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Modeling the dynamic behavior of turbine runner blades during transients using indirect measurements

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Abstract. Turbine start-up transients are induced by the wicket gates opening sequence and generate high amplitude stress cycles. These stress cycles have a detrimental effect leading to faster crack growth in the runner blades. Using a series of direct measurements taken on a prototype runner in order to find the optimal start-up parameters exposes both the runner and the instrumentation to a series of successive damaging transient events during the optimization process. To solve this, finding sensors strongly correlated to strain gauges and whose signals can be easily obtained to identify a model to predict the strain, instead of directly measuring it, would reduce the risk, cost and downtime associated with a measurement campaign. This paper shows that turbine shaft torsion measurements is highly correlated to the strain at a runner blade hotspot, and we demonstrate that the ARMAX model can be used to represent the dynamic system in order to minimize the strain on blades.

1. Introduction

Turbine start-ups generate high amplitude transient stress cycles and these transient stresses cycles have a detrimental effect on the structure; an effect consisting of faster crack growth in the runner blades. Therefore, knowing their magnitude can help the fatigue life estimation. Unfortunately, strain gauges instrumentation of the turbine runner blades hotspots (where maximum values are observed) is difficult and costly. Consequently, it is appropriate to obtain estimates of these strain amplitudes from indirect measurements from sensors located in easier to access location and more protected areas such as the main shaft or the stator structure.

For the purpose of better understanding the relationship between start-up strategy and transient stress cycles amplitudes, Hydro-Quebec has carried out *in situ* stress measurement campaigns, on prototype runners. In those measurement campaigns the magnitude of the strain (near the blade welded joints close to the hotspot) have been measured directly on the turbine runner blade during the transient for different wicket gates opening patterns (Figure 1). Beside measured blade strain and the opening pattern, sensors were also located on the shaft to allow the calculation of the rotational speed and measurement of the shaft torsion (Figure 2).

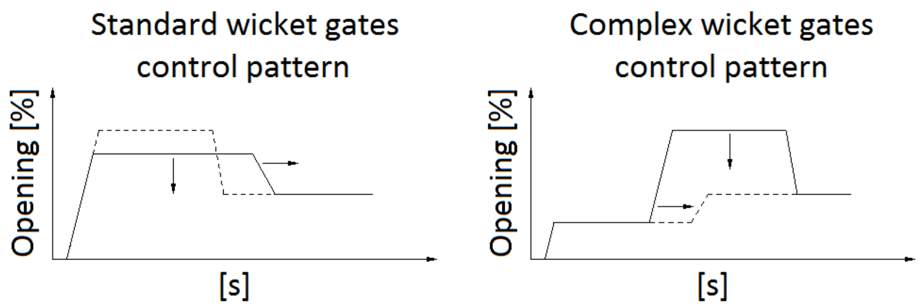

Figure 1. Governing system control patterns for opening patterns.

