydro-electric machinery. *Springer-Verlag*, London
- [12] Kobro, E 2010 Measurement of pressure pulsations in Francis turbines. Doctoral Thesis NTNU
- [13] Brekke, H 2003 Pumper og Turbiner *Vannkraftlaboratoriet* NTNU.
- [14] IEC606193:1999. Hydraulic Turbines, Storage Pumps and Pump-Turbines – Model Acceptance Test NEK *International Electrotechnical Commission*