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Operational Monitoring of Mineral Crushing Machinery

Modeling of diagnostic vibration signals in mineral processing machines.

Modelowanie diagnostycznych sygnałów drganiowych w maszynach do przeróbki kopalin.

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XLVII Ogólnopolskie Sympozjum DIAGNOSTYKA MASZYN

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Agenda

- Introduction
- Methodology
  - Identification and removal of the main sine component
  - The segments selection
  - The estimation of the autoregressive model coefficients
  - The signal construction
- Results
- Summary

Introduction

Diagnostics of industrial machinery is a topic related to the need for damage detection, but it also allows to understand the process itself.

We present the model of signal describing the vibrations of the sieving screen used in the mining industry for the classification of ore pieces by size in the ore stream.

The analysis of real vibration signals measured on the screen allowed to identify and parameterize the key signal components, which carries valuable information for the following stages of diagnostic process of that machine.

In the proposed model we take into consideration deterministic components related to shaft rotation, stochastic Gaussian component related to the external noise, stochastic α-stable component as a model of excitations caused by falling rocks pieces, and identified machine response for unit excitation

Identification and removal of the main sine component

1

- Calculating the Fourier spectrum of the signal

2

- Finding the amplitude and frequency of the strongest component on the real (amplitude) part of the spectrum, and the phase value at the identified frequency on the imaginary (phase) part

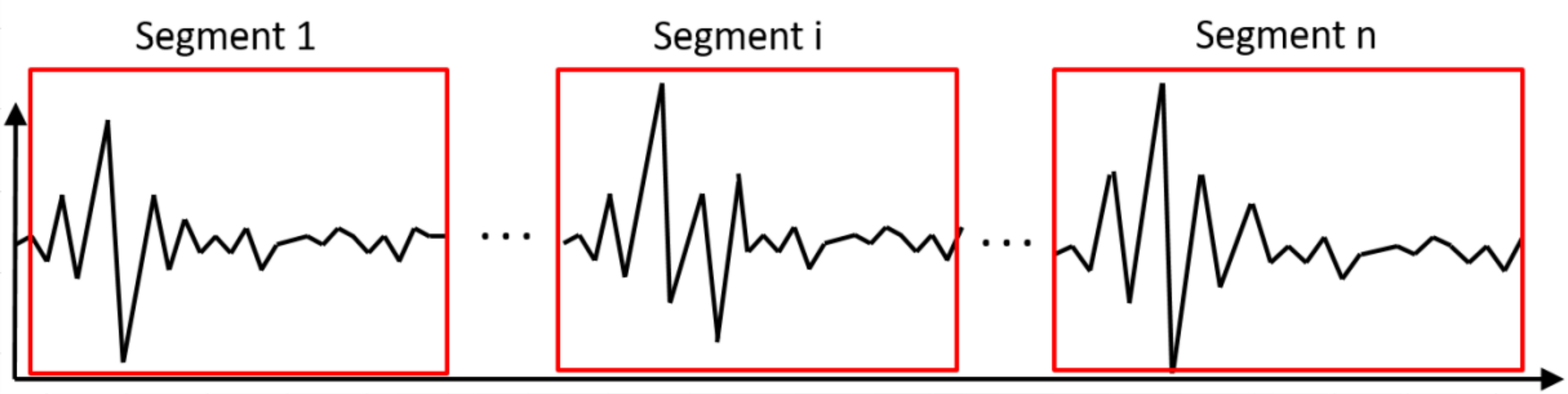
3

- Generating the identified component and subtracting it from the signal

The segments selection

From the detrended signal a transfer function of the machine has to be estimated. For the purpose of this operation we assume that the impact of a piece of ore falling into the machine is a Dirac-like unitary excitation d(t), and the impulse X(t) registered by the sensor is a machine responding to the excitation via its transfer function H according to the model:

$$X(t) = (d * H)(t)$$



The estimation of the autoregressive model coefficients

To obtain the response of the machine, we use the autoregressive (AR) model with order p. The AR(p) model is defined as follows

