14th International Conference on Structural Safety and Reliability - ICOSSAR'25
1-6 June, 2025 - Los Angeles California, USA
R. Ghanem, E. Johnson, S. Masri and A. Olivier (Eds)

ACCURACY IMPROVEMENT OF DAMAGE CLASSIFIER FOR A WOODEN BUILDING USING LONG SHORT-TERM MEMORY WITH RESPONSE SURFACE METHOD

TOSHIAKIRA MAEDA[1], MASAYUKI KOHIYAMA[2] AND TAKUZO YAMASHITA[3]

[1] Graduate School of Science and Technology, Keio University

[2] Department of System Design Engineering, Faculty of Science and Technology, Keio University

[3] National Research Institute for Earth Science and Disaster Resilience

Key words: Wooden Building, Damage Classification, SHM, Neural Network.

1 INTRODUCTION

Japan is frequently affected by earthquakes, and numerous fatalities have occurred due to the collapse of residential buildings during past seismic events. Such collapses can be caused not only by the mainshock but may also by subsequent aftershocks. To mitigate damage from repeated seismic motions, it is crucial to promptly assess the risk of building collapse immediately after an earthquake. Recently, structural health monitoring (SHM) has attracted considerable attention as a method for rapidly and efficiently assessing the damage state of buildings. However, the current application of SHM is primarily limited to infrastructure such as bridges and tunnels, as well as large-scale buildings, and has not yet been implemented in ordinary residential houses. One of the main reasons for this is the high cost associated with expensive sensors.

To address the cost-related challenges, methods utilizing neural network (NN) have emerged as a promising alternative. By applying these techniques to SHM systems that predict the structural integrity of buildings based on seismic response data, it is possible to achieve high-accuracy damage detection with a reduced number of sensors, thereby contributing to cost reduction. This study focuses specifically on Long Short-Term Memory (LSTM) networks [1], a type of NN. LSTM networks are well-suited for learning long-term dependencies in time-series data, as they effectively address the vanishing (or exploding) gradient problem commonly encountered in recurrent neural networks (RNN), and are capable of retaining and utilizing long-term memory.

This study focuses on the method for determining hyperparameters that must be predefined by the user prior to training a neural network. In many previous studies, hyperparameter values have been selected based on convention rather than theoretical considerations. In this research, we propose a method for theoretically determining the optimal values of multiple hyperparameters by employing the response surface methodology (RSM) [2], which is a type of the design of experiments (DoE) technique.

RSM is a statistical approach that combines experimental design and regression modeling, and is commonly used to optimize responses and analyze system behavior when multiple factors are involved. By constructing a regression model based on data obtained through a planned set of experiments and analyzing the resulting response surface, it becomes possible to evaluate the interactions among factors and identify optimal solutions.

In this study, we adopt the central composite design (CCD) as the experimental design framework within RSM. CCD offers the advantage of effectively approximating a second-order response surface with fewer experimental trials compared to a full factorial design, due to its strategic placement of factor levels. A composite design integrates three components: a factorial or fractional factorial design to estimate main effects and interactions, an axial (or star) design to estimate curvature (second-order effects), and repeated trials at the center point to assess experimental error.

When modeling the relationship between the response variable y and three factors x_1, x_2, and x_3 using a second-order model, the general form of the response surface equation can be expressed as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{33} x_3^2 + \varepsilon \quad (1)$$

Here, β denotes the coefficients, and ε represents the error term. The unknown parameters $\beta_0, \beta_1, \beta_2, \beta_3, \beta_{12}$, and β_{13} can be estimated by conducting experiments based on a two-level factorial design involving three factors. To estimate the quadratic terms β_{11}, β_{22}, and β_{33}, experiments are conducted at axial points, where the level of a single factor is set to a constant value α or $-\alpha$, while the levels of all other factors are fixed at zero. These experimental points are referred to as axial points.

In addition to estimating the second-order terms, several experiments are also conducted at the center point, where all factor levels are set to zero—not only to aid in estimation but also to verify the adequacy of the model. An overview of CCD for three factors is illustrated in Figure 1. In this design, the axial points are placed along each axis, and when $\alpha = \sqrt{3}$, all design points (excluding replicates at the center) are equidistant from the origin.

The objective of this study is to establish a method for configuring hyperparameters that enhance the accuracy of damage classification by conducting experiments—namely, machine learning using LSTM based on CCD.

