International Journal of Mechanical Sciences ∎ (∎∎∎∎) ∎∎∎–∎∎∎

Contents lists available at ScienceDirect

International Journal of Mechanical Sciences

journal homepage: www.elsevier.com/locate/ijmecsci

Fatigue assessment of non-stationary random vibrations by using decomposition in Gaussian portions

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ARTICLE INFO

Article history:
Received 16 January 2016
Received in revised form
13 May 2016
Accepted 31 May 2016

Keywords:
Non-stationary random vibrations
Power spectral density
Fatigue strength
Shaker testing
Fatigue damage spectrum
Structural dynamics

ABSTRACT

This paper presents a method for determining the decomposition of a non-stationary, random vibration with a non-Gaussian distribution into several stationary portions with Gaussian distributions. The fatigue load of the initial non-stationary signal, and the summarized fatigue loads of the derived Gaussian portions are identical in both a direct comparison and in a comparison of the vibration responses caused by these signals on an arbitrary linear dynamical system. As stationary Gaussian signals can be described by power spectral densities (PSD), the analysis of the dynamical response with its corresponding fatigue load can be switched from time domain to frequency domain with an enormous performance gain regarding numerical computations. Especially, a combination of a realistic non-stationary signal with a large duration (from measurements), together with huge structural dynamics models is hard to analyze numerically in time domain because of enormous computation times. The proposed PSD-based method enables a very efficient numerical analysis in frequency domain. For the estimation of load spectra in frequency domain, well established PSD-based methods can be used, corresponding to Rainflow counting in time domain. This paper gives a detailed introduction to the procedure outlined with associated equations necessary for a numerical solution. The correct modeling of the fatigue damage load is proven by applying the fatigue damage spectrum concept.

1. Introduction

Usually fatigue strength calculations are done in time domain, because well established time domain methods are available for the simulation of stress loads in dynamical systems (Finite Element Method, Multibody Systems) as well as for the derivation of load spectra (Rainflow Counting [1]). However, this approach is not suitable for all possible applications of fatigue strength calculations. Especially in the area of random vibrations, the time domain approach has major limitations due to limited time intervals. Consequently, numerically analyzed time samples have to be long enough to sufficiently approximate the statistics. For measured non-stationary random excitations, a correct determination of a sufficient minimum length is often hard to make. In combination with computation time limitations, the problem gets worse because Finite Element simulations are not capable of processing long excitation time samples in combination with huge vibrating structures. For this situation, frequency domain methods are available (see e.g. [2–6]) that are capable of modeling random vibrations adequately and also offering much faster simulations. Therefore [7] gives a detailed introduction, with concrete practical examples. Reference [8] gives an overview of the available methods for load spectra estimation directly from PSDs. Considerable research has been done to determine reliable techniques (see e.g. [9–12]). The methods of Dirlik and Tovo-Benasciutti seems to be the most reliable for general PSDs. The drawback of this set of PSD based methods is their limitation to linear vibration models, and to stationary time signals with a Gaussian probability distribution. These methods may also be applied to problems with a slight deviation from these conditions, as long as small variations in the calculated fatigue strength loads can be accepted. For major deviations from these assumptions, the derived fatigue strength results only serve as a rough approximation because of the enormous deviations (e.g. see [13,14]).

A similar problem with random vibrations occurs in the area of shaker testing. Comparable to theoretical methods shaker tests are used for an experimental analysis of fatigue strength. Typical shaker controllers are either able to perform a time replication of measured random excitations (corresponding to the aforementioned time domain analysis), or they are able to generate random signals based on a PSD of measured random excitations under the assumption of stationarity and a Gaussian distribution (corresponding to the aforementioned frequency domain analysis).

Real engineering problems are often related to random vibrations with non-stationary characteristics. Considerable research

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http://dx.doi.org/10.1016/j.ijmecsci.2016.05.024
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work has already been done, and solutions are available for a variety of specific problems. An analysis of the restrictions of frequency domain methods for load spectrum estimation is given by [15–17]. Factors to correct deviations of estimated load spectra for non-Gaussian distributions have been proposed by [18–20]; [13,21–24] suggested methods to express non-stationary random vibrations by a series of stationary Gaussian-distributed signals based on different methods or algorithms; switching loads were analyzed by [25]. References [26,27] proposed methods to consider the impact of non-stationarity by manipulating the shape of a PSD so that it represents the fatigue load of a non-stationary signal. A variety of approximation methods (Shock resonance spectra – SRS, Extreme resonance spectra – ERS, Vibration resonance spectra – VRS, Fatigue damage spectra – FDS) was used by [28] to develop a test specification for the approximation of non-stationary random accelerations. Also, in the area of experimental shaker testing, a variety of methods were published (e.g. [29,30]) that take a deviation from a Gaussian distribution into account; the corresponding fatigue damage results were analyzed by [31,32].

