A time series autoencoder for load identification via dimensionality reduction of sensor recordings

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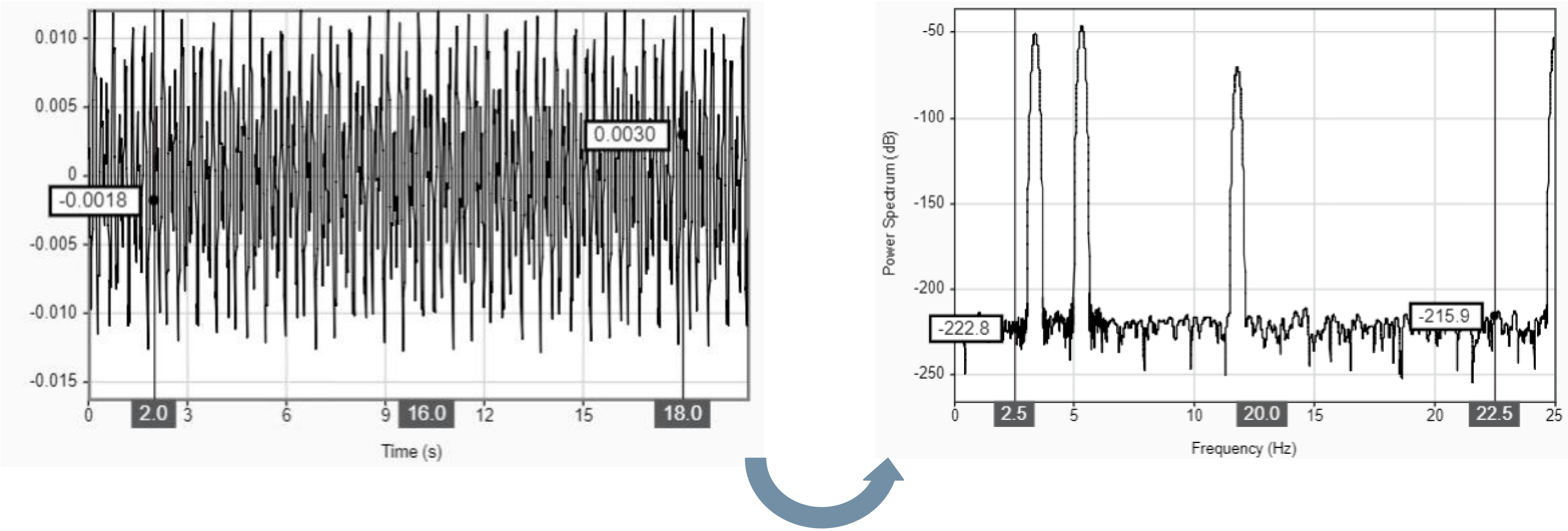
Contents

Bridge sensor acquisition system
(*from "Structural Health Monitoring" C.R. Farrar, K. Worden*)

The dimension of data acquired by **sensor systems** in civil engineering makes extremely difficult their use in raw forms.



Sensor data are usually shaped as **Multivariate Time Series** (MTS).

To manage sensor data, **synthetic features**, like peak spectral frequencies, are extracted.

AutoEncoders (AE) are special types of Neural Networks (NN) able to obtain a reduced data representation.

Advantages related to the use of AE for sensor data dimensionality reduction:

- **no feature engineering** is necessary;
- the obtained data representation can be used for **different tasks**;
- they provide the reduced representation that **best allows to reconstruct data a posteriori**.

From the reduced representation, it is possible to accomplish **regression tasks**.

In this work, we tackle the issue of **load identification** in civil structures.