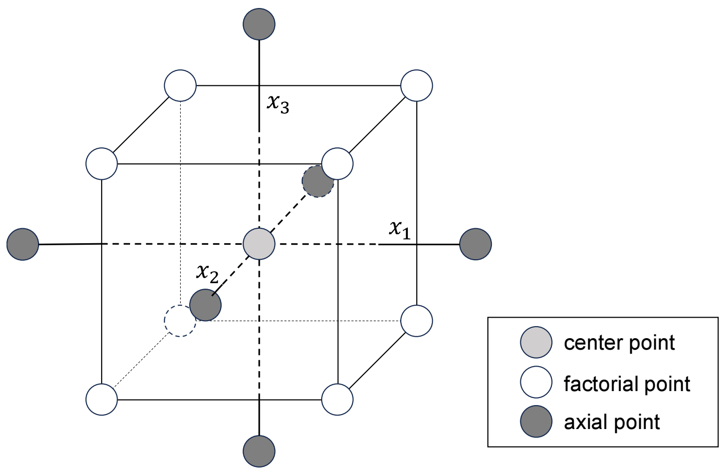


Figure 1: An overview of the CCD with three factors

2 PROPOSAL FOR HYPERPARAMETERIZATION OF DAMAGE CLASSIFIER

2.1 Overview of classification methods

Figure 2 presents a flowchart illustrating the proposed method for constructing a damage classifier using LSTM for wooden buildings. The proposed approach consists of two phases: seismic response analysis of a target building model and machine learning for the damage classifier. The seismic response analysis phase follows the method developed by Chiba et al. [3]. In this phase, a numerical model is constructed based on the architectural drawings of the target wooden structure. Structural parameters are assigned according to specified probability distributions to introduce variability in the structural characteristics of the model. Simulated seismic ground motions are then applied as input waves to the building model, and displacement response data are obtained through dynamic analysis. Subsequently, for the damaged building models, a government-specified seismic wave (hereafter referred to as the "notification wave") is applied to assess the residual performance. The notification wave is a synthetic ground motion used for design purposes and, in this study, corresponds to an extremely rare seismic event with an estimated return period of approximately 500 years, as specified in the Building Standard Law of Japan. The purpose of applying this input is to label the damage state of each building model as either "unsafe" or "safe." Here, "unsafe" refers to a condition in which the seismic performance of the structure has deteriorated to the extent that it is likely to collapse in future earthquakes. Following a previous study by Mizobuchi et al. [4] that used 1/30 rad as the safety limit for the story drift angle in wooden buildings, this study classifies models as unsafe if the maximum inter-story drift angle under the notification wave exceeds 1/30 rad.

In the machine learning phase, acceleration response data are first derived from the displacement response results obtained through seismic analysis, and multiple sets of input data are constructed. These sets are then labeled according to the residual performance of the corresponding models and used as a dataset for training the damage classifier. In order to optimize hyperparameters, RSM is employed, treating hyperparameters as factors and classification accuracy on validation data as the response. Finally, the performance of the trained classifier is evaluated using test data.

