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DATA-DRIVEN DETECTION OF STRUCTURAL NONLINEARITY IN THE TIME DOMAIN BASED ON OUTPUT MEASUREMENTS AND TRANSMISSIBILITY FUNCTION

Caglio L.[1], **Tarpø M.**[2], **and Katsanos E.**[1]

[1]Department of Civil and Mechanical Engineering, Technical University of Denmark, Kongens Lyngby, Denmark
e-mail: lucag@dtu.dk

[2]Ramboll A/S, Copenhagen, Denmark

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Abstract. *The detection of nonlinear structural behavior from vibration data in the context of Structural Health Monitoring (SHM) can be an indicator of structural damage that occurred during a dynamic event, such as a ground motion. This paper proposes a data-driven (and mechanical-model-free) methodology that combines the transmissibility function (TF) with a time-domain AutoRegressive eXogenous input (ARX) model, which is trained on linear operational data and can be used to detect nonlinearities during an extreme event. Nonlinearities are detected from the statistical analysis of prediction residuals of the TF-ARX model. A numerical validation is performed on a 2D steel frame under earthquake loading experiencing nonlinear behavior. The approach successfully detects and temporally localizes nonlinearities using only two acceleration sensors, without requiring knowledge of the input excitation or a structural model.*

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1 INTRODUCTION

Structural nonlinearities arising from material yielding or connection degradation can be indicators of structural damage [1]. A natural approach to detect nonlinearities from output-only data is to train a linear model on operational data and detect anomalies in the measured responses during a potentially damaging event. Due to the unknown and non-stationary nature of input excitations, output-only methods are, however, difficult to develop since changes in the input characteristics might be misinterpreted as nonlinear behavior. In this study, we propose a methodology that leverages the transmissibility function (TF) [2, 3], which relates two output responses and is independent of the input's (i.e., load's) time evolution and has been extensively studied for structural health monitoring (SHM) [4]. The time-domain representation of the TF via AutoRegressive eXogenous input (ARX) models, namely TF-ARX, was proposed in [5] for operational modal analysis, and recently applied for SHM of offshore mooring lines [6]. The present work applies TF-ARX modeling specifically for detecting the time instants of nonlinear behavior — an application not previously found in the literature.

2 METHODOLOGY

Consider two scalar acceleration measurements: $\ddot{x}_A$ (output) and $\ddot{x}_B$ (reference). The transmissibility $T_{AB}(\omega) = H_A(\omega) \,/\, H_B(\omega)$ [2], where H_A, H_B are the Frequency Response Functions (FRFs) from the (univariate) load to each sensor, is independent of the load's amplitude and time evolution. The time-domain representation of the TF (TF-ARX) [5] is:

$$\ddot{x}_{A,k} + \sum_{i=1}^{n_a} a_i \, \ddot{x}_{A,k-i} = \sum_{i=0}^{n_b} b_i \, \ddot{x}_{B,k-i} + e_k, \tag{1}$$

with scalar coefficients a_i, b_i estimated by Ordinary Least Squares and orders n_a, n_b selected via Bayesian Information Criterion (BIC). Under linear behavior the residuals, e_k, should be near-Gaussian and near-white; while nonlinearities change these properties.

The detection procedure is as follows: (1) **train** the TF-ARX model on linear operational data; (2) **apply** the model to a potentially damaging event; (3) **compute** residuals $\hat{e}_k = \ddot{x}_{A,k} - \hat{\ddot{x}}_{A,k}$; (4) **analyze** the residuals — herein we use QQ plots for Gaussianity, and Continuous Wavelet Transform (CWT) (time-frequency localization).

3 NUMERICAL VALIDATION

The test structure is a 2D steel moment-resisting frame (Figure 1a) with 60 DOFs modeled in OpenSees and previously employed in [7], including P-Δ effects and a nonlinear steel material (E = 210 GPa, f_y = 235 MPa, b = 0.01). The vibration frequencies of the first three modes are 0.90, 2.89, and 5.75 Hz; Rayleigh damping of 2% is applied. Two acceleration sensors are placed at the first floor (reference) and roof (output). Note that "reference" means that the sensor is used as input to the TF-ARX model, while "output" refers to the sensor whose response is being predicted. The sampling frequency is 200 Hz, and Gaussian noise with power spectral density $20\,\mu\text{g}/\sqrt{\text{Hz}}$ is added to all measurements.

Two earthquake-induced strong ground motions are used: GM1 (Imperial Valley, 1979) as the training excitation and GM2 (Friuli, 2000) as the test excitation. Two scenarios are considered:

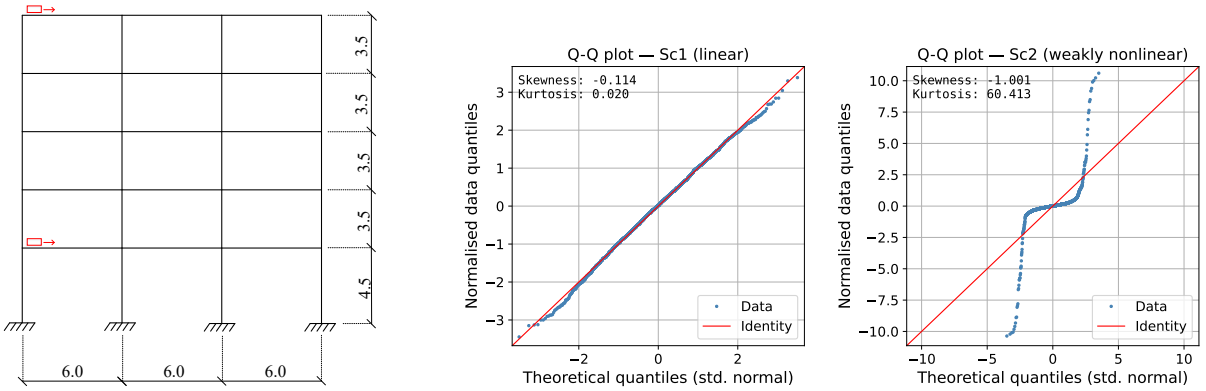
- Sc1 — training dataset: GM1×0.1; test dataset: GM2×0.5 (linear)
- Sc2 — training dataset: GM1×0.1; test dataset: GM2×1.0 (weakly nonlinear)

