Strain prediction in Francis runners by means of stationary sensors

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Strain prediction in Francis runners by means of stationary sensors

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Abstract. The assessment of the remaining useful life due to fatigue in Francis turbine runners implies complex measurements with strain gauges that have to be installed in a submerged and rotating structure, which is excited with high pressure pulsations and strong turbulent flows. Furthermore, the conditioning, storage and transmission of these signals to the stationary frame involves complicated technical solutions. In order to avoid such complex and expensive measurements, in this paper we explore the feasibility of obtaining the strain on the runner with stationary sensors, which can be easily installed and used for a continuous monitoring of the machine. Based on the experimental strain tests performed in a Francis turbine unit, strain on the runner blade is correlated with relevant indicators obtained with stationary sensors. The correlation within indicators is obtained considering linear regression models and improved with artificial intelligence techniques.

1. Introduction

Due to the massive entrance of Renewable Energies in the electrical grid, Hydraulic turbines have to work in off design conditions for a long period of time. Furthermore, start-ups, load changes and other sort of transients are more common in this new operating scenarios [1].

Recent cases in prototypes show the importance of considering and analyze the effects of fatigue in the lifetime of the unit (see for example [2,3]). This involves the determination of static and dynamic stresses on the critical points or stress hotspots of the runner for the different operating conditions[4]. There are mainly two options to determine stresses on the turbines, which are experimental tests and numerical methods. Experimental tests consist in the installation of several strain gauges in the turbine blades. Nevertheless, the installation of such sensors in a submerged and rotating structure is a complex task. Such installation involves high direct and indirect costs as it may take several weeks[4,5]. Therefore, in the recent years many authors have systematically used numerical approaches to evaluate strain and stresses in hydraulic turbines and to compare it within experimental measurements[6–8]. Nevertheless for deep part load conditions and transients, where the excitation is mainly stochastic [9,10], there can be a high discrepancy between numerical results and experimental measurements[6,11,12]. Hence, although numerical simulation is a cheaper and faster option, experimental measurements may be the only reliable method for this purpose in the present.

Another approach could be to indirectly estimate strain & stresses on the runner based on other sensors on the stationary part or in the rotating shaft, as such sensors are much easier to install and to use. As an example, Diagne et al. [13] used an ARMAX model to indirectly estimate the strain on the runner, based on the measurements of strain gauges located on the rotating shaft. Although this option greatly reduces the complexity of the installation as part of the shaft is generally accessible, it still has to overcome the problem of transferring signals from rotating to stationary frame or to store it in a data logger located in the rotating part.

In this paper, we investigate possibilities to simplify such tests by correlating static and dynamic strain & stress parameters with indicators obtained by means of sensors located in the stationary frame. A simple model based on statistical regression and a preliminary model based on artificial intelligence techniques are analyzed here. The resulting correlation model shows that some important features of strain & stresses on the turbine runner could be approximated with appropriate indicators obtained with stationary sensors.