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t$$

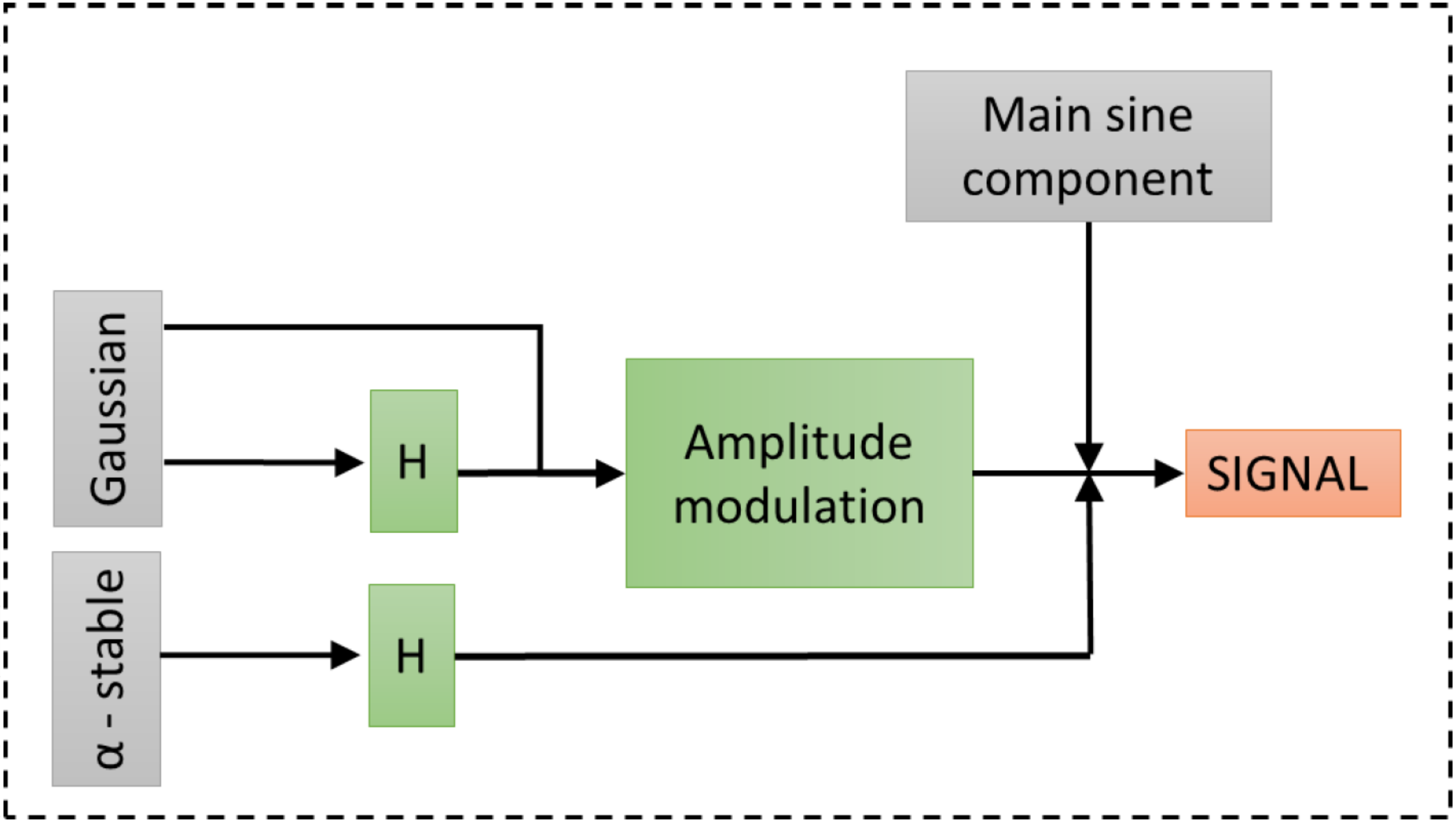
where φ_1,..., φ_p are the model coefficients, c is the constant and ε_t is the white Gaussian noise with the variance σ^2.

