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Model creation using SHM results for risk assessment in the subsequent rarthquakes

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ABSTRACT

Structural health monitoring (SHM) detects, localizes, and quantifies seismic damage, but does not provide tools to assess further damage and potential collapse in subsequent shocks. Models built from SHM results would enable these further analyses, and enhance decision-making. This paper presents an automated model creation method, converting proven hysteresis loop analysis (HLA) SHM results into nonlinear foundation models for immediate use. Accuracy, complexity, and automation are assessed using experimental data from a 3-storey full-scale structure tested at the E-Defence facility in Japan over 6 events. For all cases, the simplified nonlinear modelling method achieved a mean (5-95% Range) peak displacement error of 0.82 (0.17, 4.09)mm, and average cross correlation coefficient *Rcoeff*=0.82. The simplified modelling method captures essential dynamics very well given nonlinear HLA-identified stiffness changes as inputs, is readily automated, and is thus suitable for initial analysis on damage mitigation. This method extends proven SHM methods from a damage identification tool into readily automated application of its results for further decision-making, creating far greater utility for engineers.

1 INTRODUCTION

Structural health monitoring (SHM) provides methods to detect, localise, and quantify damage after major events, but does no more than deliver this result to experts to assess risk of further damage or collapse in subsequent shocks, as well as any need for immediate or longer-term reinforcement or repair. A computational model automatically created from the SHM results, and existing data would enable further analyses to enhance decision-making. However, model creation can be complex, time consuming, and

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require significant human input. Hence, automated or semi-automated means to turn SHM results into accurate computational models, and subsequent analyses, would provide significant benefit.

There is a wide range of SHM methods in the literature. Many model-based methods, such as adaptive least mean squares (LMS) and recursive LMS method (Chase et al., 2005a, Chase et al., 2005c, Nayyerloo et al., 2011, Chase et al., 2005b), extended Kalman filters (EKF) (Huang et al., 2010, Lei et al., 2015, Pan et al., 2016, Yang et al., 2006) and unscented Kalman filters (UKF) (Al-Hussein and Haldar, 2015, Wu and Smyth, 2008, Wu and Smyth, 2007, Xie and Feng, 2012), identify changes in structural stiffness of selected baseline model parameters to reflect the severity of seismic damage. However, there is a significant risk of a poor identification results when the chosen model used for SHM does not match the dynamics of the measured system response since the actual outcome is not fully known (Zhou et al., 2017c).

What is needed for automated structural model generation is a real-time method to accurately identify nonlinear changes in structural stiffness across individual or groups of stories to offer enough damage localization to create a useful computational model for further analysis. One method meeting these criteria is the model-free, mechanics-based hysteresis loop analysis (HLA) method (Xu et al., 2014, Zhou et al., 2015a, Zhou et al., 2015b, Zhou et al., 2017a). However, as a model-free method, it does not directly yield a model.

This study recreates the HLA identified changes in stiffness for a 3-storey apartment building subjected to 6 ground motion events on the E-Defense shake table in Japan (Zhou et al., 2017b). These identified stiffness trajectories are themselves automatically modelled, to create a nonlinear structural model post-event. Simulated ground motion results are compared to measured data for validation.

2 METHODS

2.1 Test Structure and E-Defense Shake Table Tests

A full-scale steel moment resisting frame (SMRF) test structure in Figure 1, where the left is analysed in this work. It has uniform story height of 2870mm and seismic weights of 171.85kN, 171.85kN and 90kN, respectively (Zhou et al., 2017b). Six earthquake excitations were sequentially applied in all three (x,y,z) directions, as listed in Table 1, at the E-Defense facility in Japan.

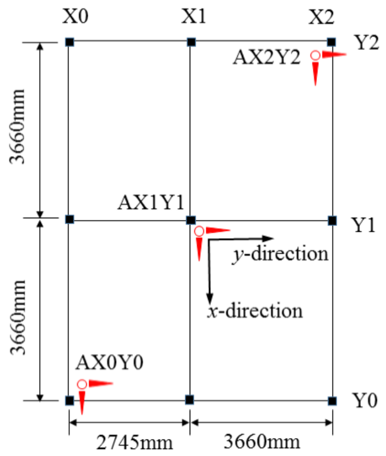

Figure 1: E-defence test structure (left) and plan dimensions showing accelerometer placement (right).

