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PARAMETER IDENTIFICATION FOR FULL-SCALE SHAKING TABLE TEST OF 5-STORY WOODEN STRUCTURE

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ABSTRACT: All over the world, the movement for the mid- and high- rise wooden building has been activated to aim for sustainable society. To promote these activities, the dynamic behavior of such buildings should be cralifised and an analysis method for such building should be verified. In this study, we targeted the full-scale shaking table test of 5-story wooden structure and analytical study was conducted. But, it is difficult to conduct analysis accurately and verification is time-consuming. One of verification method of the analysis is parameter identification. At present, the paremeter identification has been applied to detailed analysis model for buildings. This needs a lot of time if the common identification method is used, so we applied the efficient parameter identification method using quality engineering and interpretable machine learning "SHAP". Adopted method is based on comprehensive parameter search using quality engineering and "SHAP" is useful for efficient parameter search to evaluate parameter influence. The identification results showed good agreement with experiental results.

KEYWORDS: Parameter identification, Interpretable machine learning, Full-scale shaking table test, Wooden building

1 – INTRODUCTION

To promote the movement to use timber, the expansion of the wooden building market has been accelerated. For example, Cross Laminated Timber (CLT) is focused as the material for mid- and high- rise wooden buildings recently and many reserches studies about them. In addition, Many shaking table tests were conducted on wooden buildings using various construction methods [1]. These tests clarified the seismic performance of the buildings and another objective is verification of numerical analysis. If an analysis method that agrees with the experiment and phenomenon, the seismic performance can be predicted without experiment and seismic design methods can be established. In this way, it necessary to verify analysis model and parameters to reproduce the experimental results. To promote wooden building market for mid- and high- building, it is important to verify analysis method for such building.

We established the parameter identification method using quality engineering and interpretable machine learning "SHAP" [2],[3]. Parameter identification is one of effective ways of validation for analytical models and input parameters.

Detailed analytical models for CLT buildings have been presented in Japanese CLT manual [4], and recently, simplified analytical models have been developed [5]. In order to conduct more accurate analysis for medium- and high-rise wooden buildings, it is necessary to verify the analytical model for medium- and high-rise wooden buildings with the experimental results.

In this study, we tried to identify the parameters of detailed analysis model by applying the parameter identification method using interpretable AI and orthogonal array to a full-scale shaking table test of a 5-story wooden building.

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2 – MEHOD

2.1 OUTLINE OF EXPERIMENT

The target experiment was a shaking table test of a five-story wooden building conducted in 2022 [6]. Figure 1 shows an overview of the test specimen. The building is a five-story structure with a total floor area of 439.5 m^2, floor plan dimensions of 8.19 m x 12.285 m for the first through fourth floors and 5.005 m x 12.285 m for the fifth floor, with a maximum height of 16.7 m.

In the test, the seismic waves shown in Table 1 were input in sequence with acceleration control in order to determine the seismic performance of the specimen during extreme earthquakes.

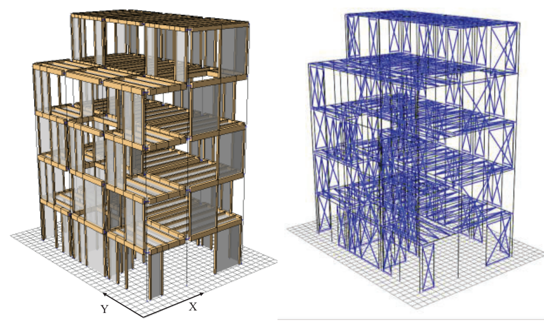
Figure 1. Over view of specimen.

Wave	PGA(gal)		
	X	Y	Z
Canogapark 100%	349 (EW)	412 (NS)	479 (UD)
Predicted Earthquake in Tokyo metropolitan area 100%	326 (NS)	400 (EW)	32 (UD)
BSL Y 100%	-	579	-
BSL X 100%	579	-	-
JMA Kobe 100%	617 (EW)	818 (NS)	332 (UD)
K-NET Ojiya 100%	1314 (NS)	1144 (EW)	820 (UD)

Table 2. PGA of input waves.