$$\mathbf{h}_m^i = 0.5 m \alpha^i \sin\left(2\pi \phi^i t\right)$$

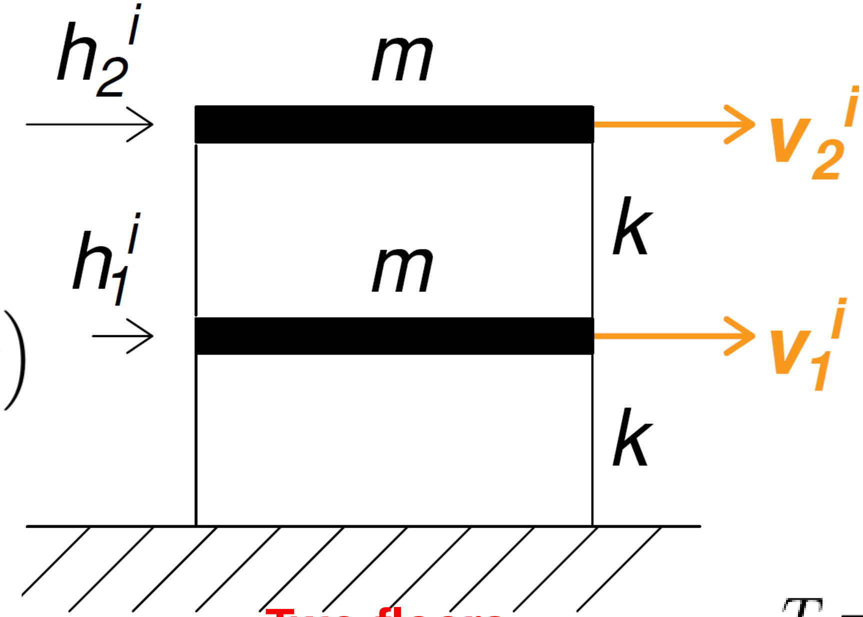
for any i we sample α^i and ϕ^i from

$\mathscr{U}\,(0.075, 1.025)\ \mathrm{kN/m}$

$\mathscr{U}\,(25, 325)\,\mathrm{Hz}$

where $\mathscr{U}$ indicates a uniform continuous probability density fuction.

$$\boldsymbol{\eta}^i = \left[\alpha^i, \phi^i\right]$$



Two-floors shear building model (undamped).

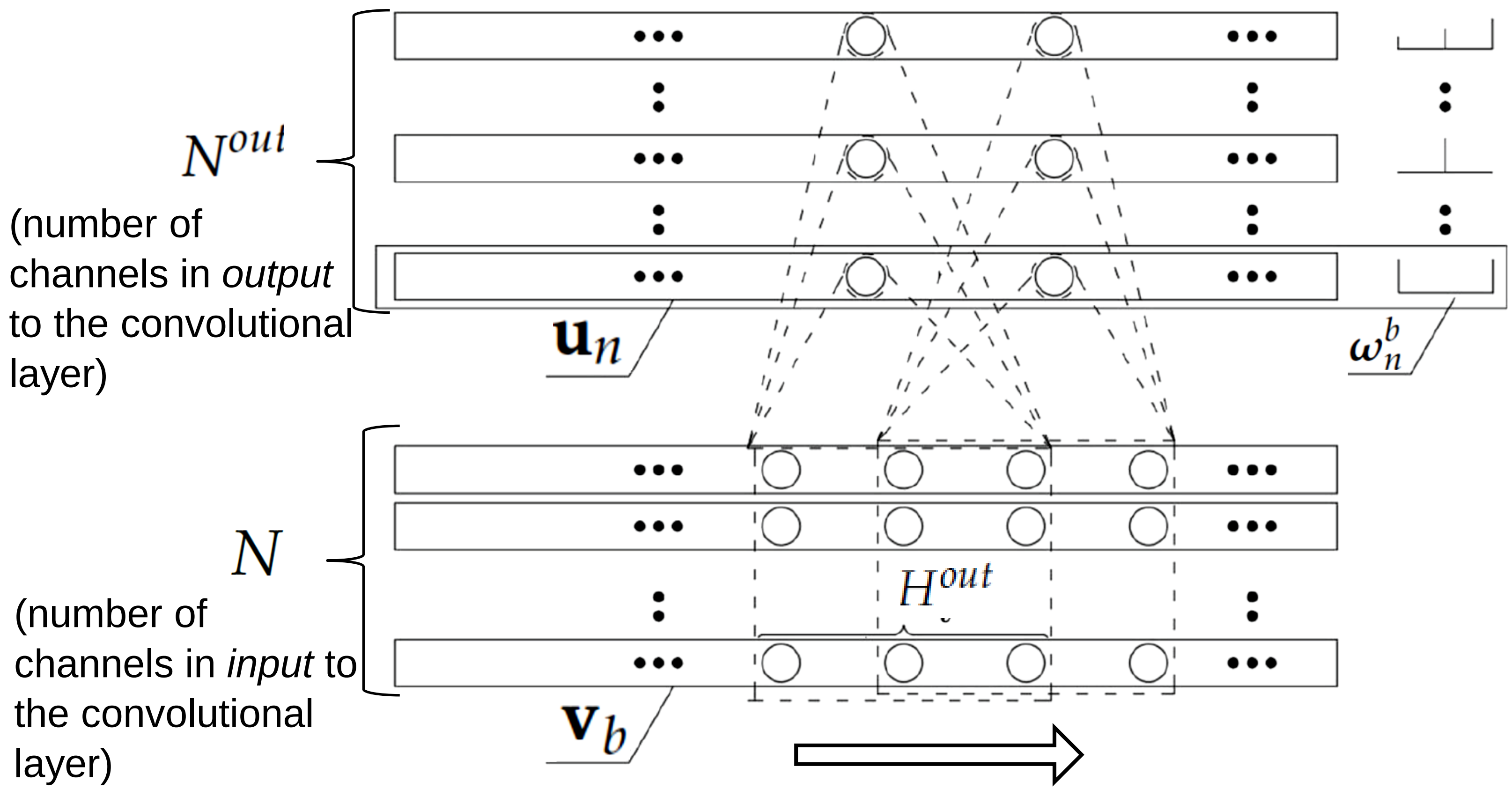
$$\mathbf{V}^i = \left[\mathbf{v}_1^i, \mathbf{v}_2^i\right]$$

