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Monitoring-based post-earthquake damage localization in an historic masonry tower using novelty analysis and surrogate modeling

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ABSTRACT
This paper presents an enhanced method for damage localization through surrogate-model based model updating and automated operational modal analysis. The localization task is performed by solving an inverse model calibration problem, where the equivalent elastic properties of certain macro-structural elements are identified by continuous minimization of an objective function comprising experimentally identified natural frequencies and mode shapes. The influence of environmental temperature on the fitted parameters is filtered out by multivariate linear regression analysis, and the damage localization is finally conducted by novelty analysis. The proposed approach is investigated through a validation case study of the 41 m high civic tower located in the city of Perugia (Italy), named Torre degli Sciri. The tower has been monitored for three weeks, since 13th February until 10th March 2019, and the modal features have been identified by automated operational modal analysis. The presented results demonstrate the effectiveness of the proposed approach for reproducing the day/night fluctuations of the elastic properties of the tower. Furthermore, the removal of environmental effects on the fitting parameters is reported to provide valuable damage sensitive features, and different simulated damage scenarios are presented to illustrate the effectiveness of the proposed approach.

1 INTRODUCTION

The seismic events that recently occurred in central Italy demonstrated the strong vulnerability of historical architectural heritage to earthquakes. In this context, the application of Structural Health Monitoring (SHM) systems to historic buildings, complemented by Operational Modal Analysis (OMA) techniques, has gained increasing interest at an international level as they represent valid tools for historic buildings' preventive conservation (Gentile et al. 2015, Cavalagli et al. 2018). These techniques allow real-time assessment of the integrity of the structure, and the collected data can be used to track variations of its dynamic features caused by early-stage damages. In such a way, condition-based decision making and preventive actions can be conducted to guarantee safety maintenance and avoid run-to-failure costs (Masciotta et al., 2017).

Operational Modal Analysis-based SHM techniques are chiefly effective for damage detection and, to some extent, damage quantification (Ubertini et al., 2018). Damage localization, on the contrary, usually requires the inverse calibration of a finite element model (FEM) of the structure, also called FEM updating (Atamturktur and Laman, 2012, Sehgal and Kumar, 2016). Nonetheless, given the geometrical complexity of most historic buildings and, thus, the need for finely meshed FEMs, along with the large number of model evaluations involved in heuristic minimization algorithms, the computational burden poses a major limitation in practice. As an alternative, surrogate models or meta-models allow bypassing costly numerical models, thereby enabling continuous model updating to be performed in a computationally efficient way and compatible with continuous SHM systems (Cabboi et al. 2017, Torres et al., 2017).

In this light, and based upon previous research work by the authors (Venanzi et al. 2019), this paper proposes an enhanced method for damage localization, based on OMA through stochastic subspace identification, Multivariate Linear Regression (MLR) analysis to remove the effects of changing environmental conditions, and FEM

Updating. The localization task is performed by solving an inverse FEM calibration problem, where equivalent elastic properties of macro-structural elements are identified by minimizing an objective function considering experimentally identified and numerically predicted damage-induced decays in natural frequencies and changes in eigenvector components. This is performed by an efficient response surface meta-model (RSM), which allows minimizing the computational effort of the calibration procedure.

The effectiveness of the proposed approach is evaluated through a validation case study of a 41 m high civic tower located in the city of Perugia in Italy, named Torre degli Sciri. The tower has been equipped with a dynamic monitoring system consisting of twelve uniaxial accelerometers that have been continuously providing data since February 13th until March 10th 2019. Different simulated damage scenarios are presented to illustrate the effectiveness of the proposed approach.