2.2 NUMERICAL ANALYSIS

The analysis model was constructed in numerical analysis software "wallstat" [7]. In "wallstat", detailed model is able to be constructed, and joints and walls are modelled as springs to reproduce member's behavior such as uplift deformation and shear deformation. Figure 2 shows the outline of analysis model. The walls were modeled with brace-substituted springs, and the column leg connections and beam end connections were modeled with tensile and rotational springs (Figure 3), and the restoring force characteristics were set based on the results of each element experiment. Floors were modeled as brace-substituted springs, as were the walls. Viscous damping was set at 2%, proportional to the instantaneous stiffness, and zero damping was set when the instantaneous stiffness was negative.



(a)Overview (b)Beam and truss elements

Figure 2. Analysis model.

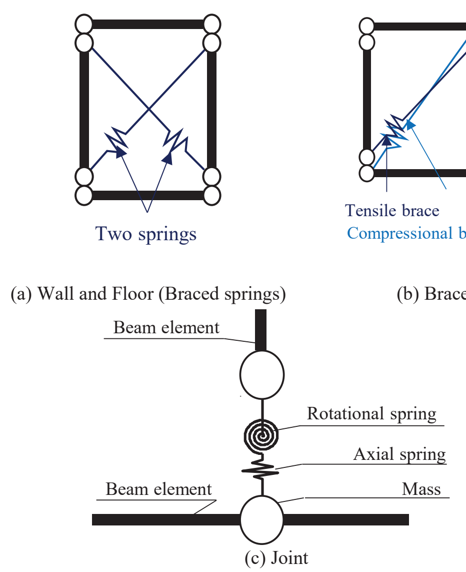


Figure 3. Details of elements.

2.3 PARAMETER IDENTIFICATION

To get opimal parameters to reproduce the experimental behavior, we adopted parameter identification method using orthogonal arrays and interpretable machine learning suggested by Tokikatsu Namba et al ([2],[3]) shown as fig. 4.

First, various input parameters are created (1. Definition of the parameters). These parameters are set for the backbone curves of the springs in the analysis model, and multiple analyses are conducted (2. Numerical analysis). The results of the multiple analyses are compared with the experiments, and the goodness of the results and analysis model will be verified. In addition, the correction factor range are analyzed. (3. Comparison). Then, the parameter ranges are narrowed down by reviewing the range using quality engineering and interpretable machine learning (4. Narrowing down the parameter range). Data assimilation was attempted by repeating these cycles multiple times. In addition, this method was verified by interpretable machine learning.

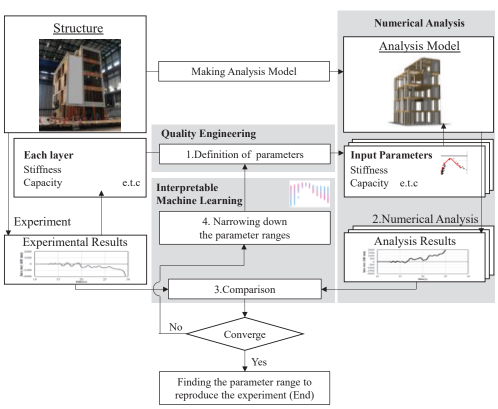
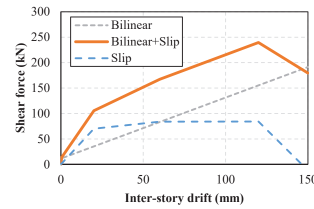


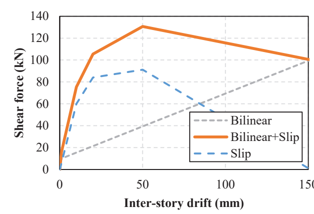
Figure 4. Outline of parameter identification [3].