Table1: Sequential shake table tests and PGA in each direction (x,y,z).

Test No.	Input event	PGA(g)		
		y-direction	*x*-direction	Vertical *z*-direction
#01	BSL2-18%	0.11	0.13	0.01
#02	Sannomal	0.22	0.16	0.01
#03	Uemachi	0.30	0.35	0.01
#04	Toshin-Seibu	0.62	0.63	0.06
#05	Sannomal	0.21	0.15	0.01
#06	Nankai-Trough	0.87	0.74	0.03

2.2 Hysteresis Loop Analysis (HLA) and Overall Hypothesis

While the details of the HLA method are presented elsewhere (Xu et al., 2014, Zhou et al., 2015a, Zhou et al., 2015b, Zhou et al., 2017a), the overall approach in this work undertakes the following steps:

- Segregate half-cycles of measured response for each (measured) storey.
- Create force-displacement hysteresis loops using storey acceleration and motion for each storey's inter-storey motion using the known or estimated story mass.
- Assess up to 4 stiffness values for each of up to 4 segments in each half-cycle using a statistical test (Zhou et al., 2015a) to find the optimal number of segments.
- Track the trajectory of linear stiffness values (and changes) over time to assess damage, where nonlinear motion and deflection are also tracked and provide further assessments of damage.

The outcome is a time-varying linear story stiffness trajectory over the ground motion. Over multiple events, the final stiffness of one event is within 5% of the initial value of the next (Zhou et al., 2017b).

This research hypothesizes time-varying linear stiffness trajectory can be used to automatically create a simplified, nonlinear structural model. If valid, simulating this model would yield the same, or very similar, displacement response as the experimental test. This outcome would in turn validate the idea of using this model to rapidly evaluate immediate and longer-term safety and repair options.

2.3 Structural Model and Simulation

The equation of motion chosen for a simplified, readily automated model of this multi-degree-of-freedom inelastic structure subjected to earthquake excitation is defined:

$$Q\big(V(t)\big) = -MI\ddot{x}_g(t) - M\ddot{V}(t) - C(t)\dot{V}(t) \tag{1}$$

where $V(t), \dot{V}(t)$ and $\ddot{V}(t)$ are displacement, velocity and acceleration vectors, M is the constant mass matrix, and $C(t)$ is a Rayleigh damping matrix in this case. $Q\big(V(t)\big)$ is the nonlinear time-varying restoring force vector determined by the time-varying structural stiffness matrix $K(t)$ and loading-unloading path. Since the E-defence test structure is a three-story SMRF building the terms are defined:

$$M = \begin{bmatrix} m_1 & 0 & 0 \\ 0 & m_2 & 0 \\ 0 & 0 & m_3 \end{bmatrix} \tag{2}$$

$$C(t) = a_0 M + a_1 K(t) = \begin{bmatrix} C_{11} & C_{12} & 0 \\ C_{21} & C_{22} & C_{23} \\ 0 & C_{32} & C_{33} \end{bmatrix} \tag{3}$$

$$K(t) = \begin{bmatrix} K_1(t) + K_2(t) & -K_2(t) & 0 \\ -K_2(t) & K_2(t) + K_3(t) & -K_3(t) \\ 0 & -K_3(t) & K_3(t) \end{bmatrix} \tag{4}$$

$$Q(V(t)) = \begin{bmatrix} Q_1(t) \\ Q_2(t) \\ Q_3(t) \end{bmatrix} = \begin{bmatrix} f_1(t) - f_2(t) \\ f_2(t) - f_3(t) \\ f_3(t) \end{bmatrix} \tag{5}$$

$$\begin{aligned} f_1(t) &= Q_1(t) + Q_2(t) + Q_3(t) \\ f_2(t) &= Q_2(t) + Q_3(t) \\ f_3(t) &= Q_3(t) \end{aligned} \tag{6}$$

