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Structural health monitoring by merging dynamic response data

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Abstract. The process of Structural Health Monitoring aims to detect changes in material and/or geometric properties, boundary conditions or member connectivity of a structural system in time. However, the transfer of research results into engineering practice poses several challenges, especially for stiff structures with very diverse geometry that could not be well dynamically exited like low and medium-rise structures under ambient vibration conditions. Noise in modal parameters from output-only modal analysis due to variable environmental and operational conditions is considered one of the most problematic aspects of detecting structural damage using a vibration-based method. This research proposes a new way to reduce environmental noise in vibration data and dynamic parameters by merging dynamic response data from two similar shear wall buildings. The object of the study is a three-story reinforced concrete building. First, the damage features as natural frequencies and zero-order temporal moment of the vibration response are studied. Further, those feature changes are explored by means of modelling wall removal/opening introduction into the finite element models. It is established that the variation in the base excitation spectrum has more impact on dynamic response than introduced structural changes. Therefore, a time-domain feature like a zero-order temporal moment of the vibration response is not applicable for the proposed method. The appropriate damage sensitive feature vector for this approach is the difference of natural frequencies from two monitored buildings. The proposed method for fusion of vibration information from several buildings that share the same environmental and operational conditions filter out environmental noise effectively and give a clear advantage in reducing false alarm possibility during continuous and automated structural health monitoring process.

1. Introduction

Structural Health Monitoring (SHM) is a process of implementing a damage detection strategy that involves the observation of a structure over time using periodically spaced or continuous dynamic response measurements. The extraction of damage-sensitive features from those measurements and the statistical analysis of these features are used to determine the current state of the system health. One of the SHM strategies is to use the vibration-based monitoring (VBM) global method by extracting the information about lower vibrational modes of the structure. Although VBM damage identification techniques are suitable for global damage assessment of large and flexible structures [1], recent advances in various technology branches allow developing new cost-effective methodologies for low and medium-rise structures. These include sensing equipment, signal acquisition and transmission, data processing and analysis, as well as

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numerical modelling. Examples of successful dynamic parameter identification for medium-rise buildings under ambient vibration excitation (AVT) can be found in the literature [2–4].

One of the most problematic aspects of implementing an SHM system in practice is that real structures undergo the changing operational and environmental variables (EOV) [5]. The changes in natural frequency estimates due to environmental and operational variables are often of the same order of magnitude as those caused by damage [6]. Still, only a few researchers incorporate the consequences of these effects on their proposed SHM system. The most common environmental effects are temperature and moisture changes, but the operational effect changes mass and ambient loading conditions. These effects may disguise the changes in modal parameters from structural damage. In their seminal work in 2007, Hoon Sohn provided an extensive review of the effects of environmental and operational variations on real structures [7]. Many structures exhibit daily and seasonal temperature variations that cause the expansion or contraction of structures and boundary conditions changes. These effects mostly investigated in bridge monitoring research (e.g. [8–11]) because bridge structures experience more severe conditions than insulated buildings.

Realistic and direct modelling of the influence of environmental and operational variables on the structure's response is an almost impossible task. Therefore, it is common to build mathematical models from experimentally measured environmental data. Vibration-based damage sensitive features of healthy structure [12–16] obtained using different techniques, e.g. from simplest linear regression models to neural networks and support vector machines. The limitation of those methods is the restricted use of only those structures on which model has been created. Also, a training period that covers the range of environmental changes is needed to filter their influence, e.g. it is about one year for temperature variations [17].

Rainieri et al. [6] presents the Second-Order Blind Identification technique and demonstrates that it can model the variability of natural frequency estimates in operational conditions and give a fundamental insight in determining the causes of such variability.

Other techniques aim to obtain the variability of natural frequencies without measuring environmental or operational variables. These algorithms, e.g. principal component analysis (PCA) [5], Mahalanobis-squared distance (MSD), auto-associative neural network (AANN), factor analysis (FA), singular value decomposition (SVD) [18] rely only on response time-series data acquired under changing operating conditions. Recently a novel distance-based anomaly detection method based on adaptive Mahalanobis-squared distance and one-class kNN rule called AMSD-kNN has been proposed to detect early damage under the environmental variability conditions [19]. The authors of the paper performed comparative studies and concluded that the proposed AMSD-kNN method is superior to the conventional MSD, PCA, and AANN based anomaly detection techniques in detecting damage and distinguishing the damaged state from the normal condition properly.

Sohn in [7] points out that data normalisation procedures need to be more focused on specific applications. For example, industries and research should focus more on tests of real structures in their operating environment than laboratory tests of representative structures. The structural monitoring case of the "Cardarelli" Hospital in Campobasso [20] is one of the rare cases of longitudinal research on frequency dependency on building temperature changes. It shows clear frequency dependency for all four closely spaced modes on daily temperature changes. The first two are transversal and longitudinal bending modes, but the other two are torsional modes. The estimates' swing systematically recurs every day, with a sudden drop in the night and a gradual increase in the morning up to the maximum value reached in the afternoon.