2. Analysed Francis turbine and sensors selected

For this study we analyze a middle head Francis Turbine located in Canada. During the final experimental campaign carried out inside the HYPERBOLE project[5,14], several sensors including strain gauges on the runner were installed, as seen in Figure 1.
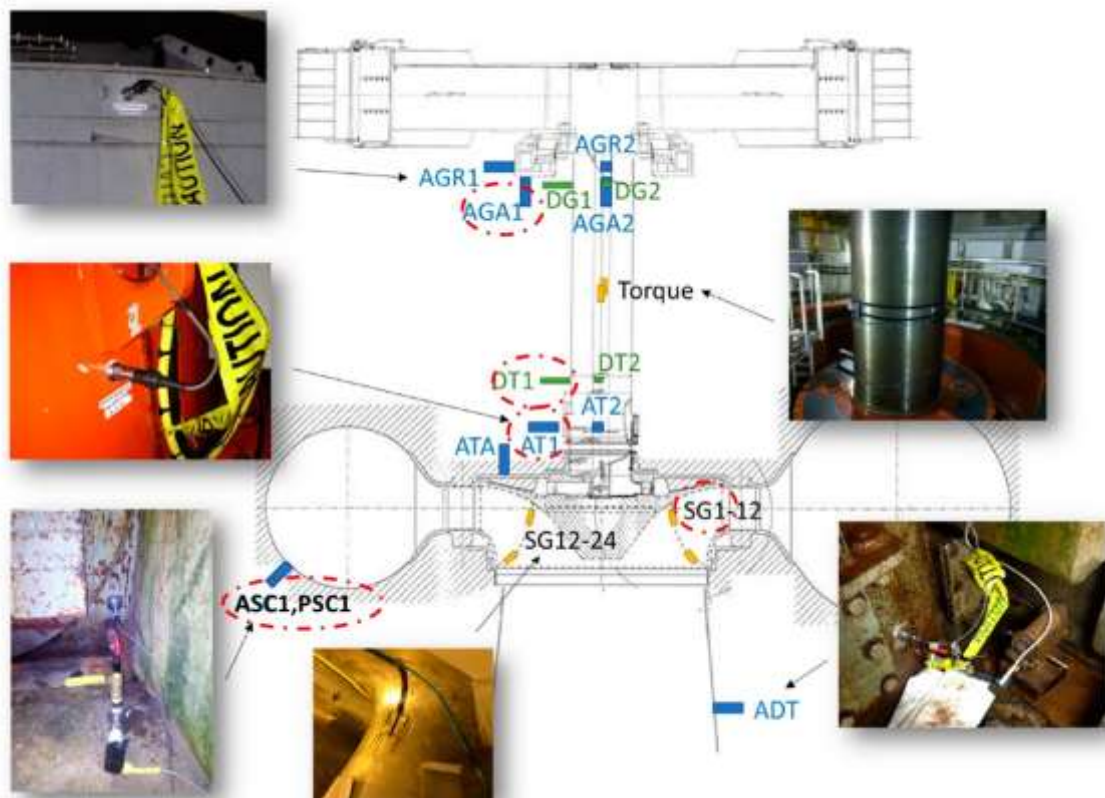

Figure 1: Sensors installed during the experimental campaign of HYPERBOLE[15]

Besides the strain gauges on the runner, displacement sensors on the shaft, accelerometers on the bearings, draft tube and spiral casing were also installed as seen in the same figure. Furthermore, several pressure sensors on the draft tube and spiral case (not shown in the figure) were used in the same tests. As operating signals, the electrical power, the gross head, the rotating speed and the guide vane opening were also acquired.

2.1. Dominant hydraulic and mechanical phenomena in the unit.

The different phenomena that affects this machine have been analysed in several papers. Here we briefly describe most of them based on the operating range:

- Deep part load condition: The unit is excited by highly stochastic inter blade vortices[16]. The frequency content of such random excitation is around 0-20 Hz.
- Part load condition and resonance: The dominant excitation is a precesing vortex rope[17] $f_{rope} = 0.6 - 0.8 Hz$. Such excitation can lead to a resonance on the hydraulic circuit which in turn origins high fluctuations on the torque and on the electrical power[15,18]
- Around best efficiency point (BEP): The unit works in a relative smooth zone but for load conditions around the BEP
- Overload: Over the BEP the machine works relatively smooth until the full load instability appears

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- Full load instability: This unit has a strong instability with a power oscillation of more than 30MW at full load condition. The oscillating frequency of the phenomena is almost the same as for the part load resonance [20,21]

2.2. Sensors selected
In order to capture the relevant characteristics of the aforementioned phenomena the stationary sensors marked on Figure 1 are selected for the present study. These are an accelerometer and a pressure sensor on the spiral case (ASC 1, PSC 1), axial accelerometer on the generator bearing (AGA1) and a radial accelerometer on the turbine bearing (AT 1). Finally, a displacement sensor measuring the shaft has been also considered (DT 1). With the time signal of these sensors, several indicators can be obtained which will be correlated with the mean and alternate strain measured with the turbine strain gauge SG1

3. Signal indicators and operating conditions analysed
Operating conditions with stabilized power have been chosen for the analysis. These are deep part load, part load, part load resonance, best efficiency point, full load and full load instability. For every operating condition, time signals of approximately 180 seconds have been analyzed. These time signals are divided in several parts of 4 seconds with a gap of 0.2 seconds between two consecutive parts. Then every part is weighted with a uniform window for the indicators in the time domain and with a hanning window for the indicators in the frequency domain.