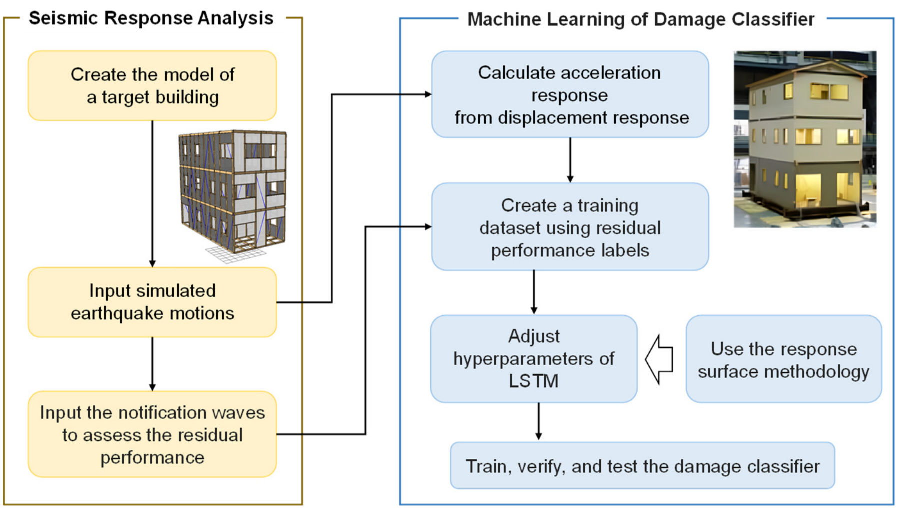


Figure 2: Flowchart of the proposed method

2.2 Generation of training data

(1) Extraction of response data

For the seismic response analysis of the building model described in Section 2.1, the wooden structure analysis software "*wallstat*" [5, 6] is utilized. This software enables the creation of a three-dimensional frame model of a wooden building, and by inputting seismic ground motions, it provides response data such as restoring force and displacement. Variability is introduced in the modeling process by assigning structural parameters. In this study, variations in the skeleton curves of walls and in the imposed loads are considered. The method for setting these variable structural parameters follows the approach developed by Chiba et al. [3].

Since *wallstat* does not directly provide acceleration response data, displacement response data are extracted instead. In addition, to assess residual performance, the maximum inter-story drift angle under the notification wave input is required; this value is computed from the displacement response data.

(2) Creation of a training dataset

Based on the displacement response data extracted in Section 2.2(1), a dataset is constructed for use in the machine learning of the damage classifier. Since the damage classifier takes acceleration responses as input, the displacement responses are first converted into acceleration responses using the central difference method, expressed by the following equation:

$$a_i = \frac{v_{i+1/2} - v_{i-1/2}}{\Delta t} = \frac{\frac{d_{i+1} - d_i}{\Delta t} - \frac{d_i - d_{i-1}}{\Delta t}}{\Delta t} = \frac{d_{i+1} - 2d_i + d_{i-1}}{\Delta t^2} \tag{2}$$

Here, a_i, v_i, and d_i represent the acceleration, velocity and displacement responses at time step i, respectively, and Δt denotes the time increment. Since the acceleration a_i is calculated using the displacement values at the preceding and succeeding time steps, d_{i+1} and d_{i-1}, acceleration data cannot be obtained for the time steps at both ends of the displacement data. Therefore, the number of acceleration data points is two fewer than that of the displacement data.

Next, the dataset is structured for training. Two key aspects in preparing input data for LSTM are the lookback size and the number of variables. The lookback size refers to the number of past time steps included in a single input. In this study, response data from the seismic analysis are obtained at a time increment of 0.01 s. Considering that the fundamental natural period of typical wooden buildings ranges from 0.1 to 0.5 s, the lookback size is set to 100. This means each input contains acceleration response data from the preceding one second. The number of variables refers to how many features are included in each time step. In this study, acceleration responses at both the first and second floors of the building model are used, resulting in two variables. Furthermore, due to the small time increment, the differences between adjacent time steps are minimal, leading to many similar input sequences and the risk of data bias. To mitigate this, a 'lag' is introduced to shift the starting index (time step) of each input sequence. Based on prior research, a lag of 10 was found to yield the highest classification accuracy, and thus this value is adopted in the present study. Figure 3 illustrates the concept of the training dataset when the lookback size is 100 and the lag is 10. In this configuration, each input sequence consists of 200 numerical values.

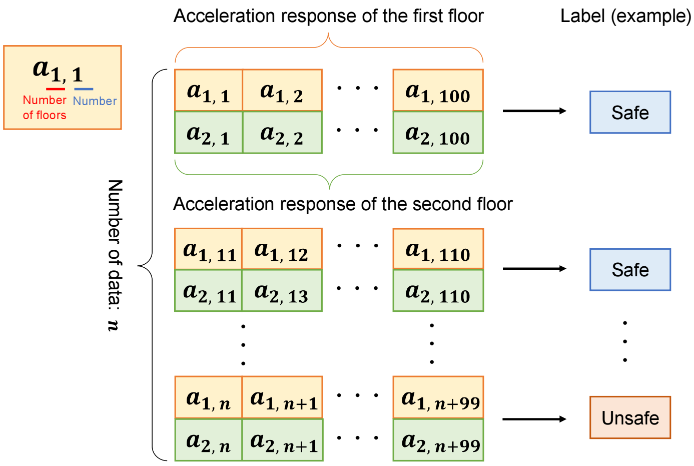
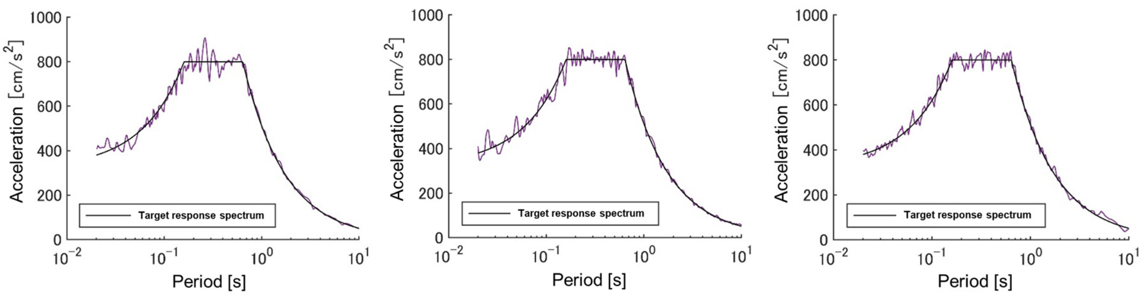