Before identification, the parameters were defined based on the results of each element experiment (standard curve). The search range was set to be 0.5 to 2.0 times the stiffness and bearing capacity of the standard curve, which is a wide search range. 33 parameters were varied by 16 levels, and 512 combinations are planned. The orthogonal table allows 512 combinations of skeletal curves and history characteristics to be planned, and time history response analysis were conducted using JAXA's supercomputer [8].

The characteristic values of beam and column members, tension and compression springs, walls and floors are target parameters of identification. The characteristic values are based on the skeleton curve (e.g., Figure 4) determined from elemental tests of each element, and the characteristic values of the skeleton curve are multiplied by a correction factor.



(a) double-sided Plywood wall



(b) Lattice wall

Figure 5. Examples of backbone curve of wall (910mm x 910m).

Parameters of the tensile springs for the joints were fixed values, and they were defined based on measured datas in the shaking table tests. For other datas of tensile springs, which were not measured in the test, the parameters were target for identification and multiplied by a correction factor to vary the stiffness and capacity of the skeleton curve (T). The same applies to compression springs (C) and floors (F). The characteristic values of members such as columns and beams were varied by multiplying Young's modulus E, which was set according to the material grade of the member, by a correction factor. Walls are considered to be the most influential parameter in the results of the analysis, so a detailed combination of variations was created. Backbone curve of wall was defined as a bilinear + slip skeleton curve. The curve was varied up and down by multiplying the stiffness of the slip skeleton curve (K_s) by a correction factor, and the bilinear properties were planned by multiplying the initial stiffness (K_b1) and secondary stiffness (K_b2) by a correction factor to combine parameters.

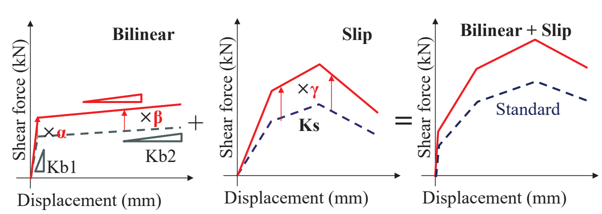


Figure 6. Backbone curve multiplised by correction factors.

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An overview is shown in Figure 6. The plywood single-sided wall, double-sided wall, lattice wall, and CLT wall used in the specimen were varied by multiplying correction factores in the x- and y-directions separately. The correction factors ranged from 0.5 to 2.0 and were equally divided into 16 levels. Since there were no elemental experiments on beam-column joint, the rotational spring was based on an elemental experiment on the rotational performance of holddown [7], and the elastic spring was set based on its initial stiffness (RK=61.5 kNm/rad). Since the original performance is unknown, a larger range of correction factors was also used, ranging from 0.5~10 times. During parameter identification, if the appropriate analytical model is not set up, the identified parameters will be unrealistic values. In the initial parameter identification, the rotational performance between the column and beam (strong axis: RX, weak axis: RY) and the wall foundation (Rbase) was not considered, and the difference between the experimental and analytical results did not decrease unless wall performance was increased. Therefore, it was decided to consider the rotational performance, and the initial stiffness RK (=61.5 kNm/rad) in the rotational performance element experiment of the holddown was set as the rotational performance between the column and beam (strong axis: RX, weak axis: RY) and the wall foundation (Rbase).

Focusing on the inter-story drift and uplift deformations of walls in the full-scale shake table tests, the difference between the analytical and experimental results were estimated for each story. Hideo Muroi et al. [9] compared some model validation criteria, but there a few studies about validation criteria. Based on the study, we adopted “index of agreement” as model validation criteria.