Calculated parameters of the AR model are used to construct the transfer function of the machines signal path. The transfer function H is represented in the following form:

$$H(t) = \frac{1}{1 - \overline{\varphi}_1 t^{-1} - \ldots - \overline{\varphi}_p t^{-p}},$$

where $[1, -\bar{\varphi}_1, \ldots, -\bar{\varphi}_p]$ is the averaged vector of coefficients corresponding to the most numerous class.

The signal construction



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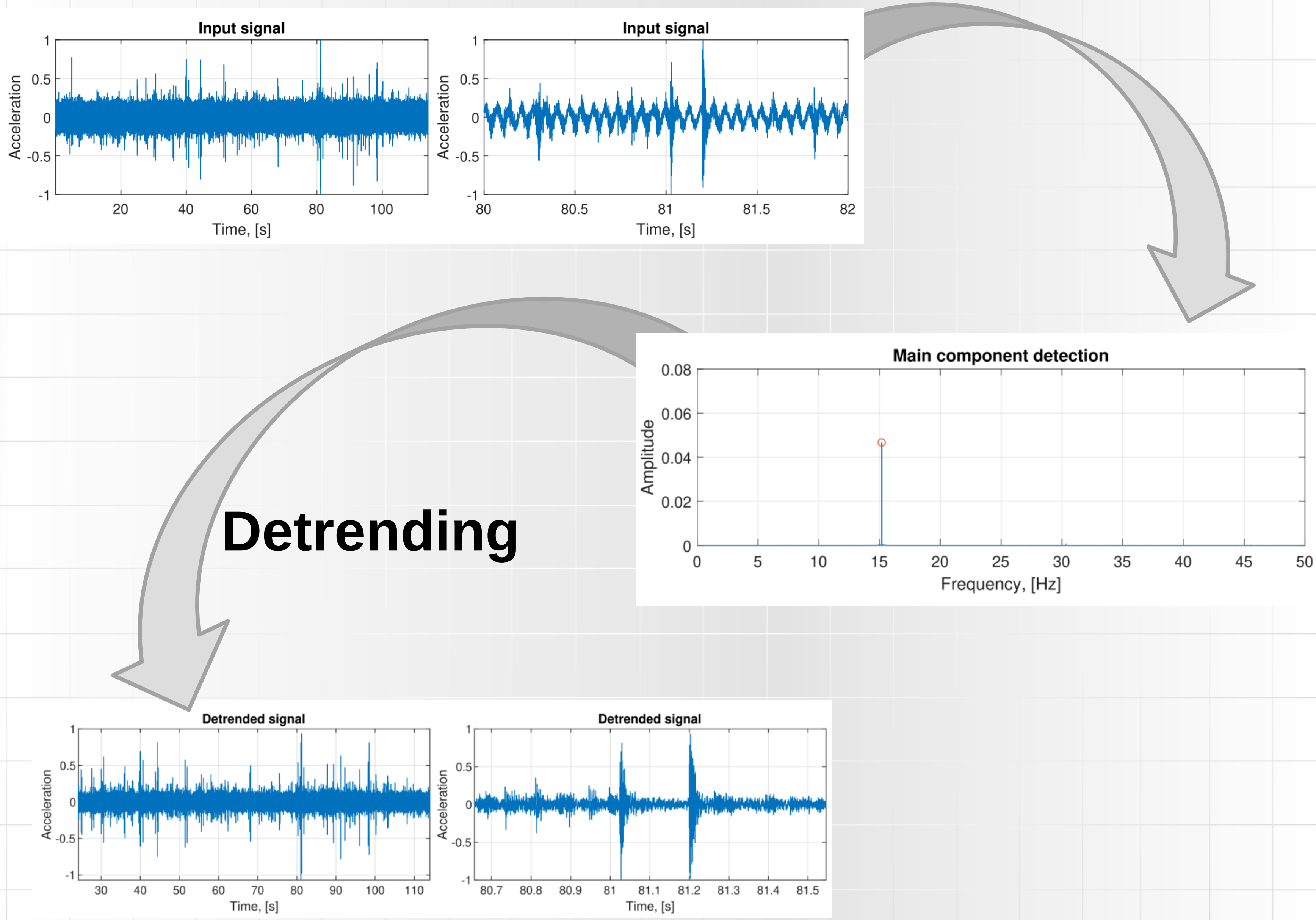
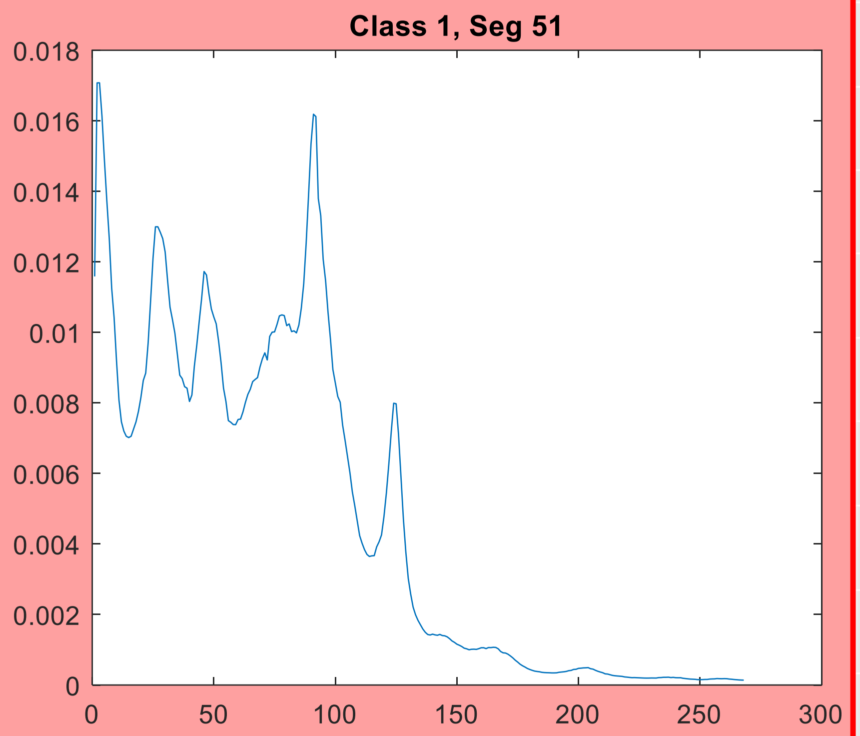
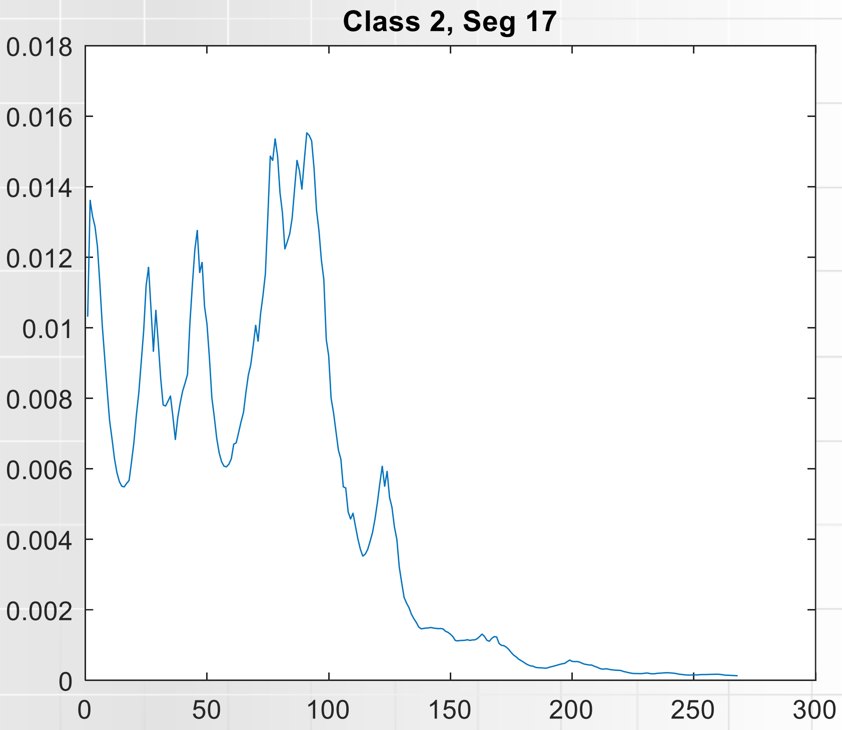
Identification and removal of the main sine component