Figure 3: Conceptual diagram of the training dataset

(3) Labeling

As described in Section 2.1, the labeling of a building as either safe or unsafe is based on the maximum inter-story drift angle when the damaged model is subjected to a notification wave. For the notification waves, three types of phase characteristics are used: Kobe, Hachinohe, and random phases, all of which conform to the acceleration response spectrum specified in the 2000 Ministry of Construction Notification No. 1461 [7]. The acceleration response spectra for each waveform are shown in Figure 4.



(a) Kobe phase (b) Hachinohe phase (c) Random phase

Figure 4: Acceleration response spectra of the notification waves (damping ratio: 5%)

If the maximum inter-story drift angle at any of the four corner columns exceeds 1/30 rad when a notification wave is input, the model is labeled as “unsafe.” Conversely, if all maximum inter-story drift angles remain below 1/30 rad, the model is labeled as “safe.” In this study, the input ground motion is applied in a single direction, and the inter-story drift angle is also calculated based on the displacement in that same direction. After inputting the ground motion, all response data obtained from models labeled as safe are treated as safe data and labeled as 0. Similarly, all response data from models labeled as unsafe are treated as unsafe data and labeled as 1.

The threshold of 1/30 rad used for labeling corresponds to the level at which the risk of collapse in wooden structures significantly increases under seismic motion. Therefore, data obtained from models with drift angles near this threshold carry a high risk of misclassification and are not suitable for training data. In particular, if an unsafe building is misclassified as safe, users may not recognize the risk of collapse and may face fatal consequences. On the other hand, a misclassification of a safe model as unsafe does not pose a life-threatening risk. To address this, a stricter criterion is applied only to safe models, as expressed in the following equation. Let γ_i ($i = 1, 2, 3,$ and 4) denote the maximum inter-story drift angle (absolute value) at each of the four corner columns. Then, the classification of models as safe or unsafe for practical application is given by the following:

$$\begin{aligned} &\textbf{Safe model:} && \max(\gamma_1, \gamma_2, \gamma_3, \gamma_4) < (1/30) \times 0.9 \text{ rad} \\ &\textbf{Unsafe model:} && \max(\gamma_1, \gamma_2, \gamma_3, \gamma_4) \geq (1/30) \text{ rad} \end{aligned} \quad (3)$$

Only the data that meet the specified criteria are selected and used for training.

2.3 Construction of damage classifier using LSTM

Figure 5 shows the architecture of the damage classifier used in this study. The LSTM is implemented using Keras, a library included in TensorFlow 2.10.0 [8], a machine learning framework developed by Google. The damage classifier consists of a single LSTM layer followed by two fully connected (dense) layers. The values in parentheses next to each dense layer in Figure 5 indicate the output dimension of that layer. The input to the classifier is the dataset preprocessed according to the procedure described in Subsection 2.2 (2), which is first fed into the LSTM layer.