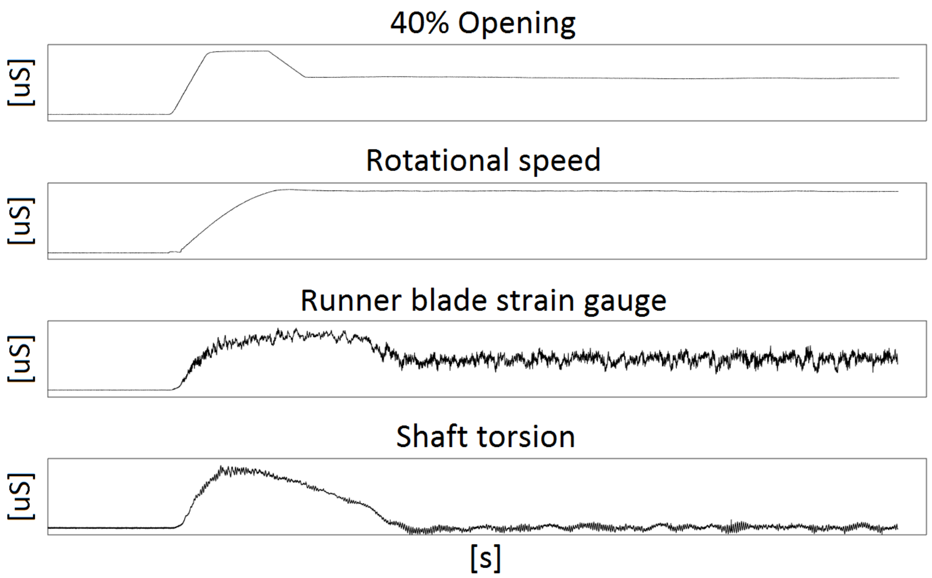

Figure 2. Typical signals of a propeller turbine for one opening sequence.

The optimal start-up is the one that minimises the strain while assuring a reasonable synchronization time. So far, no attempt has been made to optimize start-ups without directly measuring the strain on the prototype runner blades. Thus, finding the optimal start-up pattern without running all the stress measurements on the prototype runner would reduce risk, cost and downtime associated with the measurement campaign. In order to do this, Hydro-Québec decided to use the data from their measurement campaigns on Francis and propeller runners to identify and validate dynamic models that will represent the turbines behavior and enable start-up optimization. This paper follows previous work conducted at Hydro-Quebec by Gagnon et al. [1-3], and by other researchers [4, 5], on the impact of a transient operation on Francis runners, and builds on the review on fatigue damage mechanisms in hydro turbines [6].

The case studies presented in this paper come from one (1) propeller and one (1) Francis turbine. After filtering the spike noise contained in the recorded signal using the 3D phase space method [7], the sensors strongly correlated to strain gauges were found and compared with each other. In these case studies, we use the torsion measurement on the shaft as input and the strain gauge on the runner as output to identify an ARMAX model which appears to best represent the dynamic system. The ARMAX Model Structure is an Autoregressive Moving Average model with external input. It provides a description of a stationary stochastic process in terms of three polynomials, one for the auto-regression, one for the moving average and the last for the external input [8]. The model's output (predicted signal) is then compared to the measured signal from the strain gauge. For further validation purposes, a comparison is also done between the predicted signals and the measured signals from the other start-ups. Depending on the model order and the start-up scheme, only the models whose calculated root mean square error (RMS error) is less than 30 microstrains (uS) were retained. At that point, we demonstrate that instead of measuring the strain during every start-up, once a consistent and accurate dynamic model has been identified, one can predict the strain on the turbine and use those predicted signals to find the optimal start-up.

The paper is structured as follows. First, we present the statistical methods and the identification/validation procedures. Then, the results of the linear regression and the identification/validation procedure are shown. Next, to show the dependency of the identified model on the used start-up and the order of polynomials, case studies were developed. Finally, we conclude on some discussions and recommendations regarding future work.

2. Proposed methodology

In this study, we used signals from *in situ* experimental strain measurements on prototype runners. The data acquisition that led to the presented results was carried out in Hydro-Québec's run-of-the-river power plant. The strain on the blades was recorded using strain gauges located across the blade-to-crown and the blade-to-band joints where the deformations are at a maximum. The strain on the shaft was recorded using multiple strain gauge rosettes. Depending on the strain gauges used, we can obtain the torque, the flexion, and the axial thrust of the shaft.

The inspection of signals showed the presence of spike noise that did not describe the dynamic behavior of the structure and its interaction with the fluid. These spikes are mostly due to electrical phenomena and are not useful for identification. The first step was to remove this noise from the original signal. To remove the noise, we used the three-dimensional 3D phase space method [7].

Since our goal was to build a model which is meant to be a true representation of the system, we first, studied the relationship between the signal from the strain gauge and the components surrounding the runner. Since the shaft is directly connected to the runner, the second step was to find the link between the signals from the sensors on the shaft and the strain gauge on the blade and the nature of that correlation. In order to have a quick view on that relationship, we completed a series of linear regressions analysis between the strain gauge and every single combination of sensor on the shaft.. Figure 3 below presents the followed methodology.