where $\mathbf{v}_m^i$ collects the displacement recordings of the m-th floor of the i-th MTS.

$$\left.\begin{aligned} T &= 5\ \mathrm{s} \\ \Delta t &= 0.02\ \mathrm{s} \end{aligned}\right\} L = 250$$

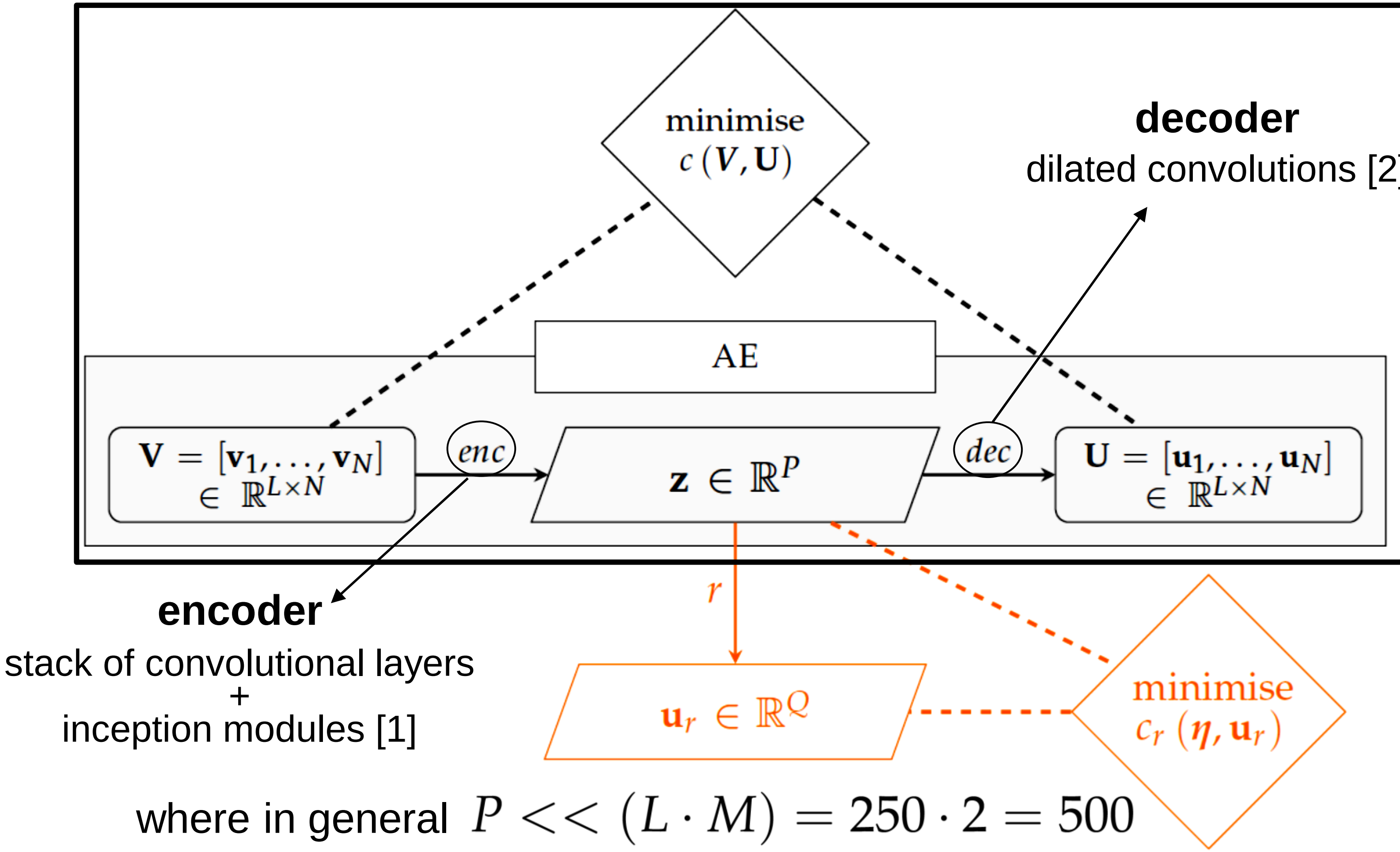
is it possible to identify the loading conditions by operating the regression of $\boldsymbol{\eta}^i$ on $\mathbf{V}^i$?