The difference between the analytical and experimental results was evaluated in terms of the difference in maximum values and the difference in time history response results. The difference of the maximum value is the difference between the experimental and analytical results of the maximum interlaminar deformation of each layer divided by the experimental result, and the smaller the value is, the smaller the difference between the analytical and experimental results is. The index of agreement [9] was calculated to evaluate the difference between the analytical and experimental results. The analytical results to be evaluated are the inter-story drift of all layers in 1-4 streets in the x-direction and 1-3 streets in the y-direction. index of agreement is defined by Equation (1).

$$d_j = 1 - \frac{\sum_{k=1}^{N} |y(k) - \hat{y}(k)|^j}{\sum_{k=1}^{N} (|y(k) - \bar{y}| + |\hat{y}(k) - \bar{y}|)^j} \qquad (1)$$

Where $y(k)$ is Experimental result in k, $\hat{y}(k)$ is analysis results in k, $\bar{y}$ is average value of experimental results. where j is an arbitrary positive integer, j = 1 is often used so j=1 is adopted in this study.

The maximum value is 1 and the minimum value is 0. The closer the maximum value is to 1, the smaller the difference between the analytical and experimental results is. Based on the calculation results for the final excitation, the parameter search range was narrowed down.

The factorial effect diagram in quality engineering was used to evaluate the analytical results in past studies (e.g., [2]). The diagram was used to identify input parameters that are sensitive to output parameters and to analyze the range of parameters that reduce the difference between experimental and analytical results. The authers tried to review the process using SHAP in ref[3] and the method was applied in this study.

First, to use SHAP, 512 analysis cases were learned by machine learning method Light Gradient Boosting Machine (LightGBM [10]). LightGBM is a powerful gradient boosting framework that is designed to be efficient, scalable, and easy to use. Kang et al. [11] presented a comprehensive comparison of 11 ML models. The results indicated that Gradient Boosting Method (GBM), Extreme gradient boosting (XGBoost), Random Forest (RF), and Decision Tree (DT) had a good accurate prediction compared with other ML method considered. Then, LightGBM method which is accelerated GBM method was applied in this study. 512 cases were learned by LightGBM method, after that, parameter study was conducted with SHAP. SHAP is often used as XAI, which is proposed to solve the long criticized black-box issue of ML models. SHAP is a collection of explainers based on a game theory approach that estimates Shapley values from an absolute average of the feature contributions over several simulations. Since the original ML model is complex, this approach uses additive feature importance measures based on a linear explanation model that is a linear combination of binary variables expressed by equation (2).

$$f(x) \approx g(\mathbf{z}') = \varphi_0 + \sum_{i=1}^{M} \varphi_i \mathbf{z}' \qquad \text{-(2)}$$

where $f(x)$ is the original model and x is the original input feature. The explanation model uses x' as a simplified input feature and links it with a mapping function $x = h_x(x')$, while local methods attempt to guarantee that $g(\boldsymbol{z}') \approx f(h_x(\boldsymbol{z}'))$ whenever $z' \approx x'$. The value φ_i is the Shapley value which is expressed by equation (3).

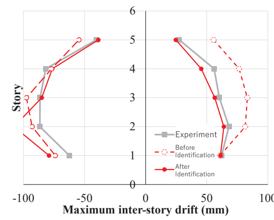
$$\varphi_i(f,x) = \sum_{z' \subseteq x'} \frac{|z'|!\,(M - |z'| - 1)!}{M!} \left(f_x(z') - f_x(z' \setminus i)\right) \quad \text{-(3)}$$

When three desirable properties (local accuracy, missingness, and consistency) are satisfied. $|z'|$ is the number of non-zero entries in z', and all z' vectors are a subset of x'. More information regarding SHAP can be found in S.M. Lundberg et al's study [12]. In this study, we used python library "SHAP" published in github [13].

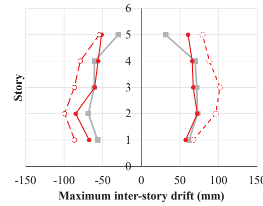
After the parameter identification, the analysis results showed good agreement with the experimental results. Detailed results are described in the conference. For more details on the parameter identification process, please refer to [2] and [3].