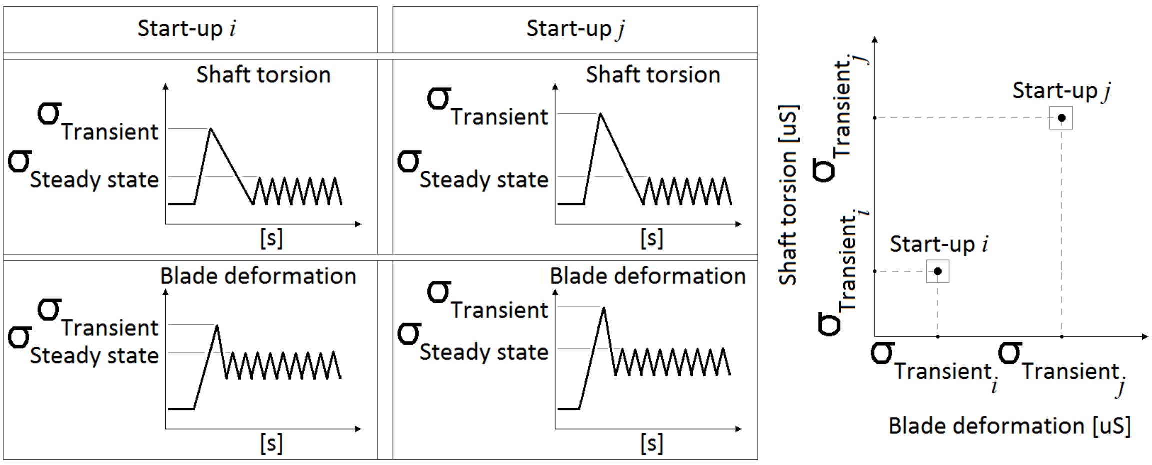

Figure 3. Plotting procedure for the regression analysis.

After finding the existence of a linear relation between the two measured signals, the third step was to find a family of linear models that could use the linear relation to predict one of the signals while knowing the other; Figure 4 presents the followed algorithm. Our choice was made on a model set from the autoregressive polynomial family. In order to choose the best model set and then choose the best model in that set, a comparison was done between ARX, ARIX, ARMAX and ARIMAX model. For each model, several orders were tested. The use of the root mean square error as a metric of comparison helped us find the best models depending on the start-up used to fit the model and the order of polynomials. The procedure is illustrated in Figure 4.