*** from now on we omit the superscript**



$$\mathbf{u}_n\left(\mathbf{V},\boldsymbol{\Omega}_n\right)=\sum_{b=1}^{N}\boldsymbol{\omega}_n^b*\mathbf{v}_b,\quad n=1,\dots,N^{out}$$

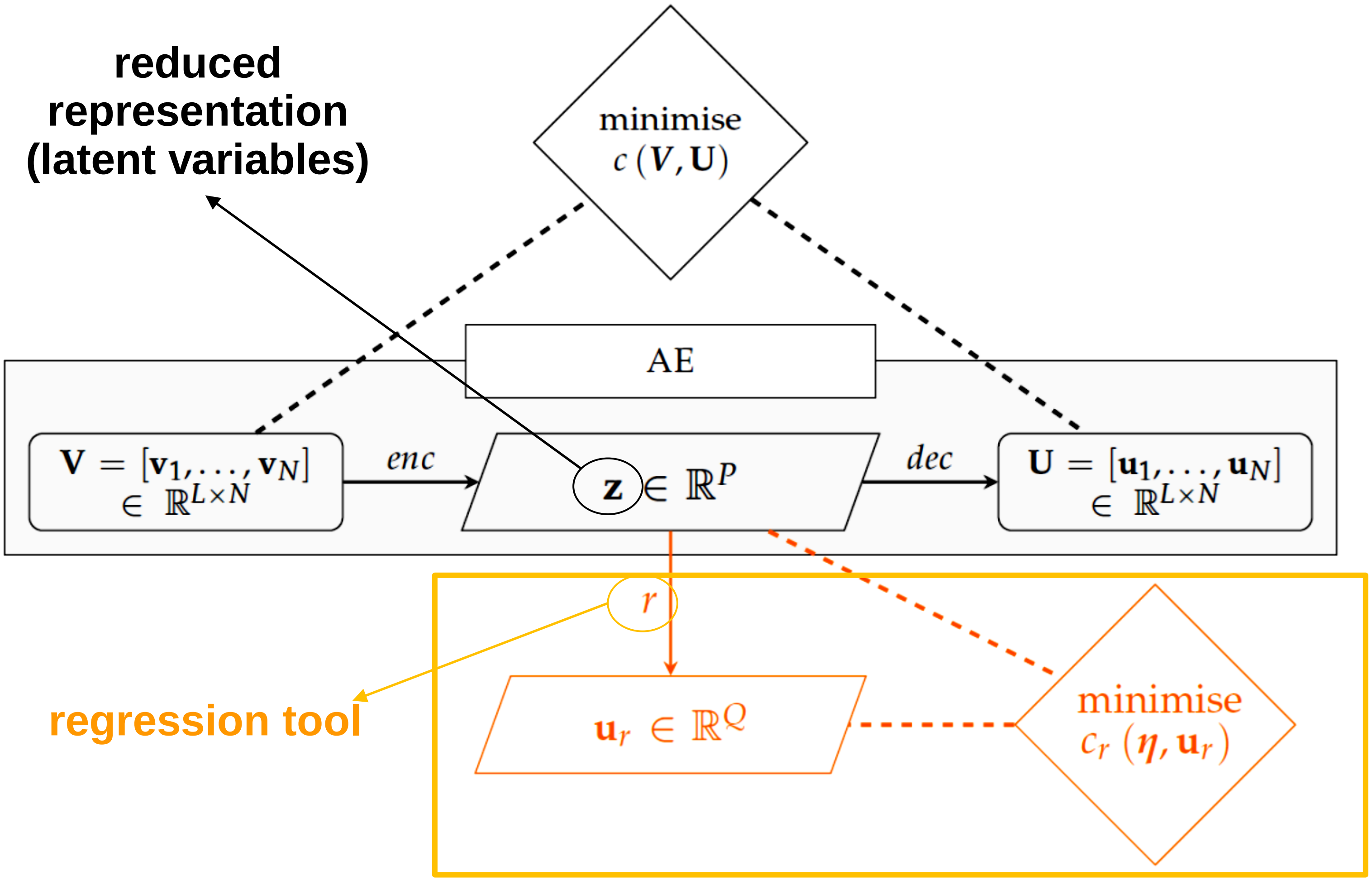
Time Series Autoencoder (dimensionality reduction)