Yuen and Kuo [21] utilise a one-year daily measurement of a 22-storey reinforced concrete building to trace the variation of its modal frequencies, which is identified using the Bayesian spectral density approach with the ambient vibration data. Their work investigates the ambient temperature variation and fundamental frequency variation during the year, and the results of the research highlight that the relative humidity could be essential for long-term structural health monitoring. Coletta et al. [19] use cointegration theory to remove environmental effects from dynamic data of the Sanctuary of Vicoforte in Italy. Their investigation showed that the different nature of the effects imposed by operational and environmental variations on structural response requires an extension of cointegration theory.

Gentile and Ruccolo [20] describe findings from one-year monitoring of EOV effects on the first six modes of Milan Cathedral. Authors conclude that the variations observed in the resonant frequencies are mainly driven by temperature, with the effect of thermal changes being very peculiar as the mode shapes in opposite do not exhibit appreciable fluctuations associated with the environmental changes.

Compiling the results from case studies mentioned above, it follows that environmental effects for building structures may introduce a variation of first natural frequencies up to 8 % depending on building structure and exposure level to those effects. On the contrary, variations in mode shapes due to EOV's seems to be less sensitive.

The recent development of the Internet of Things (IoT) rapidly expands the possibilities for the implementation of state-of-the-art SHM systems. IoT solutions for SHM purposes are commonly based on four principal components: sensor devices, gateway, Remote Control and Service Room, and Open Platform Communications server [19, 20, 22]. In the near future, low-cost sensor devices for sensor networks will be able to gather lots of vibration data remotely and aggregate it. After that, a critical analysis will be possible both for one structure and several buildings at once. Advancements of sensors with noise level as low as 60 ng/√Hz for the frequency band of interest [21] has already been reached.

This paper investigates the ways to reduce environmental noise in vibration data and dynamic parameters by merging vibration data from two similar buildings under ambient vibration conditions with variable operational and environmental situations. This work presents an approach for data fusion and verifies it by FEM simulations of two three-story buildings with very similar but not identical structural parameters nor ambient excitation. Furthermore, damage sensitive feature changes due to EOV effects is investigated.

It is found that the fusion of vibration information from several buildings that share the same environmental and operational conditions gives clear benefits in reducing false alarm possibility during continuous and automated structural health monitoring process. The advantage of the presented approach includes: filtering out damage sensitive feature variations due to EOV; potential reduction of training data required when machine algorithms applied for damage detection; no necessity for developing a reference model of a building, or gathering previous information on building dynamic response.

2. Research methods

There are four recognised paths to deal with EOV effects in SHM:

1. Development of mathematical models from experimental measurements;

2. Monitoring of structure in an undamaged state and extracting feature vectors that are later compared with damaged state feature vectors;

3. Machine learning approaches trained on the undamaged state;

4. Damage detection by using features that are insensitive to EOV effects.

However, almost all of the approaches require gathering experimentally or via model simulations vast amounts of information before the actual in-service monitoring due to the well-known SHM axiom that states:

"*The assessment of damage requires a comparison between two system states*" [23].

The authors also propose to use a reference state for damage detection–not the same building or its model in the undamaged state but rather a similar building nearby that generally share the same EOV conditions. An example of such structures might be mass housing. Fig. 1 shows three buildings with similar structural composition and materials are located near ambient vibration source – regular traffic. These kinds of buildings often have reached their intended design life. SHM system that could detect an illegal structural change like new openings in walls or entire wall removals would enhance such buildings' structural safety.

The basic underlying assumptions of the proposed method are:

- Very unlikely that the exact damage occurs simultaneously at both buildings;
- Both buildings have a similar structure and share the same environmental and operational conditions (e.g. temperature, moisture and vibration source);
- The monitored feature vector changes due to the damage event;
- Properties of the soil only slightly modify modal frequencies of the building;
- The chosen monitoring system is capable of recording a time series of sensor network located in both buildings simultaneously and extract feature vectors with a precision higher than its value changes due to the damage event;
- Preferably, at least one damage sensitive feature is extracted from the frequency domain and one from the time domain to cross-check the identified damage event to reduce false alarm situations.