To overcome existing limitations for non-stationary random excitation signals this paper presents a method to obtain more reliable results; in the context of frequency domain analysis, the limitation to linear vibration models still exists. The material is based on the assumption that a non-stationary random vibration may consist of a composition of stationary portions with Gaussian distributions. Fig. 1 exemplifies these conditions based on an assumed measured time history with switching loads $u_M(t)$, whose stationary portions are illustrated with blue, yellow and green (a real measured signal is shown in Fig. 3(a)). In total, the non-stationary signal $u_M(t)$ in Fig. 1(a) has a non-Gaussian distribution; if the division into stationary portions and the sorted reassembly of these portions is done correctly, the resulting signals $u_{G,1}(t)$, $u_{G,2}(t)$ and $u_{G,3}(t)$ in Fig. 1(c) turn out to be stationary and have a Gaussian distribution. Consequently, these three signals may also be described by their corresponding PSDs $G_1(f)$, $G_2(f)$, $G_3(f)$ with the corresponding time intervals $T_{G,1}$, $T_{G,2}$, $T_{G,3}$ without any loss of information.

This concept was tested in [13] for measured railroad track excitations by using an algorithm for dividing the non-stationary time signal into predefined classes. Fig. 2 illustrates this procedure with a plot [13] showing a classification in four categories. The results from [13] proved the potential of this approach, even if the resulting classified signals did not exhibit exact Gaussian distributions. The results show that real non-stationary signals do not switch from one signal level to an other level, they often show a continuous change in level. Consequently, the separation of a signal at a certain point in time, at its transition from one class to another, is hard to detect. In addition, many classified signal portions had a very small duration. Therefore the cutting of the signal seems to add a certain error to the actual signal.

A similar procedure based on the same concept of non-stationarity is presented by [21,22,24]. The authors used the non-Gaussian distribution of a measured non-stationary random signal, and propose an approximation of this distribution by a composition of Gaussian distributions. As the corresponding stationary signals are unknown, it is assumed that the underlying PSDs are similar to the PSD of the measured non-stationary signal. Only the respective standard deviations σ (corresponding to the area of the PSD) are different. This approach was evaluated for the railway track signals analyzed in the current paper, but it did not produce satisfactory results. The reason seems to be the assumption of similar PSDs for the different Gaussian distributed signals; the results from [13] show significant differences between these PSDs.

To overcome this limitation [33] proposes a method that is still based on an approximation of the non-Gaussian probability distribution of the non-stationary signal by a composition of Gaussian distributions. In addition it takes into account, that the deviation from a Gaussian distribution is not just a single parameter representing the whole frequency band; it considers that this deviation depends on the frequency of the signal. Using this approach different PSDs for the different stationary signal portions can be derived based on a thorough mathematical model. The drawbacks of the signal cutting procedure [13] can be avoided and a feasible approximation for non-stationary signals with a continuously variable level is possible. This concept will be reviewed in the current paper in detail in Section 3, and applied to a problem from railway engineering in Section 4. Section 5 presents a verification of the results based on the concept of Fatigue Damage Spectrum. An introduction to the analysis of a measured random vibration signal is presented in the following section.

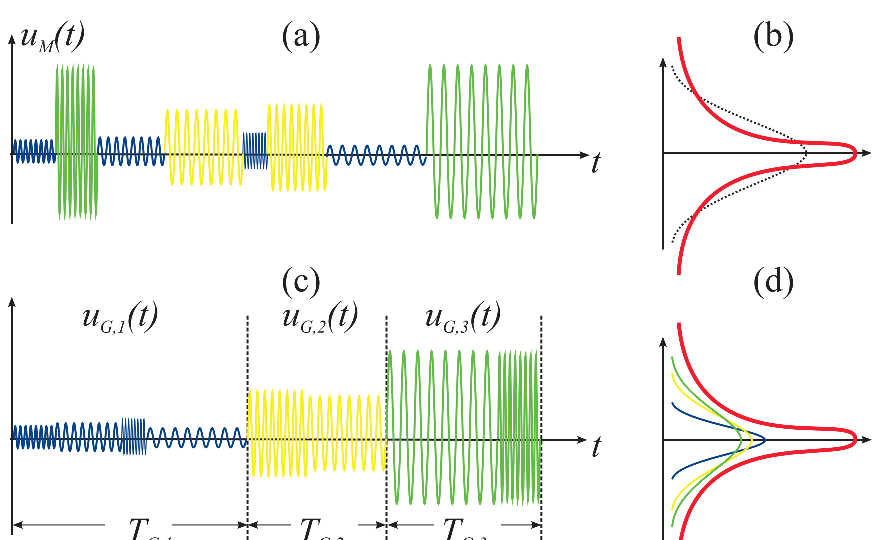

Fig. 1. Decomposition of exemplified non-stationary signal $u_M(t)$ into three stationary signals $u_{G,1}(t)$, $u_{G,2}(t)$ and $u_{G,3}(t)$. (a) exemplified measurement of a non-stationary signal $u_M(t)$; (b) probability distribution of signal $u_M(t)$ (red line) and corresponding Gaussian distribution (dashed line); (c) decomposed and rearranged stationary portions $u_{G,1}(t)$, $u_{G,2}(t)$ and $u_{G,3}(t)$ derived from $u_M(t)$; (d) corresponding Gaussian distributions of $u_{G,1}(t)$, $u_{G,2}(t)$ and $u_{G,3}(t)$ and total distribution (red line). (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

Please cite this article as: Wolfsteiner P. Fatigue assessment of non-stationary random vibrations by using decomposition in Gaussian portions. Int. J. Mech. Sci. (2016), http://dx.doi.org/10.1016/j.ijmecsci.2016.05.024