2 THEORETICAL BACKGROUND: SURROGATE MODELLING

Let us define m damage-sensitive parameters, $x_i \in \mathbb{R}$, $i = 1, ..., m$, determining the response y of a FEM. A surrogate model serves as a black-box representation of the response of the FEM as $y(\mathbf{x})$, with $\mathbf{x}$ being the vector of design parameters $\mathbf{x} = [x_1, ..., x_m]^T$. In order to construct the surrogate model, it is often necessary to obtain a training population by Monte Carlo simulations (MCS) using the FEM. A training population of N individuals is defined by a $m \times N$ matrix of design sites $\mathbf{X}=[\mathbf{x}^1, . . . , \mathbf{x}^N]$, and an observation vector $\mathbf{Y}=[y_1, . . . , y_N]^T$, with $y_i \in \mathbb{R}$ being the system's response to the input x_i. Specifically, the modal properties obtained by a linear modal analysis of the FEM are assumed in this work as outputs.

2.1 Response Surface Method (RSM)

The RSM represents a collection of statistical tools for fitting empirical models and so alleviate the computational effort of iterative processes. In this work, a second-order quadratic RSM is used as:

$$y(x) = \alpha_0 + \sum_{j=1}^{m}\left(\alpha_j x_j + \alpha_{jj} x_j^2 + \sum_{i \geq j}^{m} \alpha_{ji} x_j x_i\right) + \varepsilon, \quad (1)$$

where coefficients α_0, α_j, α_{jj} and α_{ji} stand for the intercept, linear, quadratic, and interaction coefficients, respectively. The term ε is a normally distributed statistical error with zero mean, independent, and identically distributed at each observation. The model can be written in matrix notation to account for the observations in the training population as:

$$\hat{\mathbf{Y}} = \hat{\mathbf{X}}\mathbf{A} + \boldsymbol{\varepsilon}, \quad (2)$$

where $\hat{\mathbf{X}}$ is a $N \times (m+1)(m+2)/2$ matrix collecting components $[1, x_j, x_j^2, x_j x_i]$ for each individual in the training population, A is the (m+1)(m+2)/2 vector of coefficients α_0, α_j, α_{jj} and α_{ji}, and $\boldsymbol{\varepsilon}$ is a $(m+1)(m+2)/2$ vector of random uncorrelated errors. The meta-model is determined by the coefficients vector $\mathbf{A}$, which can be obtained by minimizing $\boldsymbol{\varepsilon}$ through its least squares estimator as:

$$\mathbf{A} = \left(\hat{\mathbf{X}}\hat{\mathbf{X}}^T\right)^{-1} \hat{\mathbf{X}}^T \mathbf{Y}, \quad (3)$$

3 SURROGATE MODEL-BASED DAMAGE IDENTIFICATION OF HISTORIC STRUCTURES

The proposed surrogate model-based damage identification approach is organized into five consecutive steps: (i) Generation of the training population; (ii) Construction of the surrogate model; (iii) Continuous model updating; (iv) Removal of environmental effects; and (v) Novelty analysis. In this work, the elastic moduli of certain regions of the FEM are defined as design variables x_i. Considering l modes of vibration in the model updating, an objective function $J(\mathbf{x})$ involving both natural frequencies and mode shapes is introduced as:

$$J(\mathbf{x}) = \sum_{i=1}^{l}[\alpha\varepsilon_i(\mathbf{x}) + \beta\varphi_i(\mathbf{x})] + \eta\Theta(\mathbf{x}), \quad (4)$$

with

$$\varepsilon_i(\mathbf{x}) = \frac{\left|f_i^{\exp} - f_i^{sur}(\mathbf{x})\right|}{f_i^{\exp}}, \quad \varphi_i(\mathbf{x}) = 1 - MAC_{ii}(\mathbf{x}), \quad (5)$$

and α, β and η being weighting coefficients. The terms $f_i^{\exp}$ and f_i^{sur} stand for the i-th resonant frequencies obtained by OMA and the surrogate model, respectively. In addition, the terms MAC_{ii} are the modal assurance criterion (MAC) coefficients between the i-th experimental and numerical mode shapes. The term $\Theta(\mathbf{x})$ in Eq. (4) represents a regularization term used to limit ill-conditioning in the optimization. In this work, a simple regularization term is defined as:

$$\Theta(\mathbf{x}) = \frac{1}{m}\sum_{i=1}^{m}\frac{\left(x_i - x_i^0\right)^2}{b_i - a_i}. \tag{6}$$

where a_i and b_i are the lower and upper variation limits of the design variables x_i. Such a regularization term compels the solution to remain in the neighbourhood of a reference vector $\mathbf{x}^0$, which represents the undamaged condition. Considering that the modal features are identified by OMA at consecutive steps, the time series of the fitting parameters can be obtained by the iterative minimization of $J(\mathbf{x})$.