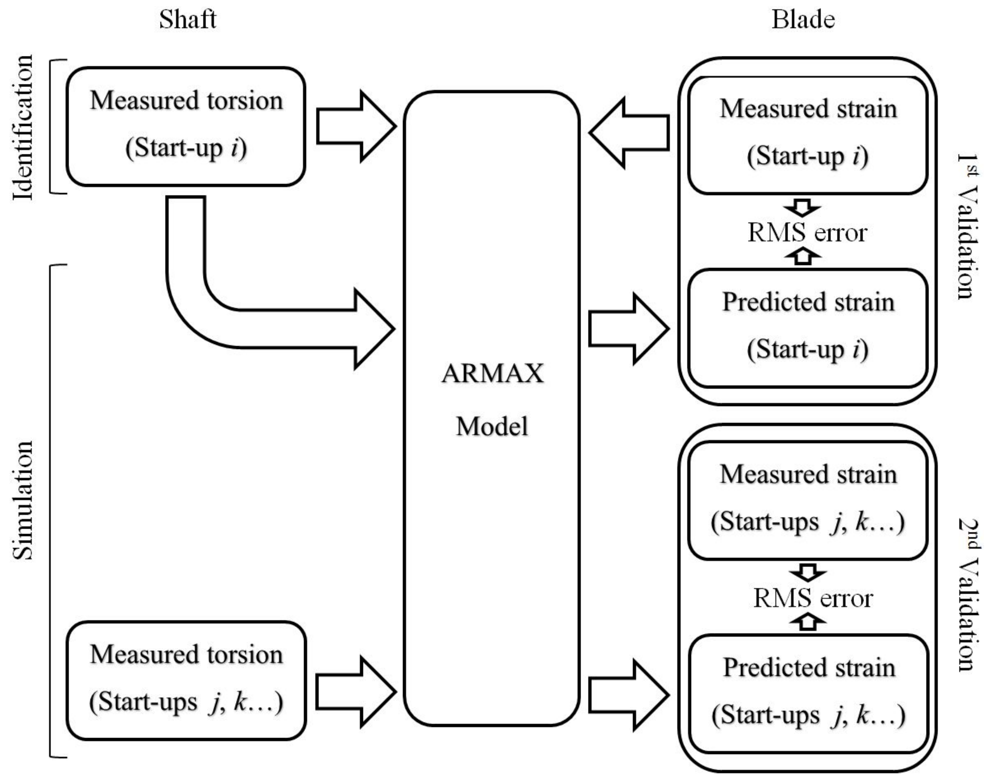

Figure 4. Identification, simulation and validation procedure.

The identification procedure consisted of identifying the parameters of a model knowing the input and the output of the system. In this study, we used the maximum likelihood estimator (eq. 1) to determine the vector of parameters $\boldsymbol{\theta}$ of the autoregressive polynomial model. To assess the adequacy of models and choose the best one, we calculated the root mean square (RMS) error (eq. 2).

$$\hat{\boldsymbol{\theta}}_{ML}\left(y_*^N\right) = \arg\max f_y\left(\boldsymbol{\theta}; y_*^N\right) \tag{1}$$

In which:

$\hat{\boldsymbol{\theta}}_{ML}$ is the vector of predicted parameters using the maximum likelihood method
y^N is the stochastic variable representing operations $y^N = \left(y(1), y(2), \ldots, y(N)\right)$
y_*^N Observed (measurement) value of y^N
$f_y\left(\boldsymbol{\theta}; x^N\right)$ is the probability density function (pdf) of y^N **:** $f_y\left(\boldsymbol{\theta}; x^N\right) = f\left(\boldsymbol{\theta}; x_1, x_2, \ldots, x_N\right)$
x^N vector of independent and identically distributed observations**:** $x^N = x_1, x_2, \ldots, x_N$

$$\text{RMS error} = \left(\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \widehat{y_i}\right)^2\right)^{1/2} \tag{2}$$

Where:

y is the measured output from the strain gauge
$\hat{y}$ is the predicted output from the ARMAX model
n is the number of samples of the output vectors

After the selection of the model structure, the identification gave us the best possible representation for the chosen structure. The generated model can be seen as the best possible in the set, but to be validated, this model needed to be able to reach our objective. The objective being to optimize the strains on a blade, the model should provide at least the static strain in steady state and have a RMS error level less than 30 uS.

After identifying, simulating and validating the model, the upcoming and last step was to use the model to predict signals and test if they could be used for the start-ups optimization procedure. To do this, the peak levels of the signals were used. The test procedure consisted of calculating, for each start-up and combination of measured and predicted signals, the ratio between the peak stress level of transients and those of the steady state. Using this ratio for the measured signals on the x axis, and predicted signal on the other axis, each start-up was represented by a coordinate. The optimal start-up being the one where the peak stress level of transient and the one of the steady state, give a ratio near one $r_i \approx 1$. An area named the optimal zone surrounding the coordinate point (1,1) has been established. The area was chosen in order to tolerate a 5% error around the optimal point on each axis. The ideal results is obtained if for each start-up, the ratio of the predicted signal is identical to the one of the measured signal; which would, by plotting the regression line, show a slope of 45°. Otherwise, the regression should go through the optimal zone. Figure 5 shows the optimization applicability test procedure used where $\boldsymbol{\sigma}_{\text{Transient}}$ and $\boldsymbol{\sigma}_{\text{Steady state}}$ represent the maximum stresses during transient and steady state, respectively.