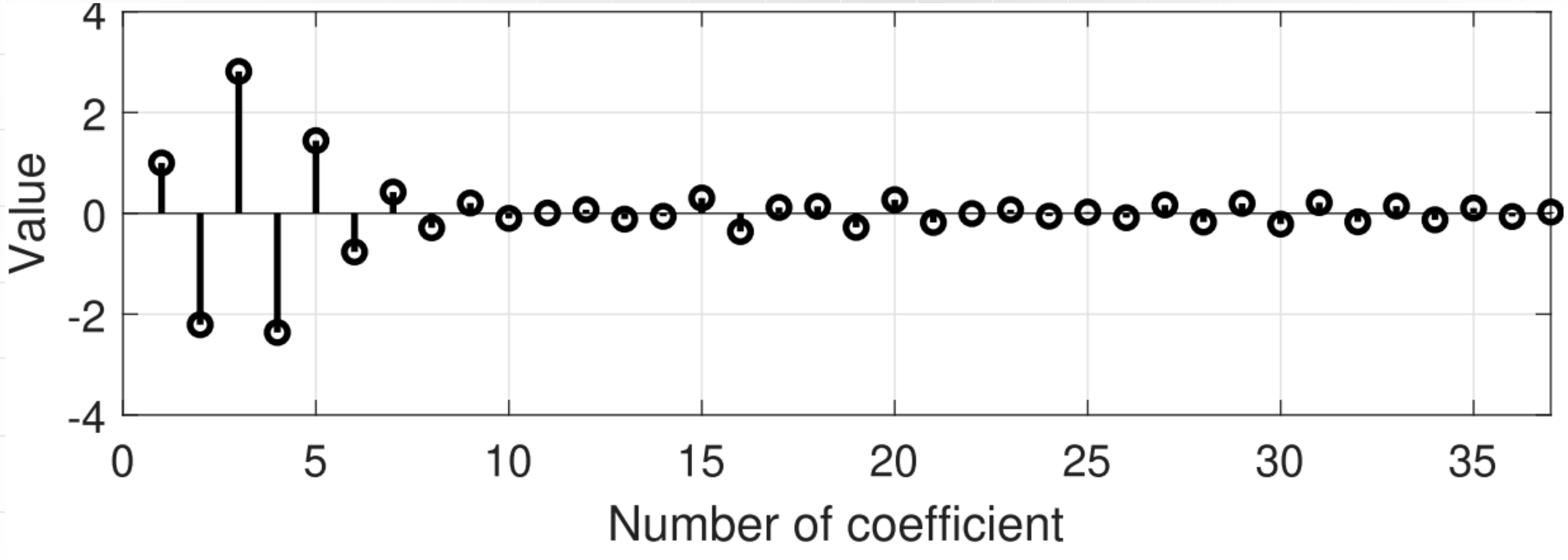


Classification

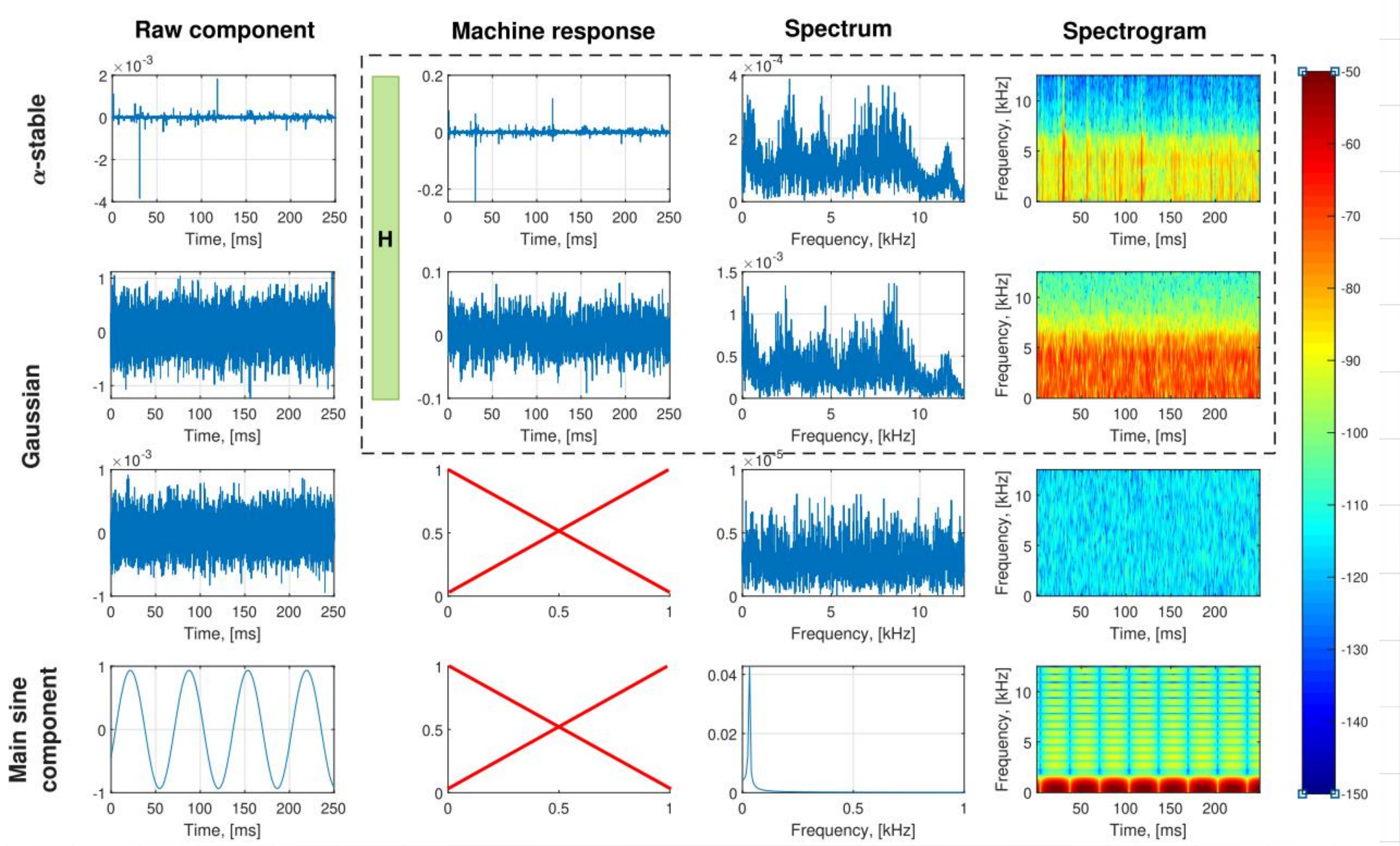




Mean of the AR model coefficients for the most numerous class



The components of the model



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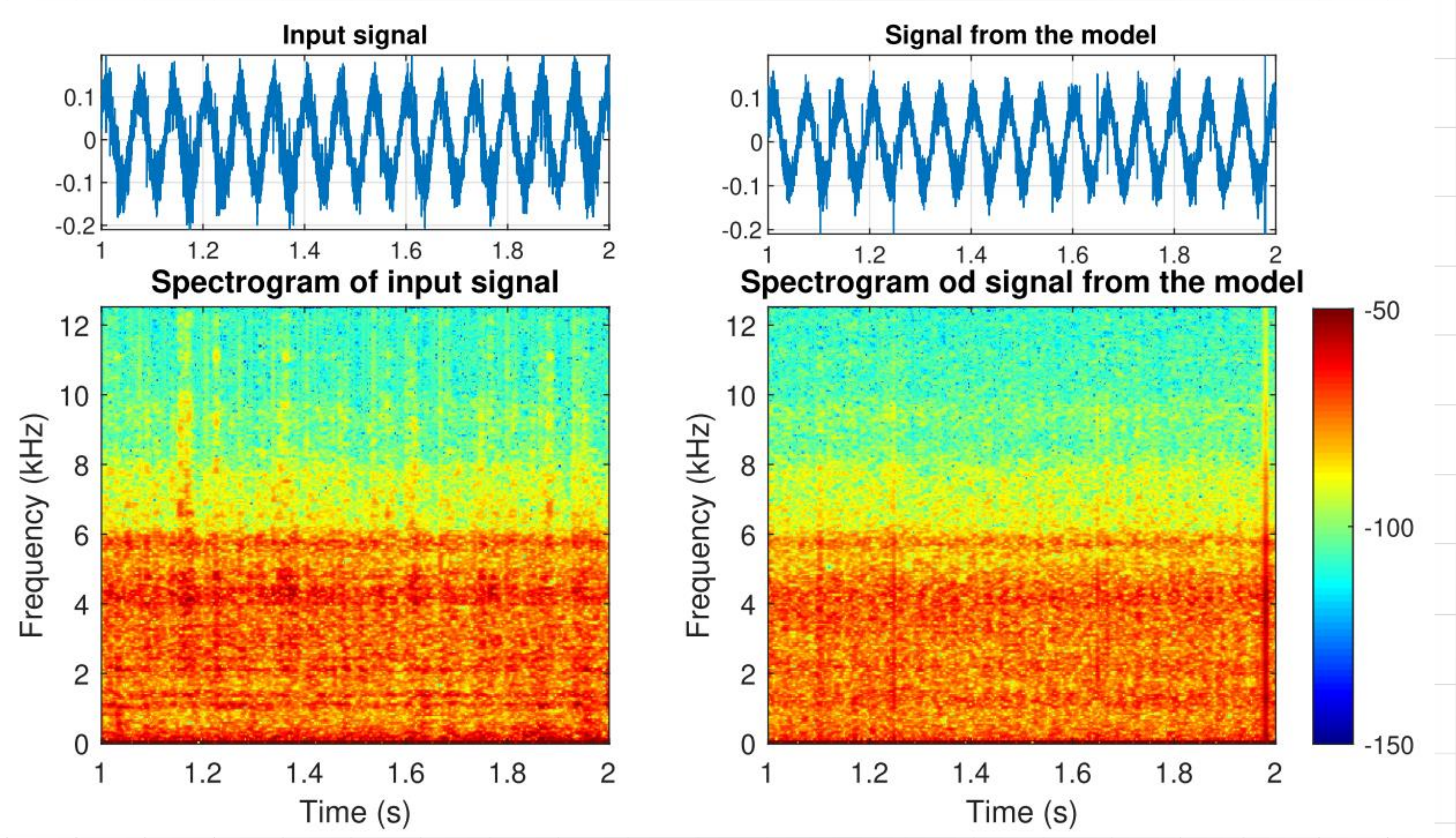
The comparison of real and modeled signal



Summary

The initial approach to constructing the signal model of the industrial vibrating sieving screen suspension vibrations has been presented.

The model is constructed based on the analysis and decomposition of the real signal measured on the actual machine operating in the mining industry.

This work is the first step to be able to understand the process of motion and vibrations characteristic to this type of machines.

It can allow to introduce model-based diagnostics of the screen elements.

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This activity has received funding from the European Institute of Innovation and Technology (EIT), a body of the European Union, under the Horizon 2020, the EU Framework Programme for Research and Innovation