Once the time series of fitting parameters are obtained, environmental effects are filtered out by multivariate linear regression (MLR) analysis. This filter adopts linear correlations between the fitting parameters and a set of independent variables called predictors (in this work, the environmental temperature). In matrix notation, the relationship between the fitting parameters $\mathbf{Y}$ and the MLR estimates $\hat{\mathbf{Y}}$ can be written as:

$$\hat{\mathbf{Y}} = \boldsymbol{\beta}^{\mathrm{T}}\mathbf{Z}^{\mathrm{T}}, \tag{7}$$

where matrix $\mathbf{Z} \in \mathbb{R}^{n \times p+1}$ contains a first column of ones (interception) and p columns containing the n-sampled time series of the fitting parameters, while matrix $\boldsymbol{\beta}$ contains the model parameters of the MLR model. The residual error matrix, $\boldsymbol{E}$, between the identified and predicted fitting parameters reads:

$$\mathbf{E} = \mathbf{Y} - \hat{\mathbf{Y}}. \tag{8}$$

The coefficients of the MLR model in matrix $\boldsymbol{\beta}$ are estimated in a least square sense by minimizing the norm of $\mathbf{E}$ over a reference training period.

Finally, once the fitting parameters have been detrended, the appearance of damage can be identified by novelty analysis of the residuals in $\mathbf{E}$ after the training period.

4 VALIDATION CASE STUDY AND DISCUSSION

The effectiveness of the proposed approach is investigated through a validation case study of a 41 m masonry tower located in the historical centre of Perugia (Italy), named Torre degli Sciri. With the aim of identifying the modal features of the tower, a continuous ambient vibration test (AVT) was performed from February 13th until March 10th 2019. Twelve high sensitivity (10 V/g) uniaxial accelerometers model PCB 393B12 were deployed at four different heights of the tower, namely z = 40.5 m, z = 33.5 m, z = 24.0 m and z = 8.4 m (see Figure 1). In addition, two K-type thermocouples were installed at the level z = 40.5 m (indoor and outdoor) and temperature was recorded at a sampling frequency of 0.4 Hz. Ambient vibrations were recorded at a sampling frequency of 1652 Hz and down-sampled to 40 Hz, and the modal features of the tower were continuously extracted from every 30-min long records using the Covariance-driven Stochastic Subspace Identification (COV-SSI) method. Six vibration modes have been identified in the range between 0 and 10 Hz as shown in Figure 2 (a), including two flexural modes in NW direction (Fx1 and Fx2), two flexural modes in SW direction (Fy1 and Fy2), one torsional mode, Tz1, and one higher order flexural mode, Fx3. Table 1 reports the identified natural frequencies, damping ratios and modal phase collinearity (MPC) values. It is noted that the MPC of all the modes are above 95% (classically damped), except for modes Fx2 and Fy2 where values of 84.9% and 80.2% are obtained, a fact that may indicate that these modes are non-classically damped.

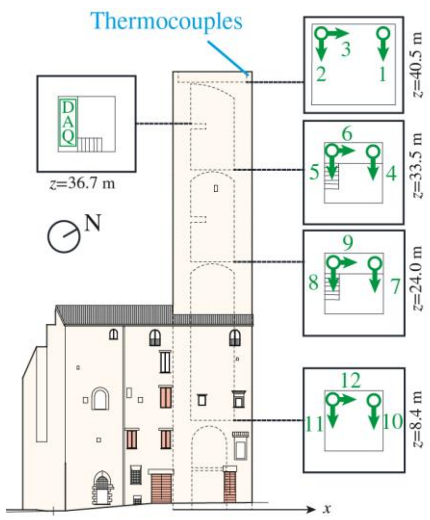

Figure 1. Sensors layout for continuous monitoring of the Sciri Tower.