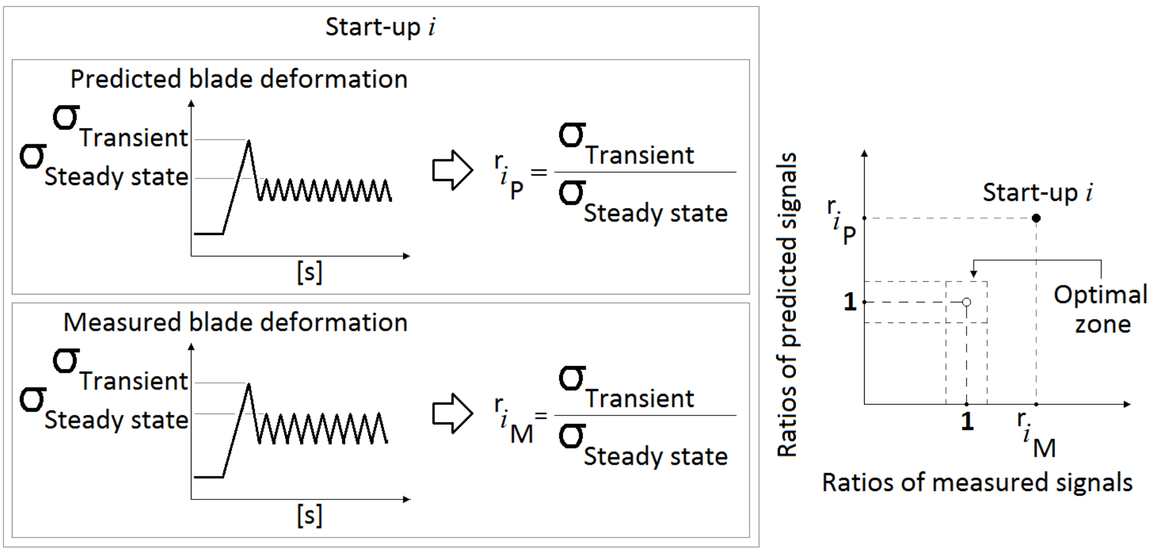

Figure 5. Procedure of the optimization applicability test.

3. Results

Notice that the relationships between main shaft sensors and the runner could also have been explored in the frequency domain if nothing was found in the time domain. In our case, we were able to find linear correlations in the time domain. During the measurement campaign, different wicked gates control patterns were tested and each one was replicated at least twice. For each of the start-ups, the maximum value was used for the response signal of the strain gauge on the runner blade and for the sensors on the shaft. Figure 6 shows the plot of the Torsion, the Axial Thrust and the Flexion of the shaft, successively, as a function of the strain on the blade.

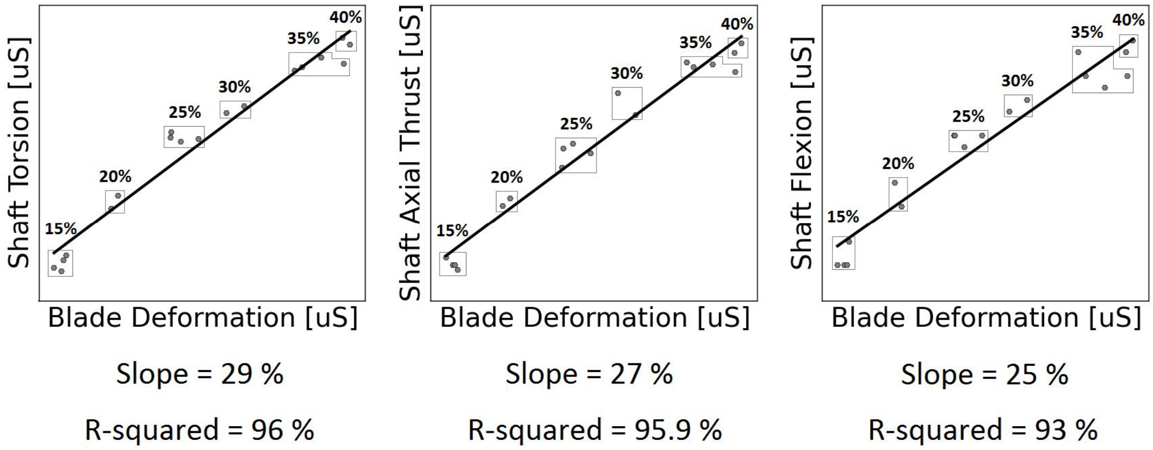

Figure 6. Torsion, Axial Thrust and Flexion as a function of the Opening.