3.1. Indicators in the time domain
For every part of every signal corresponding to the stationary sensors and strain gauge on the runner, the following indicators have been calculated:
- Mean value of the signal part
- RMS value of the signal part
- Peak- Peak value of the signal part

3.2. Indicators in the frequency domain
By means of the Fourier Transform every signal part is transformed to the frequency domain. In this the indicators calculated are the peak values associated to vortex rope frequency, rotor stator interaction frequency and rotating frequency.

## 4. Stress prediction with indicators obtained from stationary sensors
In this section, the mean and alternate (peak-peak) strain measured in the runner is correlated with the different indicators obtained with the stationary sensors. In order to evaluate the quality of the prediction we use the mean absolute percentage error (MAPE), defined as the averaged relative error between the predicted values by the respective models and the experimental observed values.

4.1. Strain prediction with linear regression model
Several multiple and linear regression models have been evaluated. In such models, inputs or independent variables are the different indicators obtained from the stationary sensors and output or dependent variable are the mean and dynamic strain measured on the runner. None of the multiple linear regression models (multiple inputs- one output) improved significantly the simple ones (one input- one output).

Regarding the mean value of the strain in the runner the best fitting is with the mean value of the pressure sensor. Nevertheless, the MAPE of the prediction is higher than 70%. For the peak to peak value, the best fitting is obtained with the peak-peak value of the accelerometer on the casing ASC 1 (statistic coefficient of determination of $R^2 \approx 0.75$) (Figure 2a.) Also with the peak-peak value of AT1

and AGA 1 reasonable R^2 values are obtained (Figure 2b). Using this simple linear regression model a MAPE value of 15.4% is obtained for the alternate strain. Best indicators of the simple linear regression models are summarized in Table 1.
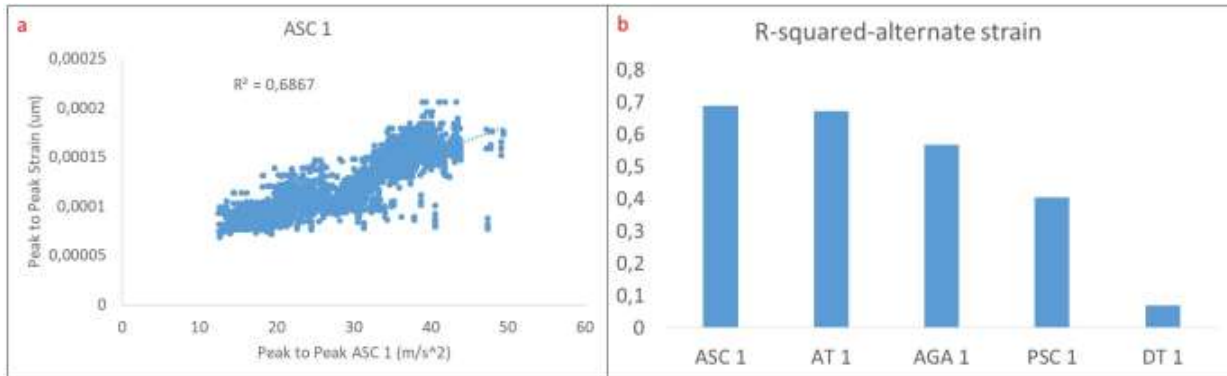
Figure 2: a) Simple linear regression model (Peak-Peak ASC 1 vs Peak-Peak Runner strain). b) R^2 values for the different sensors (alternate strain)

Table 1: Best indicators and Mean Absolute Percentage Error of the simple linear regression models for the mean and alternate strain measured in the runner

	Best indicator	Mean absolute percentage error
Mean strain	Mean value PSC 1	70.2%
Alternate strain (Peak-Peak)	Peak-Peak ASC 1	15.4%

4.2. Strain prediction with artificial neural network

In order to improve the quality of the prediction, neural networks have been used. In this case two different neural networks have been used, one for predicting the mean strain and one for the alternate strain (peak-peak). In both cases the same inputs have been used which are indicators extracted from the stationary sensors selected. Having 5 sensors the total number of inputs for the neural network is 30, which means 30 neurons on the input layer. For the neural network architecture and setup of the neural network structure, MATLAB® has been used. One hidden layer with 15 neurons has been selected.