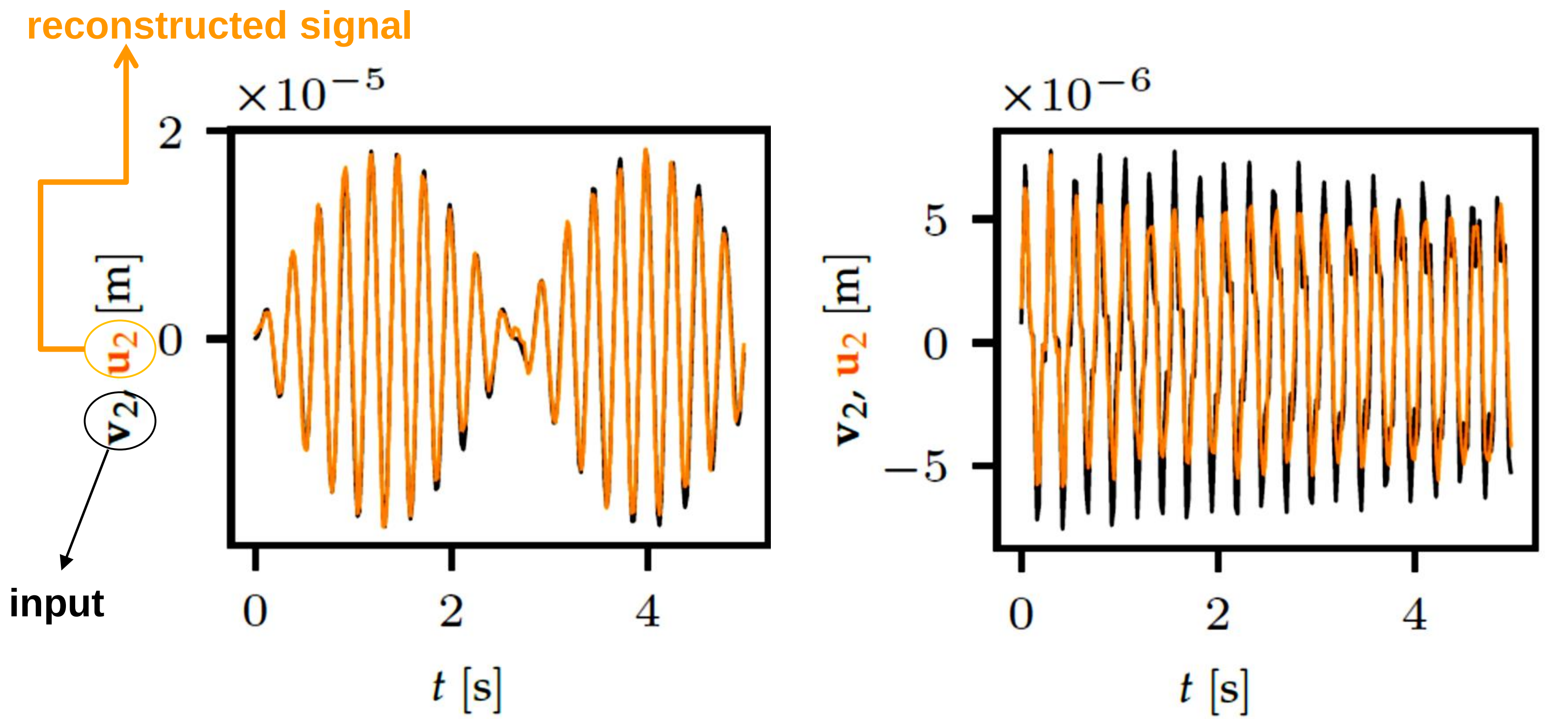
where in general $P << (L \cdot M) = 250 \cdot 2 = 500$

[1] C. Szegedy et al. *Going deeper with convolutions*, in The IEEE Conference on Computer Vision and Pattern Recognition CVPR, 26 June - 1 July, (Boston, MA), pp. 1-9, **2015**.

[2] A. van den Oord et al. *Wavenet: A generative model for raw audio,* **2016**. arXiv, 1609.03499.



reduced representation (latent variables)
minimise $c(\mathbf{V}, \mathbf{U})$
AE
$\mathbf{V} = [\mathbf{v}_1, \dots, \mathbf{v}_N] \in \mathbb{R}^{L \times N}$
enc
$\mathbf{z} \in \mathbb{R}^P$
dec
$\mathbf{U} = [\mathbf{u}_1, \dots, \mathbf{u}_N] \in \mathbb{R}^{L \times N}$
r
regression tool
$\mathbf{u}_r \in \mathbb{R}^Q$
minimise $c_r(\boldsymbol{\eta}, \mathbf{u}_r)$