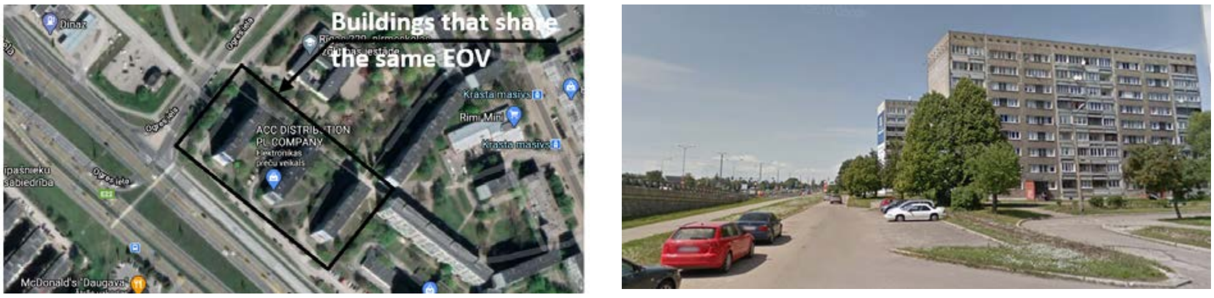

Figure. 1. Example of mass house buildings that share the same EOV and ambient vibration conditions [24, 25].

To find out appropriate damage sensitive features of medium-rise shear wall structure 60 FEM simulation cases were performed. In all these simulations, the previously outlined method for structural damage identification was applied to filter out the effects of variable environmental and operational conditions. These simulations correspond to 30 experimental measurements per year per building.

Generally, EOV effects might be sources of variations in the following structural elements and parameters: stiffness changes of the foundation base (cause: groundwater changes, freezing and defrosting of the soil); the variable inertial mass of the structure (cause: snow, rain, varying material densities, variable load etc.); the variable stiffness of the structure (cause: temperature, moisture, change in boundary conditions of elements).

Stiffness changes in the foundation base affect natural frequency values, but this dynamic parameter change does not characterise the damage of the structure. Therefore, in performed simulations, building bases are taken as fixed.

Other EOV effects are implemented in the model through variable elastic modulus and material density. A total change of natural frequencies due to EOV are in the range of 3 %. EOV deviations have a harmonic component and a stochastic component. Due to seasonal temperature fluctuations, changes represent a harmonic function of elastic modulus E (see Fig. 2), but the stochastic component of EOV effects considered by changes in material density (see Fig. 3).

Variations in the excitation signal from building to building were realised through randomly generated signal following the Gaussian distribution in the frequency domain. In calculations, mean and standard deviation values of excitation frequencies variated but remained equal for both buildings per simulation. At the same time, randomly generated amplitudes of frequencies simulate discrepancies in the excitation spectrum per building. The range of those simulation parameters was chosen based on typical spectral characteristics of sites exited by regular traffic and reported in the literature [26, 27] Input parameters for FEM simulations are presented in Table 1, and the example of generated signal a(t) is shown in Fig. 4.

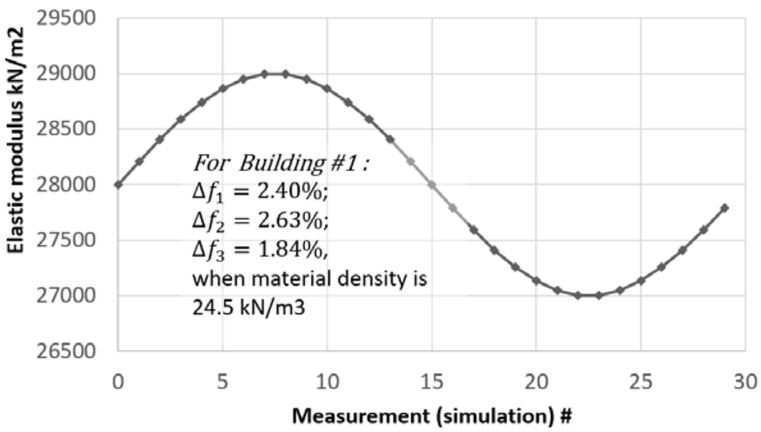

Figure 2. Applied deviations in elastic modulus E in FEM simulations (Δf – change of natural frequency).

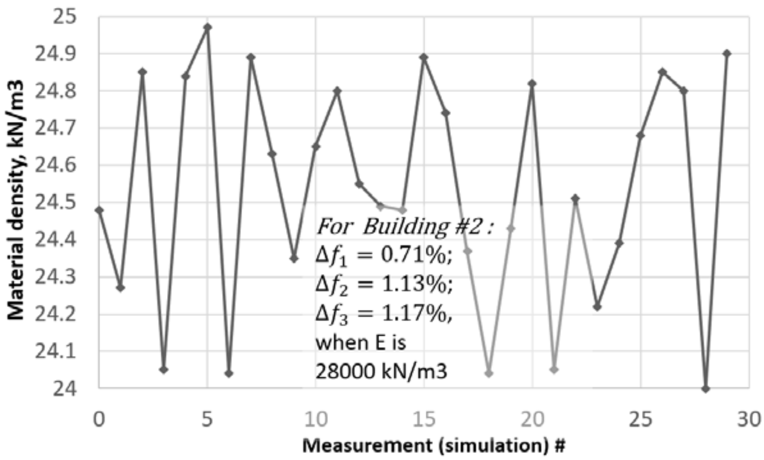

Figure 3. Applied deviations in material density in FEM simulations (Δf – change of natural frequency).