3 – IDENTIFICATION RESULTS

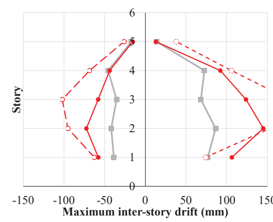
Figure 7 shows a comparison of the analytical results of the maximum inter-story drifts of all layers before and after parameter identification. Identified analysis shows the smallest difference in the time history response analysis results for K-NET Ojiya. From (a), the results for the JMA Kobe in X direction show that the initial analysis results overestimated deformation in all layers, while analysis after identification for layers 3 to 5 are in agreement with the experimental results. From (b), the maximum drift of layer 5 is overestimated during K-NET Ojiya, but the difference between the experimental and analytical results is small for the other layers. From (c), the maximum drift in Y direction is overestimated in 2 and 3 stories even after identification. The shape of the distribution of the maximum drift was close to the experimental results. Figure 8 also shows the analytical results of first story during K-NET Ojiya after parameter identification. From Figures 7(a) and 7(b), the load-deformation relationships in X and Y directions generally agreed with the experimental results. From the results of (c)-(d), it is confirmed that the drifts in each street are generally reproduced in the analysis. Similar results were obtained for the other layers, but some results overestimated the deformation.



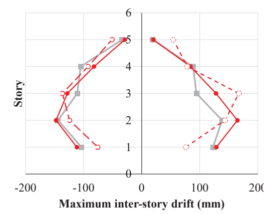
(a)JMA kobe 100% (X)



(b)K-NET Ojiya 100% (X)

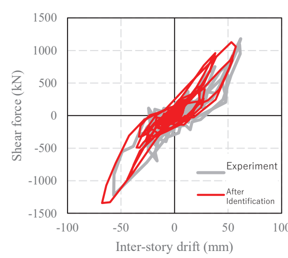


(c)JMA kobe 100% (Y)

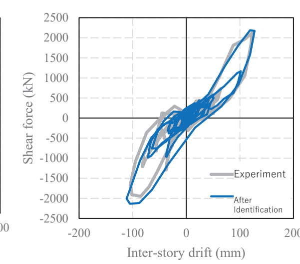


(d)K-NET Ojiya 100% (Y)

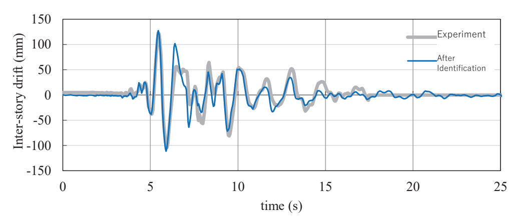
Figure 7. Maximum inter-story drifts of all layers.



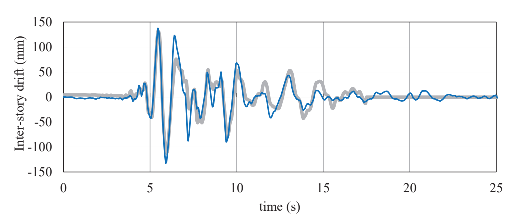
(a)X direction



(b)Y direction



(c)Y direction, street1



(d)Y direction, street2

Figure 7. Analysis results in first story.

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4 – CONCLUSION

Parameter identification using interpretable machine learning and orthogonal array for a detailed analysis model based on the results of shaking table tests of full-scale 5-story wooden structure.

After the parameter identification method, analysis results were in agreement with the experimental results, confirming the effectiveness of the parameter identification method using interpretable machine learning and orthongonal array in the detailed analysis model. On the other hand, the results of JMA Kobe excitation overestimated the drifts of 2- and 3-story, which is an issue to be addressed in the future.

By increasing the performance of some parameters, it was confirmed that the detailed analysis model could generally reproduce the experimental results. Quantitative analysis of the identification results will be the subject of future work. Although this report is limited to a full-scale shaking table test, it presents a method to review the analytical model and parameters through parameter identification based on the test.

5 – ACKNOWLEDGMENT

In the time-response analysis, we used the Japan Aerospace Exploration Agency supercomputer system "JSS3".

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