In our case studies, for the seven (7) wicket gate opening patterns, we investigated the torsion signal which appears to be most correlated to the strain gauge on the blade and the ARMAX model with polynomial orders one (1) to ten (10). The metric for the model comparison was the root mean square (RMS) error; the best models being the ones minimising it.

3.1. *Case study #1: Propeller turbine*

For ARMAX models with polynomials of order two (2), Figure 7 presents a comparison of the measured and predicted signals for high and low quality models using the 15%-30% and the 40% start-ups.

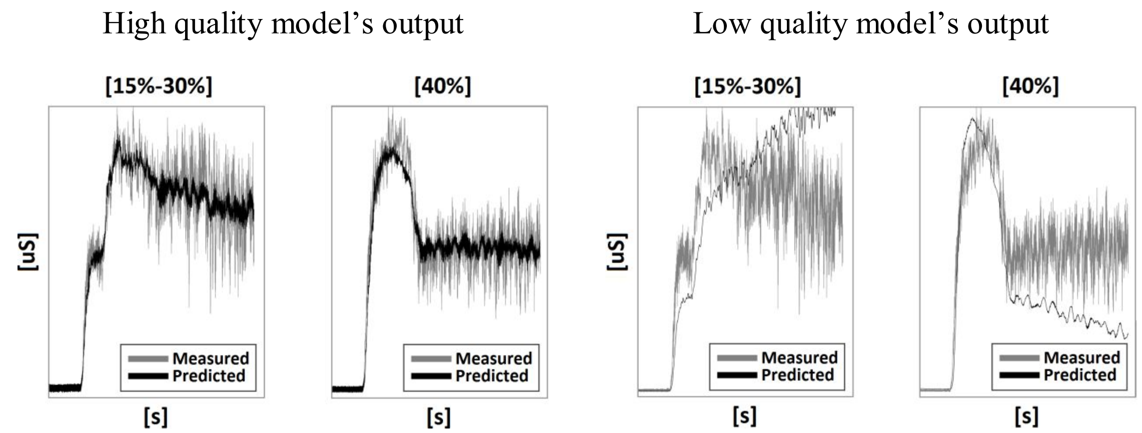

Figure 7. Propeller Turbine's measured and predicted signals for ARMAX models.

An important step is testing if the predicted signals can be used to do a start-up optimization. In Figure 8 and 9, we observe that; for measured and predicted signals, if the model is of high quality, the ratio between the strain level during transient and the level during steady state intersect within the optimal zone for the optimal start-up found experimentally. However, if the model is a low quality one, the ratios will never intersect in the optimal zone, and then, those models cannot be used for optimization purposes.