Table 1. Input parameters for FEM simulation.

Case*	Gaussian kernel parameters of the excitation signal (frequency domain)		Obtained RMS of the base excitation signal (time domain), m/s^2		Parameters for modelling of EOV effect			
	(Max; min) of Standard deviation, Hz	(Max; min) of Mean value, Hz	Max	Min	Elastic modulus (for stiffness variation), kN/m^2		Density (for mass variation), kN/m^3	
					Max	Min	Max	Min
A + B	(3.75; 2.03)	(13.32; 8.13)	$2.69 \cdot 10^{-4}$	$1.81 \cdot 10^{-4}$	28 995	28 000	24.95	24.00
A + C	(3.91; 2.04)	(13.69; 9.18)	$2.76 \cdot 10^{-4}$	$1.87 \cdot 10^{-4}$	28 866	27 257	25.00	24.11
D + B	(3.86; 2.42)	(13.92; 8.43)	$2.72 \cdot 10^{-4}$	$1.88 \cdot 10^{-4}$	27 792	27 005	24.99	24.01

* A+B is the case when Building #1 and Building #2 is undamaged; A+C is the case when Building #1 is undamaged, and Building #2 is damaged by damage case I; D+B is the case when Building #1 is damaged by damage case II and Building #2 is damaged before by Case I.

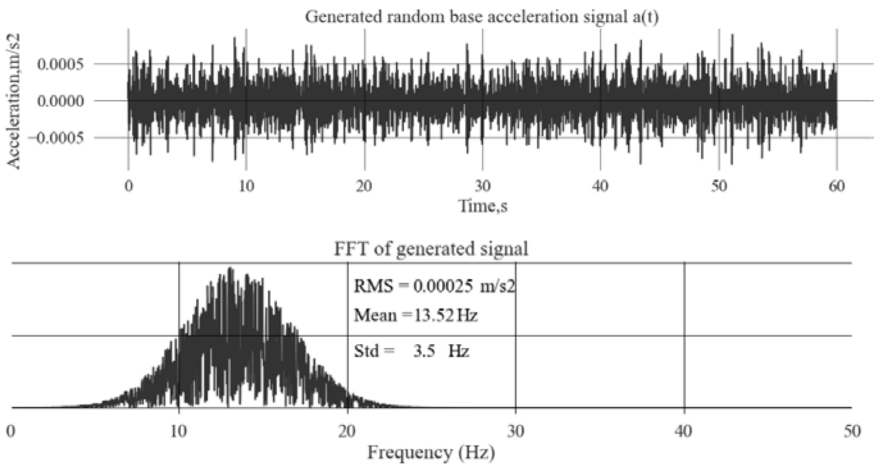

Figure 4. Example of generated and applied base excitation signal to FEM model.

Four FE models of three-story RC shear buildings were developed. Model A and B correspond to undamaged states of building. Model C corresponds to the damage state of building B, but model D corresponds to the damaged state of building A. Dimensions, stiffness of springs that models shear walls, and measurement point locations are presented in Fig. 5. Model B (Building #2) is not an exact copy of model A (Building #1) because to simulate differences in applied base excitation amplitudes, model B is turned by 15 degrees in the plane. It has shear walls in all directions for the middle axis of the building and has reduced stiffness due to different opening composition in one of the building's outer walls. These structural differences from model to model are highlighted in the drawing of Fig. 5.