   Results show a clear improvement with respect to the simple linear regression models. As an example, Figure 3 shows the predicted and measured mean strain for the Best Efficiency Point condition. As seen in the figure, a small deviation between measured and predicted values are observed. Finally, on Figure 4 the MAPE coefficients for the different operating conditions are shown for the prediction of the mean and alternate strain. As seen in this figure, a maximum value of 4% of MAPE is obtained for the part load condition in the mean stress (Figure 4a). For the alternate stress, the MAPE value is approximately 3-3.5% for the full range operation of the machine.
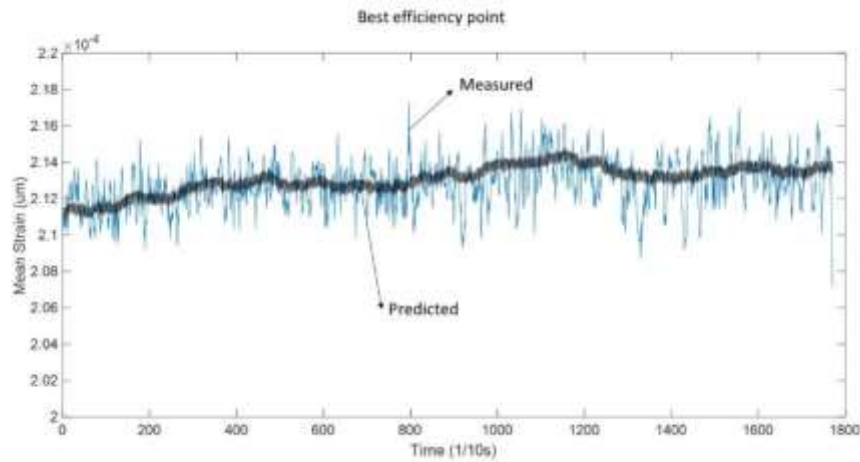
Figure 3: Predicted and measured strain for the BEP based on the neural network approach
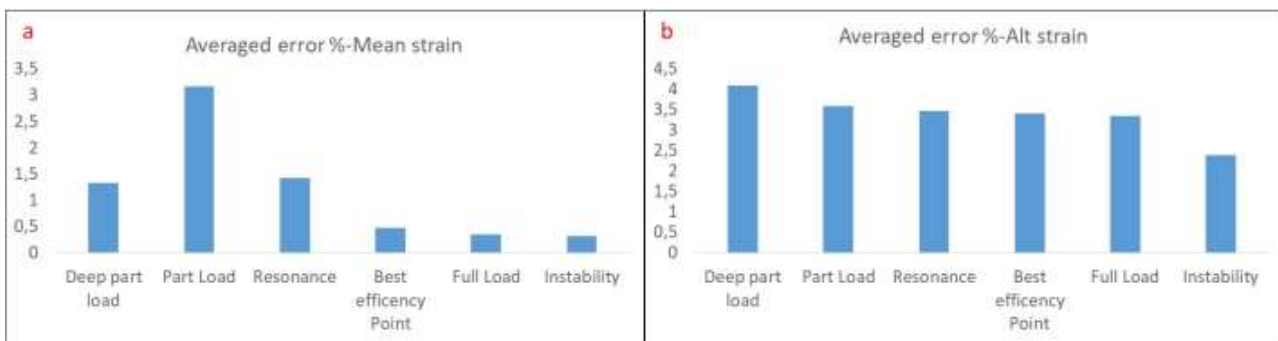

Figure 4: MAPE values (relative error) of the prediction for the mean (a) and alternate strain (b)

5. Conclusion

In this paper, the feasibility of using stationary sensors to predict the main features of the strain on the turbine runner has been explored. Such procedure could be used in the future to simplify complex strain measurement campaigns in hydraulic turbines, which is always an expensive and complex task.

According to the present analysis, linear regression models using indicators obtained from stationary sensors have a limited predictability of the mean and alternate strain measured in the runner. Multiple linear regression models do not significantly improve simple linear regression models. The best correlation has been found for the peak-peak value of the accelerometer installed on the spiral casing with the peak-peak value of the strain. Nevertheless, the quality of the predictability of the mean strain with linear regression models and indicators used has been found to be poor.

The quality of the prediction is greatly increased when using artificial intelligence techniques such as neural networks. In the present study, using the proposed sensors and indicators, it has been found that mean and peak-peak values of the strain measured in the runner could be accurately predicted for some operating conditions. Such procedure will be further explored and improved in future studies.

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