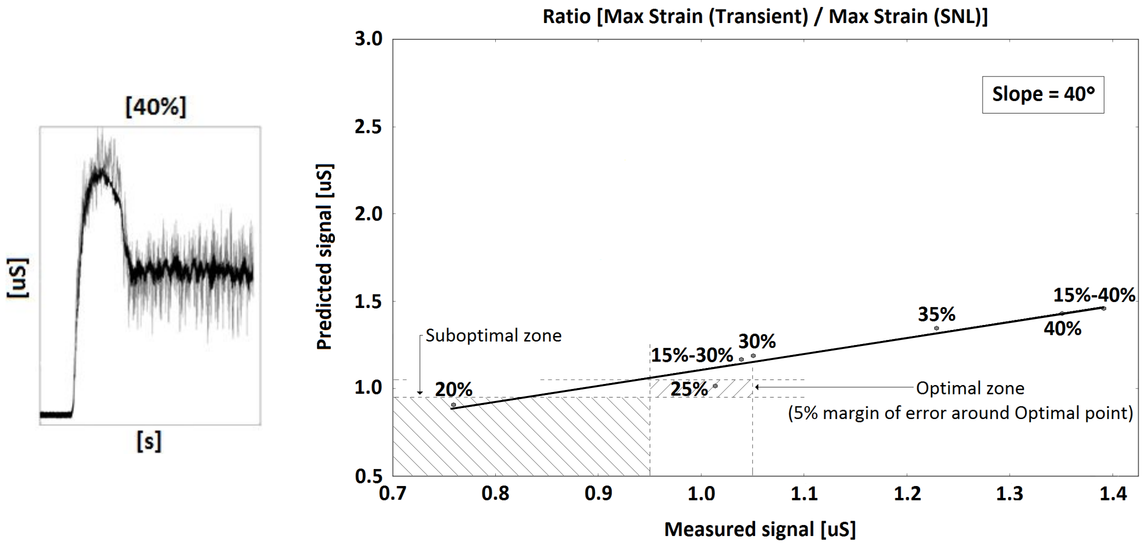

Figure 8. Propeller turbine high quality models' optimization test results.

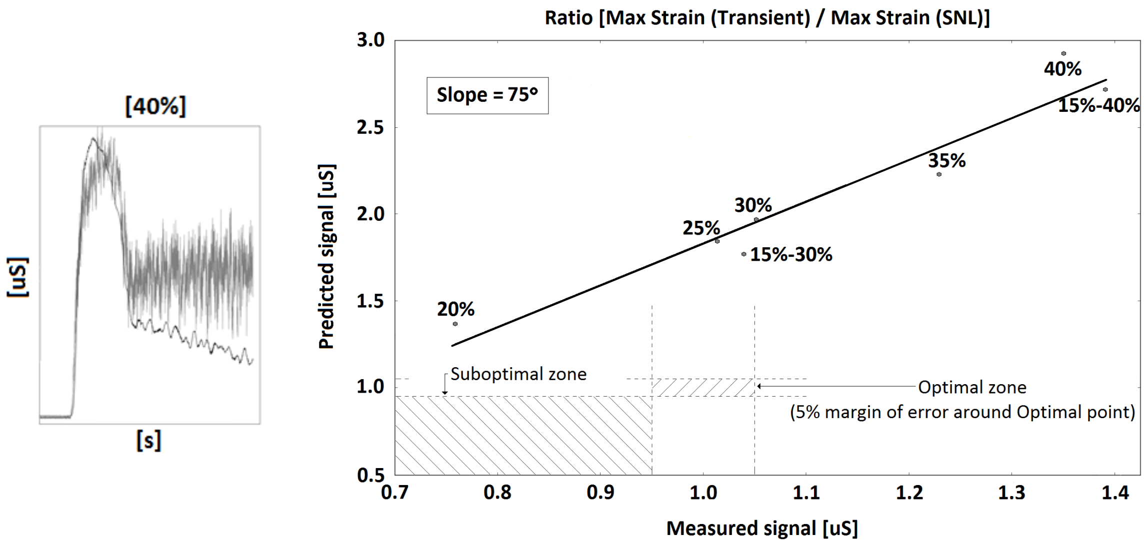

Figure 9. Propeller turbine low quality models' optimization test results.

3.2. Case study #2: Francis turbine

The application of this methodology is not limited to propeller turbines and produces results just as satisfactory on Francis turbines. For ARMAX models with polynomials of order two (2), Figure 10 presents a comparison of the measured and the predicted signals for high quality models for the 30% and the 20% start-ups.

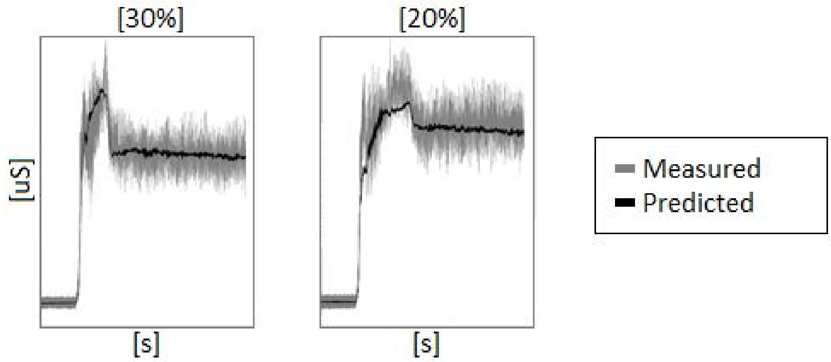

Figure 10. The Francis turbine's measured and predicted signals.