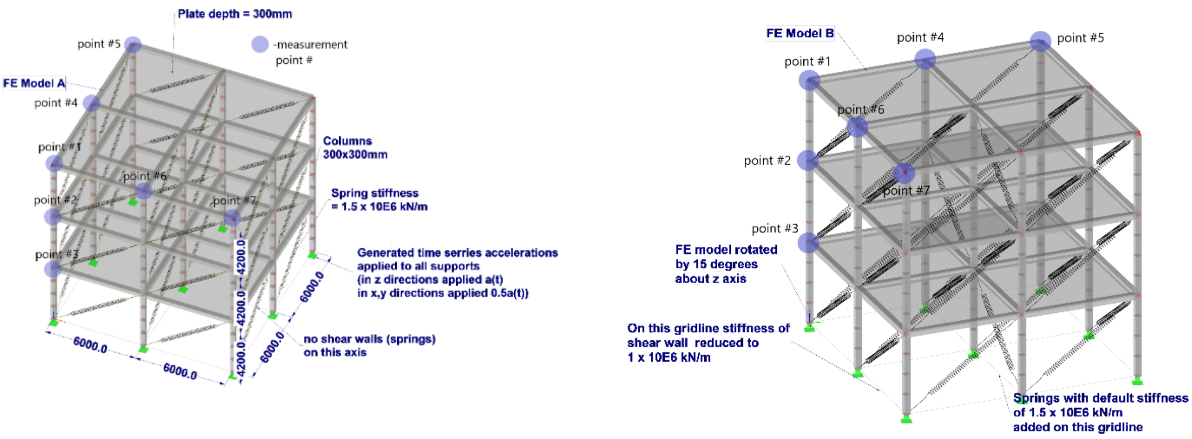

Figure 5. FE Models of buildings for the undamaged state with response measurement point notation (for model B highlighted only structural differences in the drawing).

Structural damage generally causes changes in structural parameters, and it affects the dynamic behaviour of the building. Deviation from the structure's original geometry and changes in element boundary conditions mostly affect the local/global stiffness of the structure. Therefore it introduces variations in natural frequencies of elements/structure. The deviations in material properties, such as cracks, may change all modal parameters: natural frequencies, mode shapes and damping. In this research, damage state assumed shear wall removal or shear wall stiffness reduction due to the new opening that does not cause changes in the damping parameter. All building models damping ratio is taken as 5 %. Introduced structural changes for Building #1 (FE Model A) and Building #2 (FE Model #B) is presented in Fig. 6.

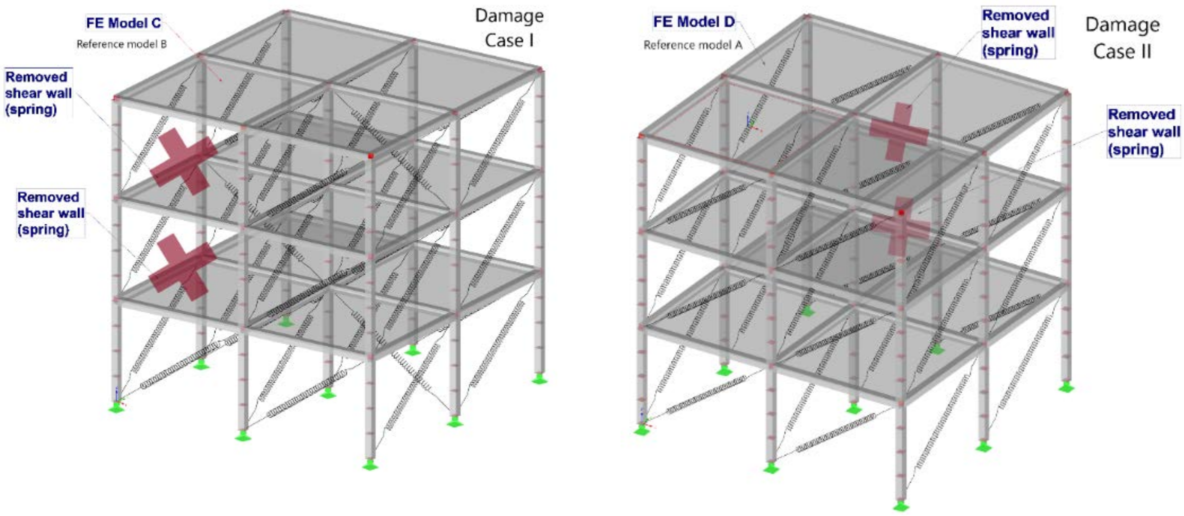

Figure 6. FE Models of buildings for damaged state (highlighted only introduced structural differences due to damage).

The difference between first natural frequencies (first transverse, first longitudinal and torsional) between both buildings is proposed as the damage identification feature vector from the frequency domain analysis:

$$\{\Delta f_i\} = \frac{\{f_{2i}\} - \{f_{1i}\}}{\{f_{2i}\}} \cdot 100\%, \tag{1}$$

Δf_i is natural frequency difference for mode shape i; f_{2i} is natural frequency of monitored building for mode shape i; f_{1i} is natural frequency of reference building for mode shape i.

As mentioned before, it is useful to have also a damage sensitive feature vector from the time-domain analysis. The output-only modal identification process's errors could be identified if the statistic parameters of the response signal are used as the damage-sensitive features. An example of such metrics is the temporal statistics of signals developed by Smallwood [28]. One of the temporal statics' metrics is temporal moment $m_n(t_s)$ of a time history $a(t)$ about a time location t_s and is defined as the square of a time history:

$$m_n(t_s) = \int_{-\infty}^{+\infty} (t - t_s)^n a(t)^2 \, dt, \; n = 0,1,2,3,..., \quad (2)$$

$a(t)$ is acceleration time series; t_s is reference time; n is order of the temporal moment.