Table 1. Experimentally identified natural frequencies f_i, damping ratios ζ_i, and Modal Phase Collinearity (MPC) estimated through COV-SSI on 13th February 2019 at 14:00 UTC.

Mode	f_i [Hz]	ζ_i [%]	MPC_i [%]
Fx1	1.69	0.92	99.8
Fy1	1.89	0.78	99.4
Fx2	5.54	3.07	84.9
Fy2	5.92	2.18	80.2
Tz1	8.20	1.78	99.8
Fx3	9.80	1.37	98.9

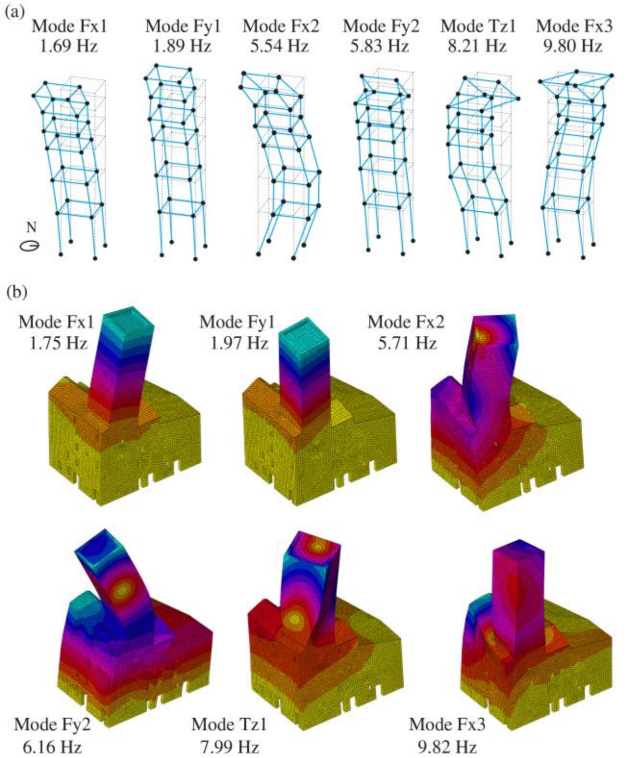

Figure 2. Experimental (a) and numerical mode shapes (b) of the Sciri Tower.

4.1 Finite element modelling

Owing to the strong constraints imposed by the building aggregate where the tower is inserted, a three-dimensional FEM of the Sciri Tower and the adjoining buildings has been built using the commercial software ABAQUS 6.10 (see Figure 3). The elastic parameters of the masonry have been selected after a thorough sensitivity analysis, including the Young's modulus E = 5.77 GPa, shear modulus G = 2.31 GPa, Poisson's ratio ν = 0.25, and mass density w = 2.20 t/m^3. The numerical mode shapes are in good agreement with the experimental ones as shown in Figure 2 (b) with MAC values above 0.8 (except for modes Fx2 and Fy2 which are excluded from the analysis because of their high level of complexity), as well as relative differences in resonant frequencies below 5%.

The FEM has been parametrized considering four macro-elements M_i, i = 1, ..., 4, as illustrated in Figure 3. According to this partition, the Young's moduli E_i of the elements contained in the macro-elements M_i have been defined as random variables as:

$$E_i = E_i^0 (1 + k_i), \tag{9}$$

with E_0 being the nominal value of the Young's modulus of the i-th macro-element. Parameters k_i are proportionality coefficients of the elastic moduli of macro-elements M_i, and constitute the design variables $\mathbf{x} = [k_1, k_2, k_3, k_4]^T$ in the model updating procedure.

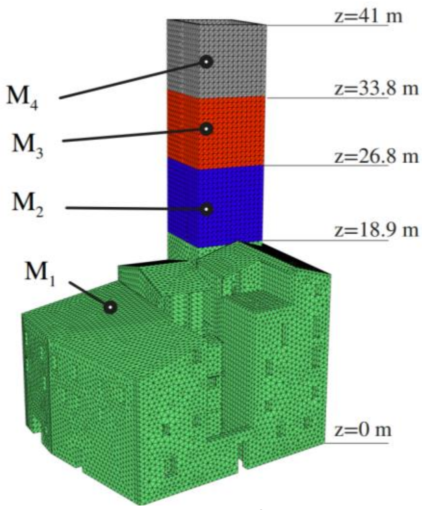

Figure 3. Finite element model of the Sciri Tower and the adjoining building, and division into macro-elements M_i.