4. Discussion

At this point, we can say that using autoregressive polynomial models to predict strain on blades can be an alternative to minimize the number of direct measurements needed. Nevertheless, it is difficult to select autoregressive polynomial models parameters depending on the consistency and the accuracy of the predicted signal. A categorization needs to be done among the order of polynomials according to the wicket gates opening pattern. Table 1 presents the models' RMS error for the seven (7) start-ups and orders of polynomials from one (1) to ten (10).

Table 1. ARMAX model RMS error as a function of the start-up and the order of polynomials for 1^{st} validation.

Wicket gate opening

Order of Polynomials	MODE A					MODE B	
	[20%]	[25%]	[30%]	[35%]	[40%]	[15%-30%]	[15%-40%]
[1]	42.2	47.7	54.7	57.8	69.4	44.4	54.8
[2]	**23.4**	**23.3**	**23.1**	**25.1**	**29.6**	**21.5**	**19.4**
[3]	38.2	107.6	136.9	357.8	**27.2**	**21.4**	74.1
[4]	37.1	40.3	166.3	179.8	**27.3**	**21.4**	163.9
[5]	**27.5**	134.4	**23.1**	388.9	38.4	106.3	244.6
[6]	57.7	**21.3**	**22.9**	**25.1**	**27.3**	131.7	**19.3**
[7]	**21.7**	**22.2**	136.2	274.9	**27.3**	**21.9**	407.7
[8]	126.6	**22.2**	**23.3**	**26.8**	**27.2**	128.2	**19.3**
[9]	**26.1**	**22.2**	127.6	264.7	**27.1**	147.2	**19.3**
[10]	**22.6**	121.1	131.5	**25.1**	182.3	122.8	169.6

ARMAX model with a RMS error less (<) than 30 uS
ARMAX model with a RMS error greater (>) than 30 uS

Looking at Table 1, we observe that no matter the start-up pattern, a model of order one (1) cannot be used to predict the strain. Due to the fact that the model is built to include, at each point, the previous one, in the vector of observation, it does not seem enough to extract all the information contained in the vector of observation. Another observation is that a model of order two (2) can be used to predict the signal of any start-up satisfactorily. We also observed that many models with a RMS error below 22 uS are obtained using a complex wicket gates control pattern. The 15%-30% start-up gives around 21 uS RMS error and the 15%-40% start-up gives less than 20 uS. Another observation is that the 40% opening, which was the maximum opening during the measurement campaign, gives a relatively good constancy compared to the other start-ups with a RMS error around 27 uS. Building on the last three observations, we can say that the start-ups which solicit the structure the most (40% standard opening, 15%-30% complex opening, 15%-40% complex opening) gave the best quality, or the best constancy, in model estimation.

5. Conclusions

From the results presented in this study, we have confirmed the following:

- The stresses on the shaft are significantly correlated to the stresses on the runner blades.
- An autoregressive polynomial model (ARMAX) identified using a carefully chosen start-up and with suitable order can be used as a consistent and accurate representation of the system for optimization.
- The more solicited is the structure from the wicket gate opening pattern, the more easy is to fit the model and obtain lower RMS error.
- All the models with satisfying results for the first validation give satisfying results for the second one.

More specific to the data, it is a prudent to detect and filter the spike noise due to the fact that this increases the fidelity with which we are able the fit a model to represent the system. At this stage in our study, the model identified is specific to a given runner design. As for the models' output, even though the static level of the stress is quite well predicted, the expected range for the dynamic behavior is less accurate which reduces the fidelity of the results.

Future research should investigate the use of multiple inputs and outputs to obtain more accurate models. Moreover, other models families are available like state space and distributed parameters models which could increase the conformity between the predicted signal and the measured signal.

6. References

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