(a) $\alpha^i = 702$ N, $\phi^i = 3.56$ Hz **(b)** $\alpha^i = 4341$ N, $\phi^i = 9.45$ Hz

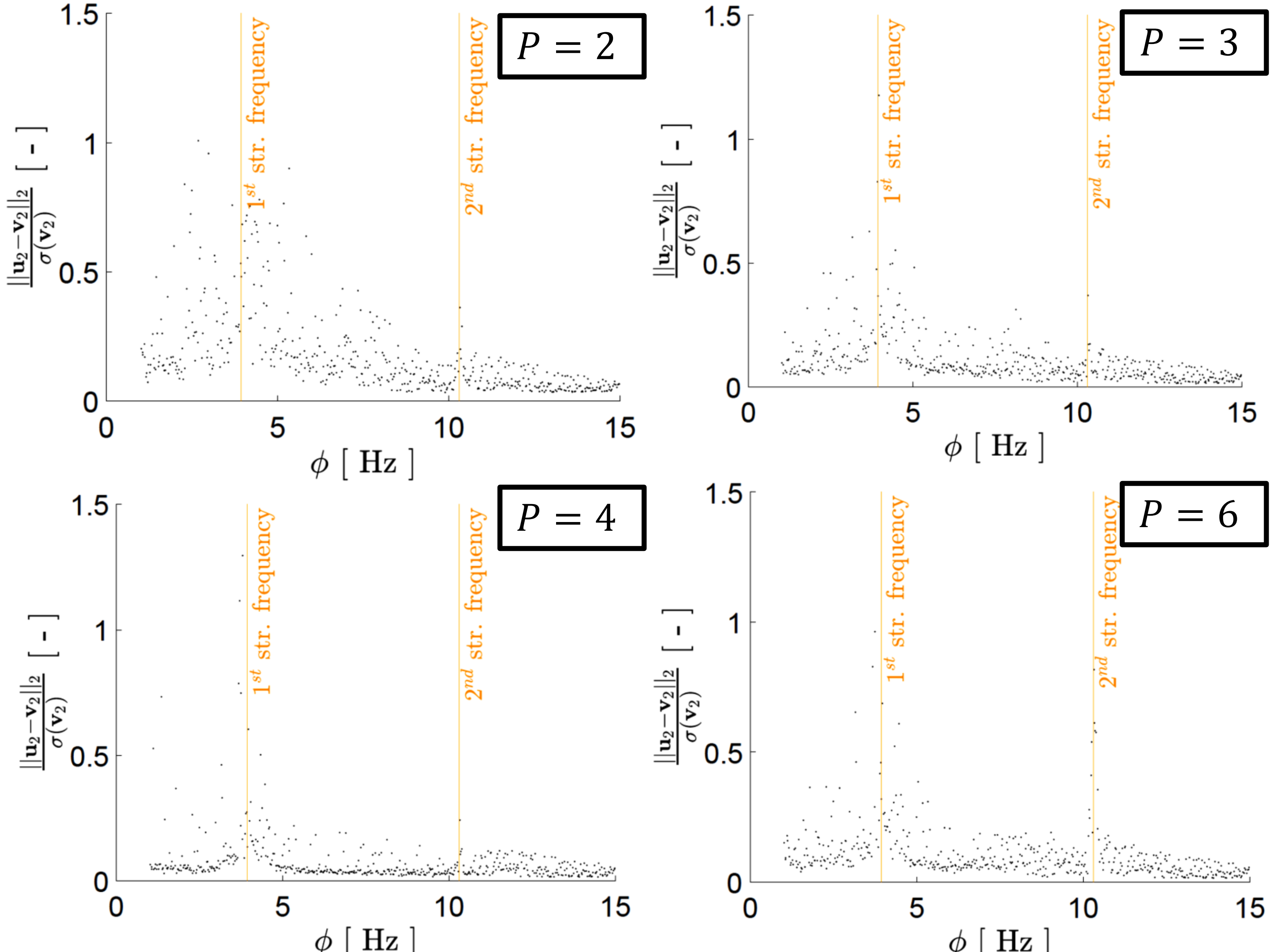
AE signal reconstruction when ϕ^i is close to the structural frequencies $\mathbf{f}^{str} = [3.93, 10.3]$ Hz

Numerical results: effect of P / 1

reconstruction error computed for 512 $\mathbf{V}^i$ unseen during the training of the AE according to the **standardised L^2 error norm.**