4.2 Surrogate model-based continuous structural assessment of the Sciri Tower

Firstly, the training population has been generated by defining the stiffness coefficients k_i as random variables with upper/lower limits of ±15%, and random samples have been drawn uniformly using the quasi-random sequence of Sobol. From the results of a convergence analysis (not included here because of space constraints), a training population of 512 individuals has been selected. Once the surrogate model has been constructed, continuous surrogate model-based system identification has been applied to each set of identified modal features (30 min). Herein, a reference vector $\mathbf{x}_0$ = [-0.07, -0.06, 0.02, 0.01]^T has been selected, and the mode shapes of modes Fx2 and Fy2 have been excluded from the analysis because of their high complexity as reported in Table 1. The minimization problem has been iteratively solved using a Particle Swarm optimization algorithm with weighting parameters α = 0.8, β = 0.3, and η = 4.

Figure 4 shows the time series of environmental temperature, identified resonant frequencies, and fitted parameters k_i. The results of the surrogate-based model updating report stiffness values about 7% larger in the last two macro-elements (M_3 and M_4). It is also interesting to note that day-night oscillations are found in both the natural frequencies and the fitted model parameters. Specifically, there exists a positive correlation with temperature as shown in Figure 5. This behavior, also found in the natural frequencies, is ascribed to the closure of cracks induced by thermal expansion. In this figure, it is noted that the sensitivity to temperature variations decreases with height, what may be due to stronger thermal effects close to the base of the tower where expansion is more constrained and the material is more heterogeneous.

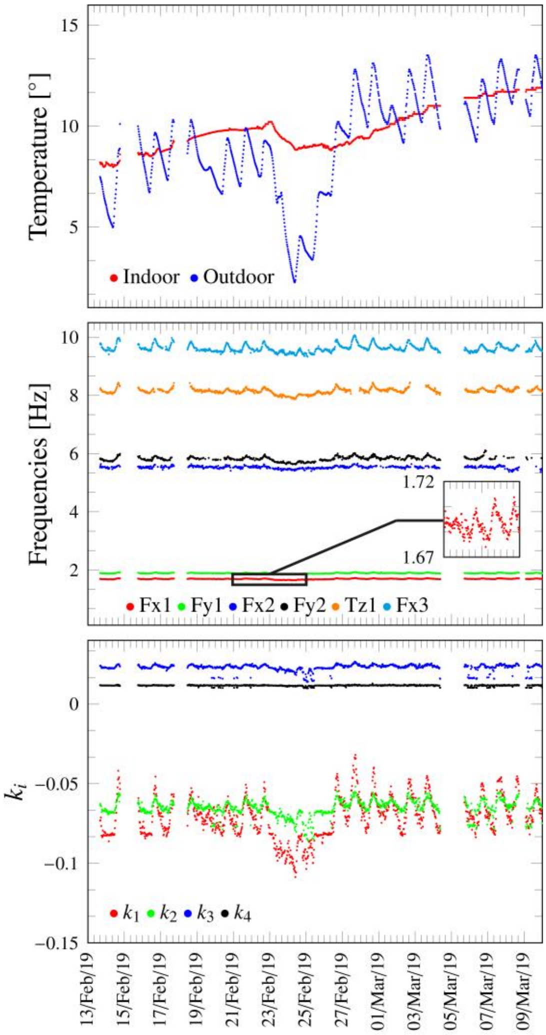

Figure 4. Temperature time series, frequency tracking, and time series of updated model parameters k_i in the Sciri Tower since 13th February until 10th March 2019.