As the zero-order temporal moment is independent of the time shift t_s and taking to account that all experimentally obtained data from sensors are discrete, the data equation (2) can be rewritten as:

$$m_0 = \sum_{i=1}^{k-1} \frac{\Delta t}{2} \left(a_j^2 + a_{j+1}^2 \right), \quad (3)$$

a_j is data point *j* in acceleration time series; Δt is time step in acceleration time series.

The square of the time history is used to avoid the problem of negative amplitudes, and this definition allows it to relate it with an energy E.

Ambient response time series are not unimodal, i.g., they have more than one maximum. Therefore, kurtosis obtained from 4th order central moment normalised by energy E is another potentially useful metrics. For further details, see reference [26]. Different mode shapes respond differently to the same structural change due to the discrepancies in generalised mass and generalised stiffness per mode shape. This property might also be utilised for damage detection purpose.

Linear modal analysis based on the structure's eigenvalues and mode shapes is used to decouple the system and obtain building response to simulated base excitation. It is appropriate because experimental research, e.g. [29], shows that buildings under ambient vibrations due to very small vibration amplitudes behave elastically.

3. Results and Discussion

Thirty data points are obtained for each of the building, which simulates 30 measurements during the year by recording acceleration time series with a sample rate of 100Hz under variable EOV, base excitation and two damage scenarios: Case I is damaged Building #2; Case II is damaged Building #1. Acceleration time series of transversal and longitudinal directions is obtained from seven points best-suited to represent the first translational, longitudinal, and torsional vibration modes. As these are results from simulations, no additional data processing is required. However, data detrending due to sensor inaccuracies, for example, sensitivity to temperature changes, should be performed in practice before the dynamic parameter identification process.

It is found that for a three-story shear wall building with three bays in each direction is possible to identify changes in wall stiffnesses due to the wall removal or implementation of openings by analysing first frequency (transverse, longitudinal and torsional) changes. The fusion of modal information from two buildings gives a clear advantage to filter out frequency variations due to environmental and operational conditions when properties of the soil only slightly modify modal frequencies of the building. The building could behave as a dependent unit against ground response as one rigid mass for the soft-soil condition [30]. Then method could be used for the identification of changes in the building support conditions.

Figure 7 represents the traditional way of showing the frequency changes where the negative effects of EOV can be easily identified. Similar graphs could be found in experimental works of other authors, e.g. Fig. 3 un [20] and Fig. 2 in [20]. Variations in natural frequencies of buildings due to these effects are presented in Table 2. In contrast, Fig. 8 has "flat" regions, and jumps occur only due to introduced building damage scenarios. Thus, variations due to EOV effects are successfully filtered out.

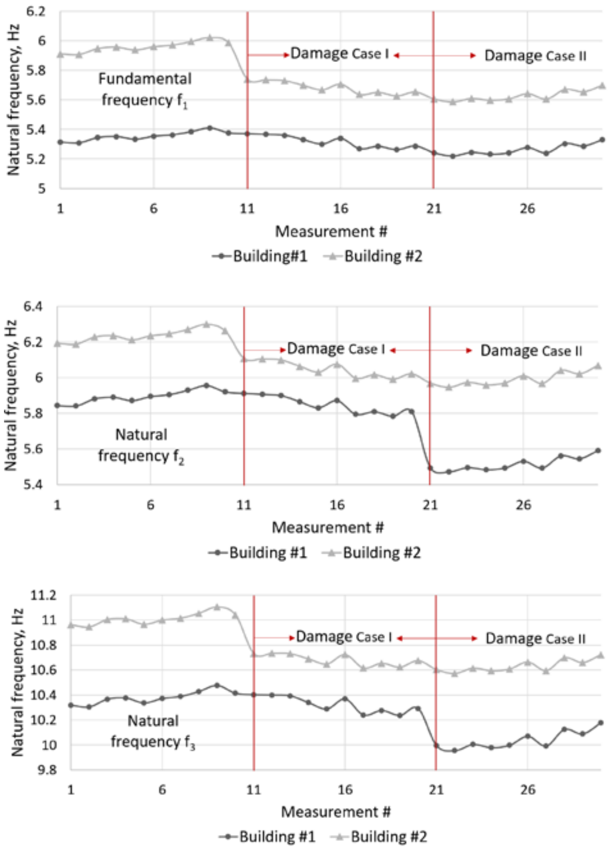

Figure 7. Building frequencies due to EOV and introduced damages.