Where m_1, m_2 and $m_3$are the mas for the first, second and third story, respectively. $K_1(t), K_2(t)$ and $K_3(t)$ are the time-varying story stiffness values identified using HLA. Parameters a_0 and a_1 are mass-proportional and stiffness-proportional damping coefficients calculated to yield 5% damping for the first and third modes, respectively, using *M* and *K(t)*, yielding time-varying damping, *C(t)*. Finally, $f_1(t), f_2(t)$ and $f_3(t)$ are the net hysteretic restoring forces on each floor based on *f* = *K(t)*V(t)*, which thus define the elements of the vector, *Q*, or $Q_{1,2,3}(t)$ the nonlinear restoring forces for each storey.

Thus, the model structure is relatively quite simple, while containing potentially significant nonlinearity. Such a simple model is important, as initial decision-making will require an overall approach, and thus a detailed analysis may not be necessary or possible.

The next step is to turn identified trajectories of storey stiffness, *K*(*t*), in *x* and *y* directions into simplified functions of time for model simulation. Figure 2 shows the identified storey stiffness trajectories over all six events (Zhou et al., 2017b). Linear functions are used to simply and algorithmically convert Figures 2 into readily simulated *K(t)* functions for each storey, as a series of linear lines. Changes less than 5% are considered constant. Table 2 shows the number of segments used in each story and event.

Table 2: Linear approximation of stiffness evolution for all 6 events and both (x,y) directions.

Event.	***x*-direction**			***y*-direction**		
	1st story	**2nd story**	**3rd story**	**1st story**	**2nd story**	**3rd story**
#01	3	3	1	3	3	1
#02	3	3	3	3	3	1
#03	3	1	3	1	3	1
#04	4	4	4	4	4	4
#05	1	1	1	1	1	1
#06	4	4	4	4	4	4

2.4 Analyses and Evaluation

Simulations use Newmark-Beta and a 0.005 seconds time step matching the experimental sampling rate. All 6 events are simulated and compared to measured responses. Results assess accuracy of the simple model creation method and provide an overall validation of the stiffness values found by HLA. Two metrics compare simulated and measured response for all events (6), stories (3), directions (*x*, *y*):

- **Peak Absolute Displacement Error**: A metric associated with structural damage.
- **Correlation Coefficient (R_{coeff})**: A metric capturing whether the two displacement responses compared have the same specific shape over time. It is more rigorous than the typically used average absolute error.

These metrics assess the quality of the automatically created model, where a good match would validate the approach to generating models for further decision making from SHM results and the HLA method.

3 RESULTS AND DISCUSSION

Table 3 shows peak absolute errors for each event (#1-6), direction (*x*,*y*) and storey (1-3), where error estimating displacements from experimental accelerometer and other measurements is 0.5-1.0 mm (Xu et al., 2015). Table 4 shows the correlation coefficients for each event. Table 3 has median [75th percentile] absolute errors of 0.84 [1.99] mm. The median is within estimation error, where 21 of 36 are less than 1.0 mm and the 75th percentile is relatively small. The 90th percentile error is 2.96 mm. Thus, the overall peak response is captured well, although not perfectly.