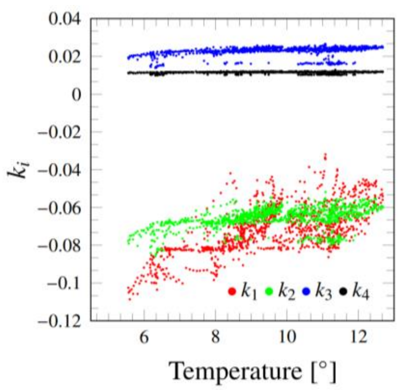

Figure 5. Updated model parameters k_i of the sections of the Sciri Tower included in the macro-elements M_i versus mean environmental temperature.

4.3 Surrogate model-based damage identification

This last section reports the results of the application of the surrogate model-based damage identification approach previously introduced in Section 3 to the Sciri Tower. Figure 6 shows the time series of the fitted elastic moduli of macro-elements M_i (see Eq. (9)) as well as the predicted ones adopting a MLR model. To do so, a training period of two weeks and a half has been defined to construct the statistical model. It is observed that the MLR model approaches well the experimental data and, except for the presence of some outliers (especially in the macro-element M_4), the residuals approximately follow a Gaussian distribution.

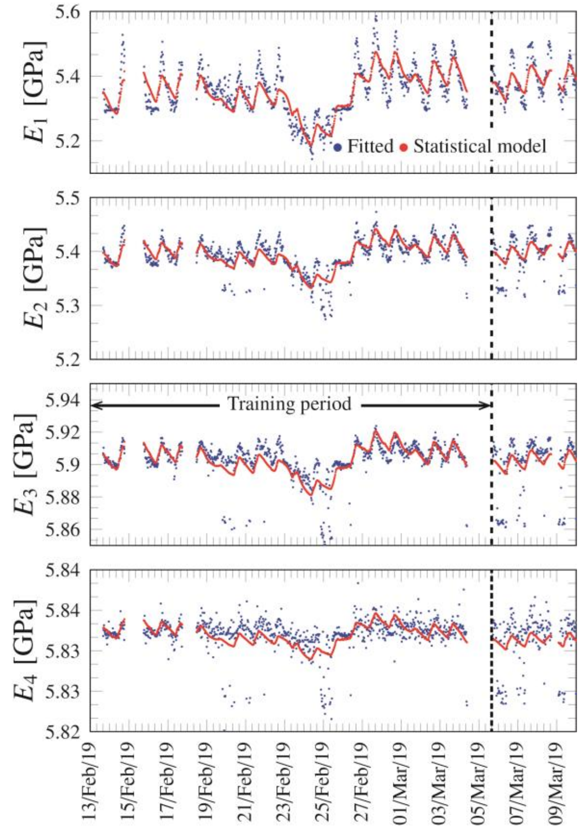

Figure 6. Predicted (MLR) versus fitted Young's moduli.

In this light, and in order to illustrate the effectiveness of the proposed approach for damage identification, three different simulated damage scenarios are studied in Figure 7. These include the undamaged configuration (a), reduction of 5% of the Young's modulus of macro-element M_1 (b), and reduction of 70% of the Young's modulus of macro-element M_4. In the latter case, damage localized in the uppermost part of the tower has little influence on the modal properties of the tower, therefore the consideration of a larger damage degree was necessary. The effects of the considered damage scenarios have been included in the experimental modal features after the training period in terms of frequency decays (reported in Table 2) and mode shapes simulated by the 3D FEM of the tower. In this light, Figure 7 depicts the absolute value of the residuals of the elastic moduli of macro-elements M_i throughout the monitoring period. Moreover, confidence levels of 95% obtained assuming a t-Student distribution are indicated with dashed red lines in the figure in order to ease the identification of permanent variations in the statistical distributions of the residuals.

Table 2. Simulated frequency decays by the 3D FEM of the Sciri Tower. (a) Undamaged condition; (b) 5% reduction of the Young's modulus of macro-element M_1; (c) 70% reduction of the Young's modulus of macro-element M_4.

