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Extrapolation of dynamic load behaviour on hydroelectric turbine blades with cyclostationary modelling

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ABSTRACT

In this paper, we present the application of cyclostationary modelling for the extrapolation of short stationary load strain samples measured *in situ* on hydraulic turbine blades. Long periods of measurements allow for a wide range of fluctuations representative of long-term reality to be considered. However, sampling over short periods limits the dynamic strain fluctuations available for analysis. The purpose of the technique presented here is therefore to generate a representative signal containing proper long term characteristics and expected spectrum starting with a much shorter signal period. The final objective is to obtain a strain history that can be used to estimate long-term fatigue behaviour of hydroelectric turbine runners.

1. Introduction

Information about a component's strain history is crucial to the study of its fatigue behaviour. Using this history, simulations can be performed to estimate its long-term reliability [1]. However, obtaining this history in the specific case of hydroelectric turbines is very expensive and not always feasible, hence the need for numerical models to generate synthetic and consistent estimates. The problem studied here is related to the relatively short period over which the measurements can be obtained due to the extreme hydraulic conditions to which the measuring instruments are exposed. The data is generally collected over a period of a few seconds or minutes, which is short compared to the actual usage which is measured in terms of years. Hence, the measured history provides only a snapshot of realistic long-term behaviour.

To remedy the situation, simulation tools based on signal acquisition over a short period of time need to be put in place to generate estimated signals over a longer period. The idea is therefore to build a model with the help of a reference signal recorded over a period of t_{ref} ($\sim 10^0 - 10^1$min) and to conduct a simulation over a period of time which is more representative of reality ($t_{sim} \sim 10^7$ min). In this way, it is possible to evaluate fatigue cycles over hypothetical usage measured in days or years as shown in Fig. 1.

The resulting simulation should reasonably predict both the deterministic and the random signal components which

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0888-3270/

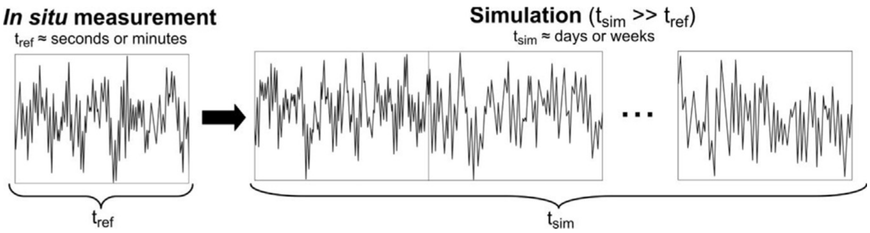

Fig. 1. Pattern extrapolation from a reference signal.

have an influence on fatigue life. Note that a stochastic (i.e. random) component can have a significant impact on stress cycles extremes in the extrapolated signal and therefore, have a significant influence on fatigue life [1,2].

This paper is organised as follows: First, a brief background overview is presented followed by an introduction to the cyclostationarity theory which is used to extrapolate the short-term signals. Next, the proposed algorithm is presented together with the two case studies used to illustrate the method. Finally, we conclude on the proposed methodology's applicability.

2. Background

The modelling of stationary and non-stationary signals is a topic that has been widely studied in scientific literature. For example, simulations of wind [3,4], sea levels [5], climate [6] and earthquakes [7] represent areas where many models have already been applied. In order to present models that are relevant to our case, Fig. 2 shows some of the approaches used in the literature. This list is grouped according to the main theories and approaches used to construct the models [4,5,7–13].

Among these models, some have the advantage of focussing solely on signal extremes which facilitates model creation. This is the case with the Kernel estimator and the theory of extreme values. However, the loss of information during modelling makes it harder to explain divergent cases. We observe that ARMA models and spectral representations, including their many variations, have been widely used in various fields. However, and this being the case with most models, parameter choice can be highly suggestive and difficult to interpret. Thus, the results obtained are not easily linked to the physical phenomena which have generated the signal.

To circumvent these difficulties, we propose a methodology derived from the theory of cyclostationarity which minimises the information loss during the model's creation while maintaining accurate temporal content (phase information) and reference signal frequency by separating periodic and random components (stochastic measurement variations).

3. Cyclostationary modelling

Cyclostationarity is a theory that has significantly contributed to the study of periodic signal behaviour [14]. In the field of mechanical systems, it has been successfully used in many applications to analyse acoustic signals or vibrations originating from rotating machinery. For example, techniques have been developed for the fault diagnosis of rotating systems [15], the separation of periodic sources [16] and the analysis of periodic and quasi-periodic phenomena [17]. One of the main contributions of cyclostationary analysis is that the periodic components extracted during the signal decomposition can be used for physical interpretation.

According to cyclostationary modelling [18], a signal $x(t)$ measured on a rotating machine contains two parts: a cyclostationary part $CS(t)$ and a residual part $R(t)$ which should be, by definition, random. The cyclostationary part is made up of the cyclostationary moments CSn for each cyclical frequency α_i. The extracted component can be used to study the signal's periodic and quasi-periodic behaviour. Eq. (1)

$$x(t)=\sum_{n}\sum_{i}\left[CSn(t)\right]_{\alpha_i}+R(t) \tag{1}$$

is the generic mathematical representation where n is the cyclostationary order and α_i is the cycle frequency of interest.

Time domain	Rainflow and Markov domain	Frequency domain	Time-Frequency domain	Others
- ARMA [8]	- Kernel estimator [9]	- Spectral representation [11]	**-Cyclostationary modelling**	- Neurones networks [13]
- Extreme value theory (with timeseries) [2]	- Extreme value theory (with up-crossing) [2]	- Random gaussian process transform [12]	- Stationary Wavelet Decomposition (SWD) [4]	
	-Markow chains of Turning Points [10]	- Laplace driven moving-average [5]	- Empirical mode decomposition (EMD) [7]	

Fig. 2. Signal simulation model categories.

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