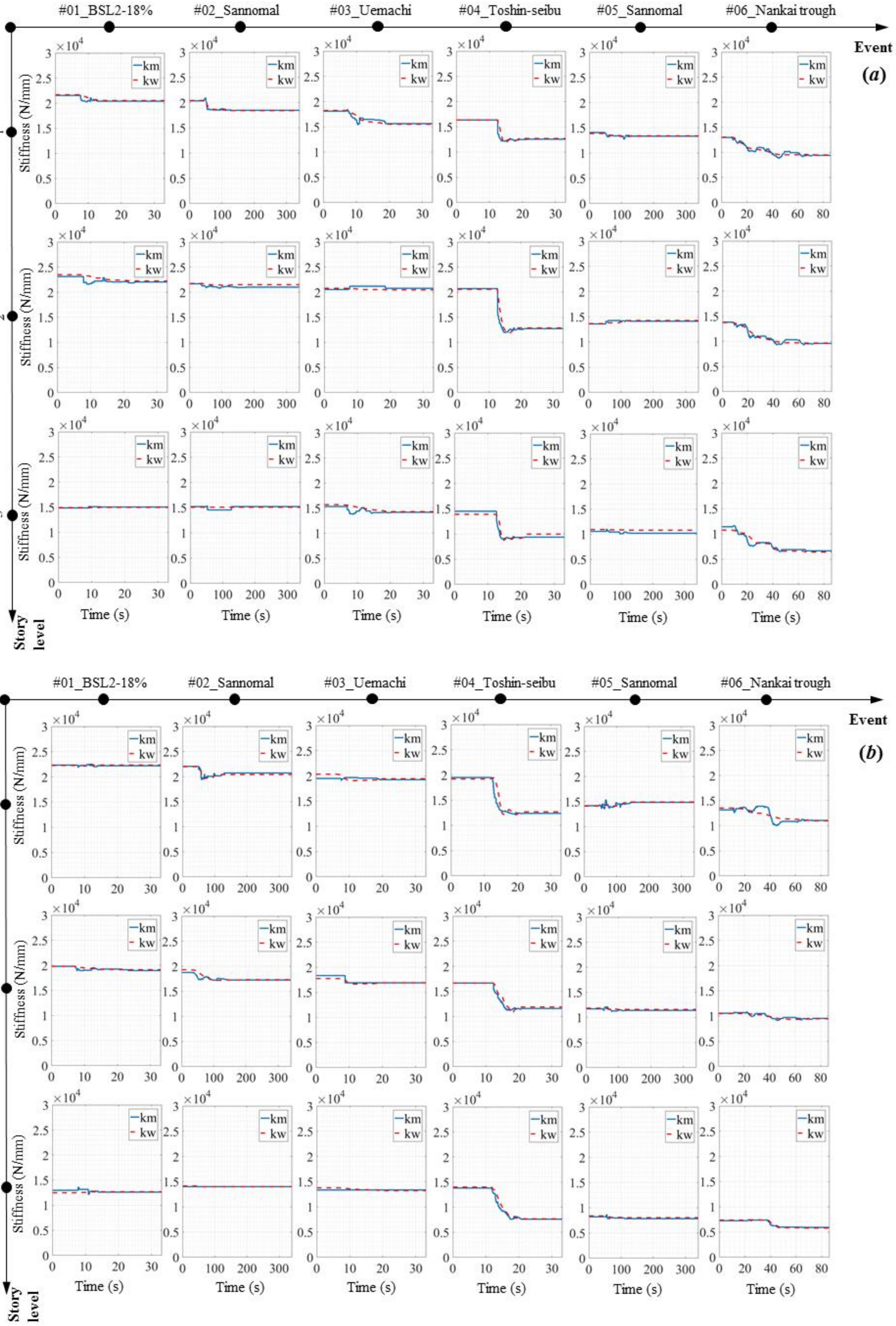

Figure 2: Identified evolution of effective elastic stiffness (ke) in: (a) x-direction; and (b) y-direction for all events. The solid line km is the moving average and the dashed line kw is smoothed (Zhou et al., 2017b).

Table 3: Peak absolute displacement error (mm) between simulated and measured response for all 3 storey's and all 6 events in both x and y directions.

Event.	***x*-direction**			***y*-direction**		
	1st story	**2nd story**	**3rd story**	**1st story**	**2nd story**	**3rd story**
#01	0.17	0.01	0.39	0.30	0.21	0.77
#02	0.84	0.46	0.67	0.70	0.15	0.19
#03	0.50	0.87	1.09	2.09	1.30	0.70
#04	2.96	3.96	2.32	6.27	2.34	4.49
#05	1.02	0.54	0.39	0.93	0.80	0.48
#06	2.58	2.96	3.82	1.19	1.99	0.43

Table 4: Correlation coefficients, Rcoeff, for all events, storeys and directions, and overall mean value.