Mode	(a) $\frac{\Delta f_i}{f_i}$ [%]	(b) $\frac{\Delta f_i}{f_i}$ [%]	(c) $\frac{\Delta f_i}{f_i}$ [%]
Fx1	0	-2.11	-0.31
Fy1	0	-2.00	-0.41
Fx2	0	-2.14	-0.74
Fy2	0	-1.89	-1.38
Tz1	0	-1.62	-2.03
Fx3	0	-1.65	-2.46

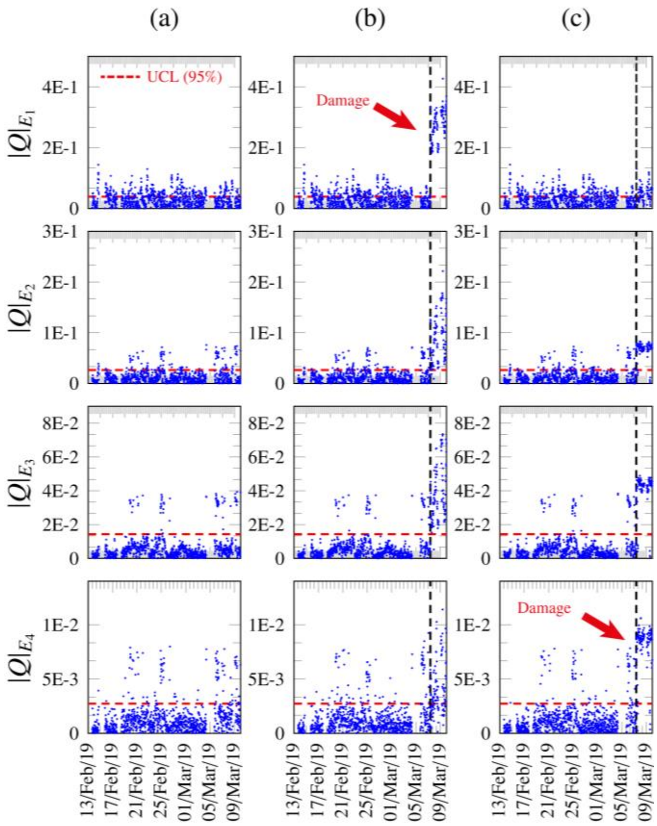

Figure 7. Absolute value of the residuals Q of the fitted elastic moduli E_i of macro-elements M_i. (a) Undamaged configuration; (b) Reduction of 5% of the elastic modulus of macro-element M_1; (c) Reduction of 70% of the elastic modulus of macro-element M_4.

It is observed in Figure 7 (b) that, when damage is localized in the bottom macro-element, a clear disturbance is found in the residuals of the elastic modulus of the macro-element M_1 after the training period. Although the damage location is clear in this case, some disturbances are also found in the macro-elements M_2 and M_3. This may be attributed to ill-conditioning issues in the optimization problem, as well as inherent limitations of the full FEM to represent the experimentally identified modal features. Finally, it is observed in Figure 7 (c) that damage in the uppermost macro-element can be also identified in terms of permanent variations in the residuals of E_4. In this case, notable disturbances are also found in the elastic moduli of the macro-elements M_2 and M_3, which hinder the exact localization of damage. Nevertheless, although ill-conditioning limitations may provoke some scatter in the residuals in the neighbouring of the actual location of damage, these results provide valuable information about its approximate location and may be used for decision-making of rehabilitation interventions.

5 CONCLUSIONS

This paper has presented a surrogate model-based damage identification approach for historical buildings. The proposed approach consists in the continuous updating of certain model parameters on the basis of modal features experimentally identified by automated OMA. Damage localization is performed through novelty analysis of the fitting parameters. To do so, environmental effects are removed by applying MLR. The validation case study of the Sciri Tower located in the city of Perugia (Italy) has been presented to illustrate the effectiveness of the proposed approach. The reported results demonstrate the capability of the proposed method for identifying the environmental effects on the intrinsic stiffness of the structure. Finally, simple simulated damage scenarios have been investigated to illustrate the effectiveness of the proposed approach. The reported results have proved the suitability of the proposed approach for damage localization, and evidence the possibility of developing SHM systems based upon novelty analysis of modal features and fitting parameters with superior damage identification capabilities.

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