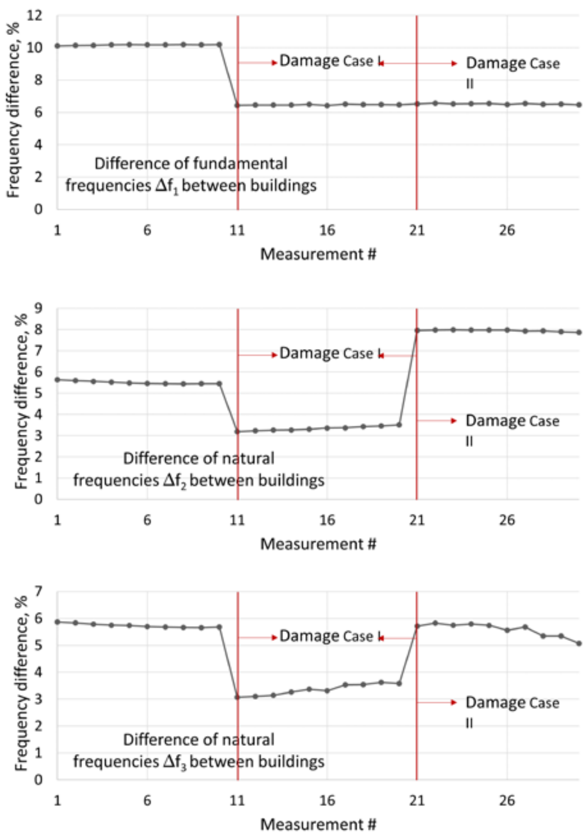

Figure 8. Building frequency difference plots due to EOV and introduced damages.

By exploring three frequency difference plots together, partial damage localisation might be done. For example, in damage Case II structural changes do not affect the first transverse frequency. Therefore, it follows that structural changes are not introduced in this direction. Potentially characteristic frequency jumps could be mapped for typical shear wall building structures, and machine learning algorithms applied for further damage localisation.

The required precision of dynamic parameter structural identification from the ambient response signal is dependent on the detection capability of a particular change point algorithm. This problem is not in the scope of the article but will be considered in further investigations.

Table 2. Natural frequency changes due to change in EOV simulation parameters.

Case		Frequency changes due to EOV $((f_{max} - f_{min})/f_{max})\cdot 100$ Transverse mode (f_1)	Longitudinal mode (f_2)	Torsional Mode (f_3)
Non damaged case (measurement # 1-10)	Building #1	1.85 %	1.93 %	1.63 %
	Building #2	1.89 %	1.78 %	1.44 %
Damage case I measurement # 11-20)	Building #1	2.01 %	2.18 %	1.60 %
	Building #2	1.97 %	1.92 %	1.10 %
Damage case II (measurement # 21-30)	Building #1	2.08 %	2.15 %	2.19 %
	Building #2	1.98 %	2.03 %	1.41 %

While performing result analysis, all variable and first mode frequency pairwise Pearson correlations were found. The main results are presented in Table 3. The results indicate that frequency domain damage sensitive feature i.g., mode frequency, are more sensitive to elastic modulus changes than mass changes.

Table 3. Correlations between 1st frequencies of buildings and EOV simulation parameters.

EOV parameter	Building #1 natural frequencies			Building #2 natural frequencies		
	Transv.	Long.	Torsion	Transv.	Long.	Torsion
Elastic modulus E	+0.905	+0.921	+0.854	+0.913	+0.896	+0.774
Material density, γ	–0.486	–0.450	–0.577	–0.536	–0.568	–0.738

Time-domain feature for cross-checking of damage identification is also explored, namely change of vibration energy amplitude (first temporal moment) at sensor locations that measures the overall building dynamic response strength. It is found that the first temporal moment (energy) of each measurement time series may represent the distinct dynamic behaviour of each building due to the variable excitation and EOV (see Fig. 9).