↓

highest error for ϕ^i **close to the structural frequencies.**

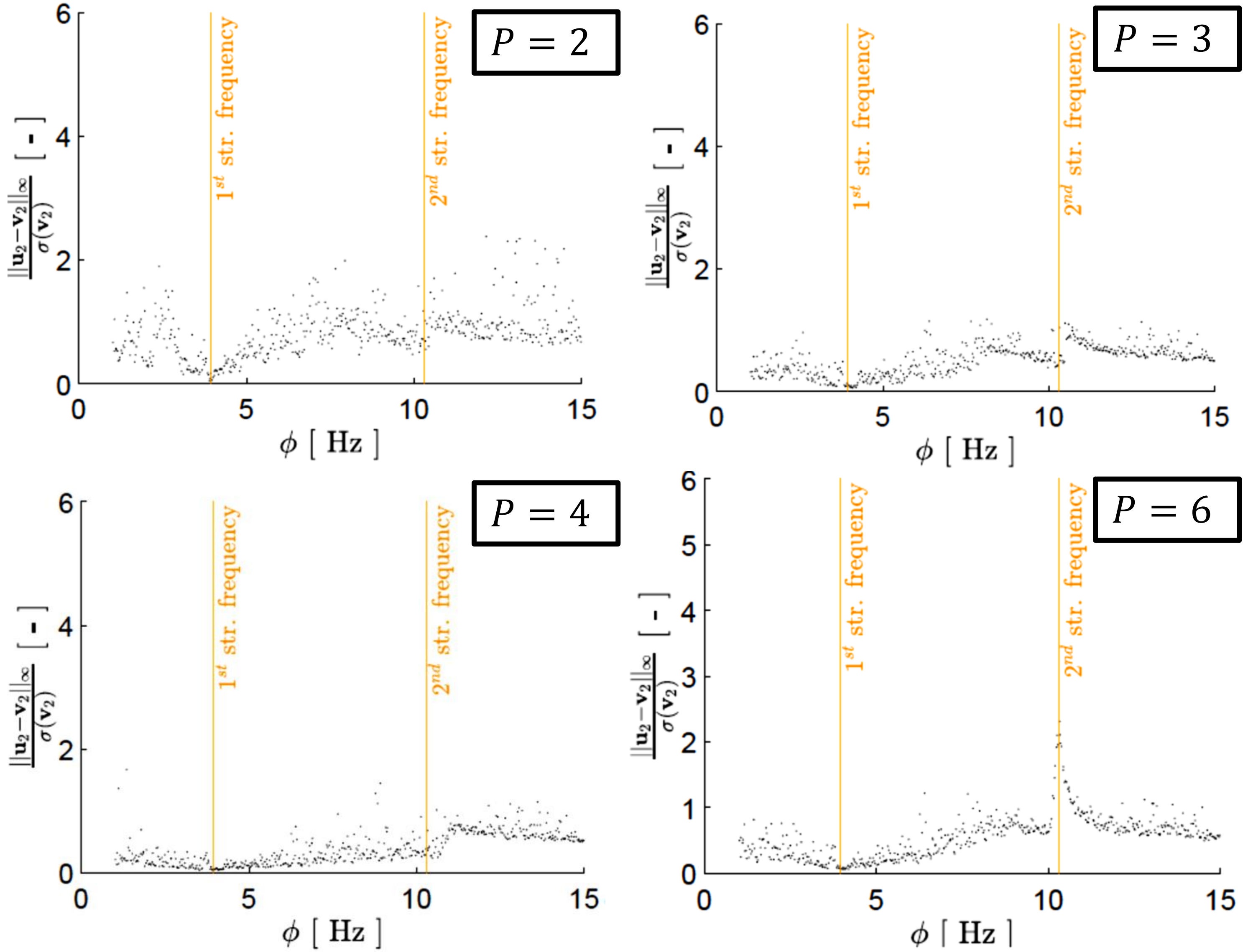


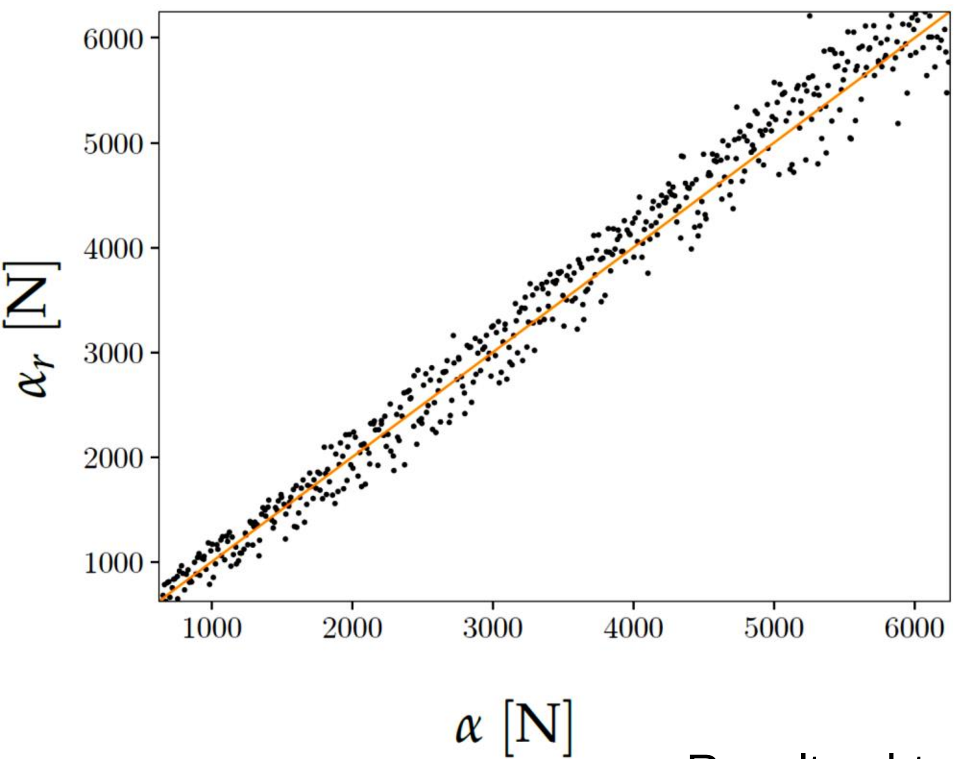
Numerical results: **effect of P / 2**

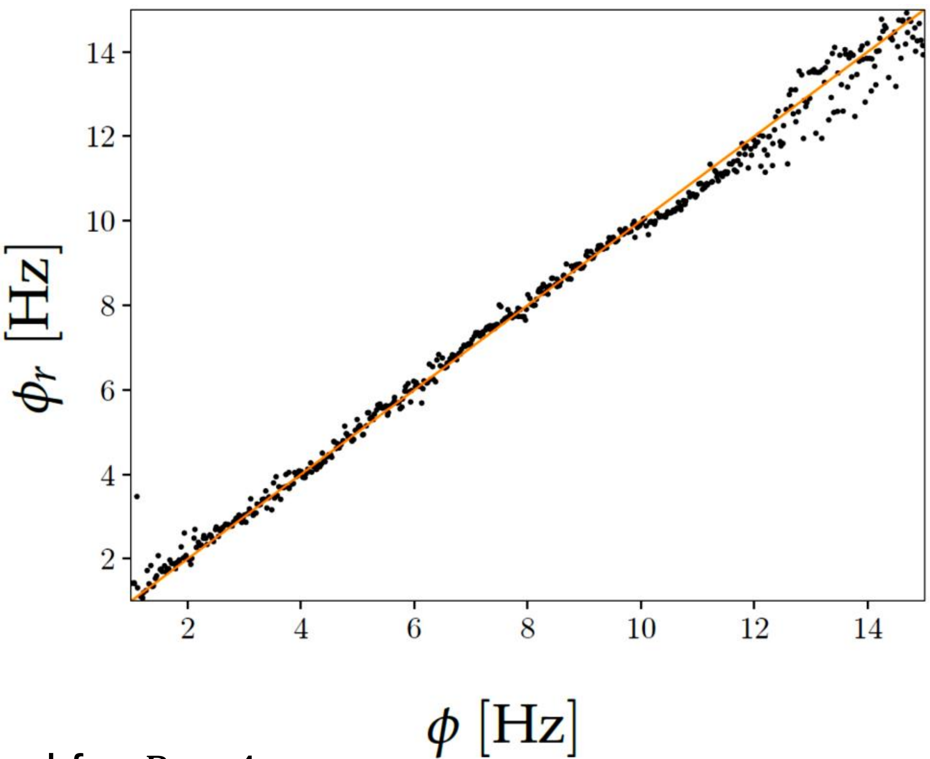
reconstruction error computed for 512 $\mathbf{v}^i$ unseen during the training of the AE according to the **standardised L^∞ error norm**.

↓

highest error for ϕ^i **close to the second structural frequency**.







Results obtained for $P = 4$.

Load identification is satisfactorily accomplished through the regression of α^i and ϕ^i on $\mathbf{z}$.

Thank you for your attention!

Essential Bibliography:

L. Rosafalco et al. *Fully convolutional networks for structural health monitoring through multivariate time series classication*, Adv. Model. and Simul. in Eng. Sci., vol. 7, p. 38, **2020**.

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Rosafalco, L et al. *A Time Series Autoencoder for Load Identication*. In preparation.