Event.	***x*-direction**			***y*-direction**			***x & y***
	1st story	**2nd story**	**3rd story**	**1st story**	**2nd story**	**3rd story**	**Mean**
#01	0.89	0.86	0.85	0.93	0.91	0.87	0.89
#02	0.91	0.88	0.81	0.82	0.82	0.72	0.83
#03	0.82	0.77	0.77	0.62	0.60	0.72	0.72
#04	0.88	0.84	0.80	0.81	0.79	0.75	0.81
#05	0.89	0.86	0.79	0.86	0.86	0.79	0.84
#06	0.87	0.84	0.80	0.89	0.88	0.83	0.85

In all cases, modelled motion is a good match for the measured motion with correlation coefficients averaging 0.72-0.89 (0.82 overall) for all storeys, directions, and events. The third ground motion input is the worst with $R_{\mathrm{coeff}} = 0.71$, and eliminating it raises the average to 0.85. Qualitatively, the worst case for the third storey, and in general, is the *x*-direction for Event #6 where there are clear underestimations of motion, reflected in relatively lower $R_{\mathrm{coeff}} = 0.80$ in Table 4 and larger 3.82mm peak error in Table 3.

This relatively poorer result in the *x*-direction for Event #6 is offset by qualitatively very good results for the *y*-direction with higher $R_{\mathrm{coeff}} = 0.83$. This comparison shows there may be differences in the simplified model chosen and the actual structure, as should be expected. However, these differences are not enough to alter what are otherwise qualitatively good correlation results, where it is important to reiterate the correlation coefficient is a more rigorous test of accuracy than any single point or group of points comparison.

More specifically, using the correlation coefficient places value on the step-to-step shape of the response over time. It thus has lesser weight for peak values, which may also be important. Thus, this analysis uses Table 3 to provide a damage related metric of model fit and goodness. In turn, Table 4 and the correlation coefficient evaluates the model's overall quality in capturing dynamics. Together, they provide an overall view of the model's ability to represent the structure.

In further analysis, one could add additional nonlinearities for better future prediction. Equally, the linear damage approach is simple and provided good results. However, a more accurate or complex realisation of the time-varying stiffness in Figure 2 might have resulted in a more accurate outcome, where errors in peak displacement in Table 3 might have been lower with a more accurate representation of the change in stiffness due to damage. Again, there is a potential trade off and compromise amongst increasing complexity, increasing accuracy, and simplicity / automation. In this case, the results were considered "good enough".

Combining all these results shows the simplified modelling approach provides a good and functional model on which further mitigation or other analyses could be based. The method is very simple to create and could be readily automated. Hence, the outcome SHM result using the HLA method is not only damage and localisation, but can also include reasonable baseline dynamic models for further analysis and assessment.

4 CONCLUSIONS

This short paper presents a simplified model creation method for use with model-free structural health monitoring methods. The goal is to create accurate baseline models using data from SHM damage identification and localisation methods to create models suitable for further investigation and analysis on safety, damage mitigation, and thus re-occupancy. Such models would take SHM from being a tool for damage identification and extend them into further decision-making, creating far greater utility for engineers and owners, which could further spur impetus for investment in monitoring.

The specific method presented is validated against experimental data from the E-Defence facility in Japan for a 3-storey apartment structure subjected to six events and suffering significant damage in some but not all events. Comparison of model results to the experimental data shows qualitatively good matches for peak displacements and correlation coefficients, where the first metric assesses damage and design related outcomes, and the second assesses how well the overall structure dynamics are captured. In general, results were very good and demonstrate a good baseline model can be generated for immediate use and longer-term evaluation of structural outcomes and mitigation. A further main outcome is that a relatively simple model structure can capture significant nonlinear behaviour more accurately than might be expected, validating both the SHM results used as model inputs, as well as the overall approach to model generation.

The method is simple and generalizable. It can be readily extended to more complex models or other similar approaches using different modelling approaches depending on the sensor density and resolution of SHM results. Future work should also consider extending these methods to creating far more predictive, nonlinear models if possible, especially given the Christchurch series of earthquakes where major shocks were followed by almost equally large second shocks.

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