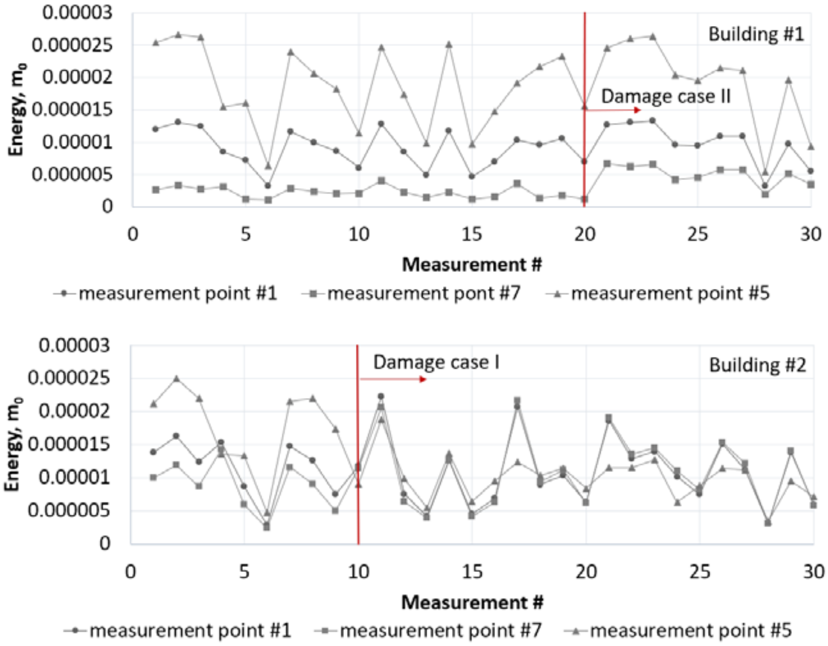

Figure 9. Energy changes due to variations of base excitation and EOV.

However, for damage detection, this is not an appropriate feature. Visually some disparities in energy difference for various damage situations might be spotted (see Fig. 10). Still, there is not simulated additional sensor self-noise in this research that could reduce the possibility of identifying damages from this feature.

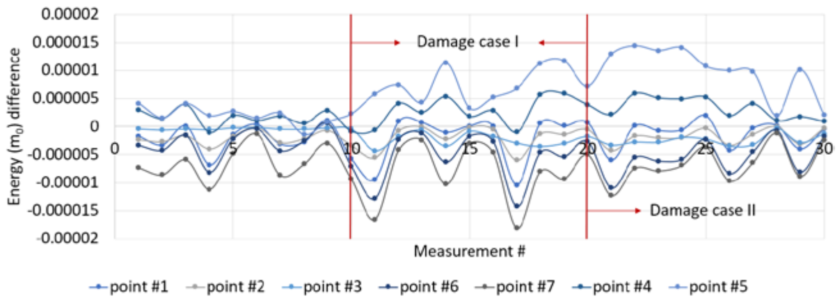

Figure 10. The energy difference between the response of buildings to the base excitation variations.

The steady linear growth in the cumulative sum plot (Fig. 11) of functions presented in Fig. 10 confirms that damage identification using pure statistics of time series is not feasible. For both buildings, variations of the base excitation spectrum have more impact on dynamic response than structural changes due to introduced damage scenarios.

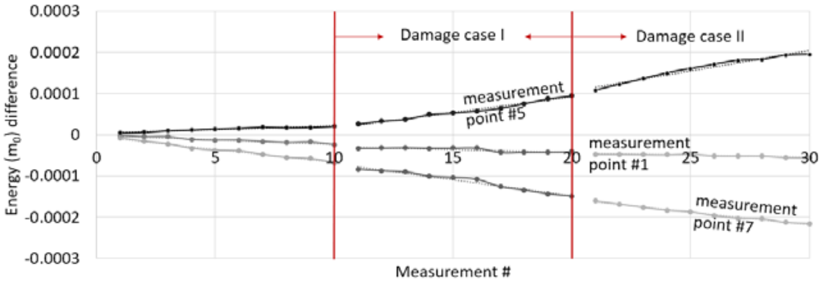

Figure 11. The energy difference between the response of buildings to the base excitation variations (cumulative sum plot).

4. Conclusion

This research proposed a new approach to reduce environmental noise in experimentally obtained vibration data and dynamic parameters by data fusion of dynamic response of two similar buildings under ambient vibration and variable operational and environmental conditions referred to as EOV's. Data fusion capabilities are investigated by using FEM simulations of two three-story shear wall buildings with very similar but not exact structural parameters or ambient excitation.

By utilising one of the buildings as a reference state instead of the same building, it is possible to identify shear wall removal or new opening implementation from the damage sensitive feature vector taken as natural frequency differences of both buildings. In this way, successfully filtered out natural frequency variations due to EOV effects, leaving the jumps in a data which cause is a damage introduction in one of the structures. Implementation of natural frequencies differences series for damage detection potentially significantly reduce training data required when machine learning analysis is used on data which is one of the distinctive advantages of this data fusion approach. Also, outliers from erroneous output-only modal identifications might be easily spotted, and different novelty detection algorithms can be applied for damage recognition.

The required accuracy of the dynamic parameter structural identification from ambient vibration testing depends on the effectiveness of the chosen change-point algorithm for the damage state detection. Investigation of the time-series data statistics showed that the approach is not effective for the time-domain analysis. Variations in base excitation signal influence more the dynamic response of building than structural changes due to introduced damage scenarios for medium-rise buildings.

The fusion of building dynamic response data from several buildings that share the same environmental and operational conditions give a clear advantage in reducing false alarm possibility during continuous and automated structural health monitoring process. Further full-scale experimental investigations are planned to assess the proposed approach's effectiveness for real structures in their operating environment.

5. Acknowledgement

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