This setup is motivated by the foreshock–mainshock sequence common in seismic events: the low-intensity GM1 excitation acts as the foreshock during which the structure remains linear, while the stronger GM2 excitation represents the mainshock that may induce nonlinear behavior. In both scenarios, the same TF-ARX model trained on the response to the weak GM1 excitation is used. Using the BIC criterion, the model orders are selected as $n_a = n_b = 73$ (memory window of 0.365 s).

4 RESULTS

Sc1 (linear): Training residuals are near-Gaussian and near-white, confirming good model fit. Applied to GM2×0.5, the Q-Q plot (Figure 1b, left) shows residuals closely following the Gaussian line, the CWT scalogram (Figure 2, left) is essentially featureless, with the amplitude of the coefficients being very small, and the instantaneous frequencies remain constant. No false alarms are raised.

Sc2 (weakly nonlinear): GM2 at full scale induces mild yielding around $t \approx 4$ s. The TF-ARX residuals clearly flag the event: the Q-Q plot (Figure 1b, right) shows heavy tails indicating non-Gaussian residuals, and the CWT scalogram (Figure 2, right) exhibits a localized energy burst at $t \approx 4$ s and ≈5 Hz. The instantaneous natural frequencies, extracted from the finite element model and not available from the sensors, are shown in Figure 2 (bottom) as independent validation: while Sc1 frequencies remain constant, Sc2 exhibits a visible drop at the same instant, consistent with stiffness reduction due to yielding.



(a) Steel frame and acceleration sensor positions (in red).

(b) Q-Q plots for Sc1 (left) and Sc2 (right). Sc1 residuals follow the Gaussian line; Sc2 shows heavy tails.

Figure 1: Left: 2D steel frame with sensor positions. Right: Q-Q plots of TF-ARX residuals under linear (Sc1) and nonlinear (Sc2) loading.

5 CONCLUSIONS

A data-driven TF-ARX-based methodology for output-only nonlinearity detection has been presented and validated on a 2D steel frame under non-stationary earthquake excitation. The method correctly produces no false alarms under linear loading, and successfully detects and temporally localizes a weak nonlinear event. The method requires two acceleration sensors, no input measurement, and no structural model. Future work includes multi-input transmissibility formulations for distributed loading, automated detection indices, and experimental validation.

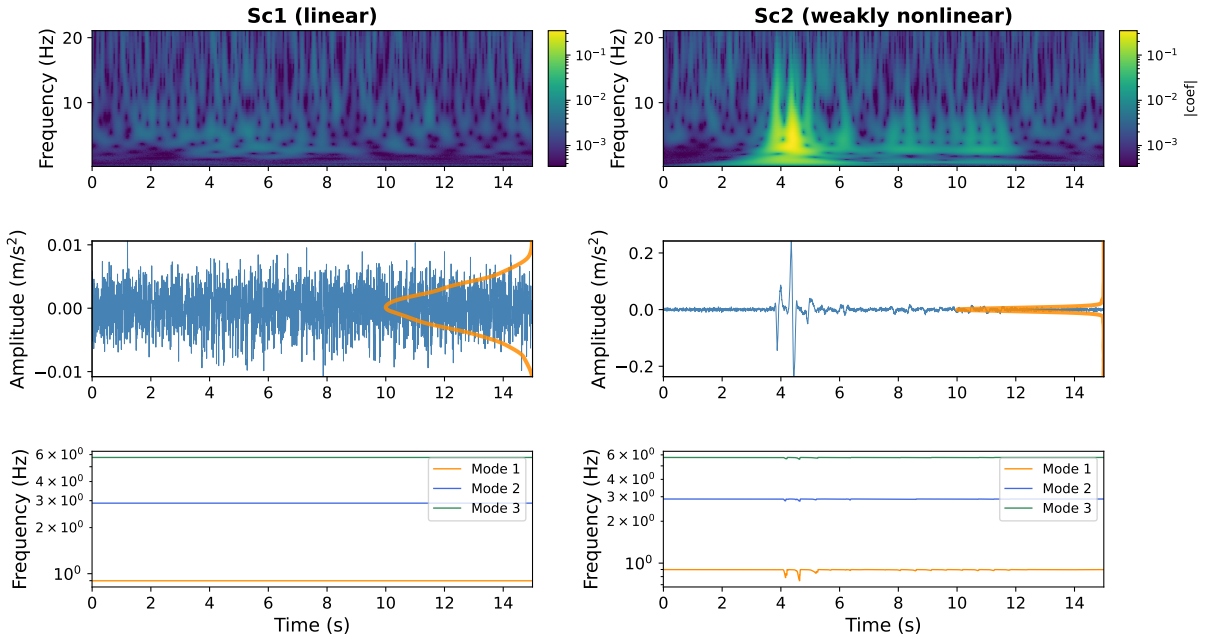


Figure 2: CWT scalogram of TF-ARX residuals (top), residual time series (middle), and instantaneous structural frequencies (bottom) for Sc1 (left) and Sc2 (right). Under linear loading (Sc1) the scalogram is featureless; under nonlinear loading (Sc2) a localized energy burst appears at $t \approx 4$ s and ≈5 Hz, coinciding with the frequency drop due to yielding.

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