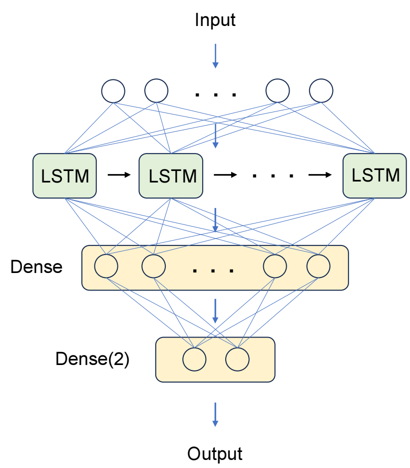


Figure 5: Architecture of the damage classifier using LSTM

To improve generalization and suppress overfitting, a dropout is applied to the dense layer after the LSTM layer with a dropout rate of 0.3—i.e., 30% of the outputs from the LSTM layer are randomly deactivated. Subsequently, the data pass through two dense layers. The output of the final layer consists of two values: 0 indicating safe data and 1 indicating unsafe data. The first dense layer uses the rectified linear unit (ReLU) activation function. The second dense layer has two nodes, corresponding to the number of output classes, and uses the softmax activation function.

For parameter optimization, this study employs the cross-entropy loss function and adopts adaptive moment estimation (Adam), one of the most widely used optimization algorithms.

This study focuses on how to determine the hyperparameters that must be set before training the damage classifier. As mentioned in the introduction, RSM is used to determine the hyperparameters. The hyperparameters considered are: (1) the number of LSTM units, (2) the number of nodes in the first dense layer, and (3) the learning rate. To prevent overfitting, the training data are divided into training and validation sets, and cross-validation is performed. During the split, the data are randomly shuffled to ensure that no bias is introduced between the training and validation sets.

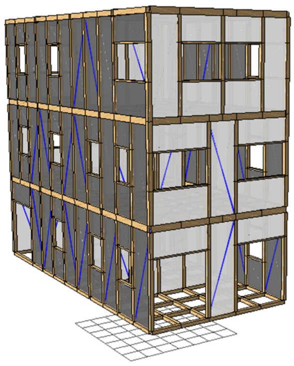
3 PERFORMANCE EVALUATION OF THE PROPSED METHOD

3.1 Outline of target building

In this study, we use experimental data from Specimen 4 of the project titled "*Experimental Verification of the Design Method for Three-Story Wooden Frame Structures*" [9], which is available in the "ASEBI" database published by the National Research Institute for Earth Science and Disaster Resilience (NIED). The specimen is a three-story wooden post-and-beam structure with slate tile roofing and fiber cement siding as exterior cladding. The total floor area is 136.65 m², and each floor has an area of 45.55 m².

The building was designed to meet Seismic Grade 1 under Japan's Housing Performance Indication System. As it was constructed for a shaking table test, it has no foundation and is mounted on an H-steel frame fixed to the shaking table. For model creation and analysis, we use *wallstat* ver. 5.1.10.0. Figures 6 show the overall view of the full-scale test specimen used in the experiment and the analytical model created with *wallstat*, respectively.

(a) Overall view of the full-scale test specimen [9]



(b) Analytical model

Figure 6: Target building

To evaluate the residual performance, the inter-story drift angle θ is calculated using the following equation, based on the displacements δ_1 and δ_2 at the first and second floor levels of the corner columns. Here, H denotes the story height, which is H = 2.8 m for the test specimen used in this study.

$$\theta = |\delta_2 - \delta_1| \, / \, H \tag{4}$$

3.2 Load setting

The weight of the target building is modeled as a lumped mass system, with the mass weights before introducing variability—i.e., the weights used in the analytical model—denoted as w_1, w_2, and w_3 from the bottom story upward. These values are set to 103.1 kN, 104.3 kN, and 61.2 kN, respectively, corresponding to the applied loads for Specimen 4 in the referenced experiment. The fixed loads d_1 and d_2 are also set to the same values used in the experiment: 50.76 kN and 50.14 kN, respectively.

3.3 Details of seismic waves

The input ground motions used in this study consist of 1,000 non-pulse-like and 1,000 pulse-like simulated earthquake motions, generated using the method described in Mizobuchi et al. [4]. In this method, as illustrated in Figure 7, pulse-like ground motions are created by superimposing a velocity pulse component onto a non-pulse-like velocity waveform. The magnitude of each simulated ground motion is determined based on the moment magnitude M_w and the source-to-site distance R. By adjusting these two parameters, the level of structural damage to the target building can be controlled. Following the approach of Mizobuchi et al. [4], the parameters are uniformly distributed within the ranges $6.5 \leq M_w \leq 8.5$, $0.5\ \text{km} \leq R \leq 16\ \text{km}$ in this study.

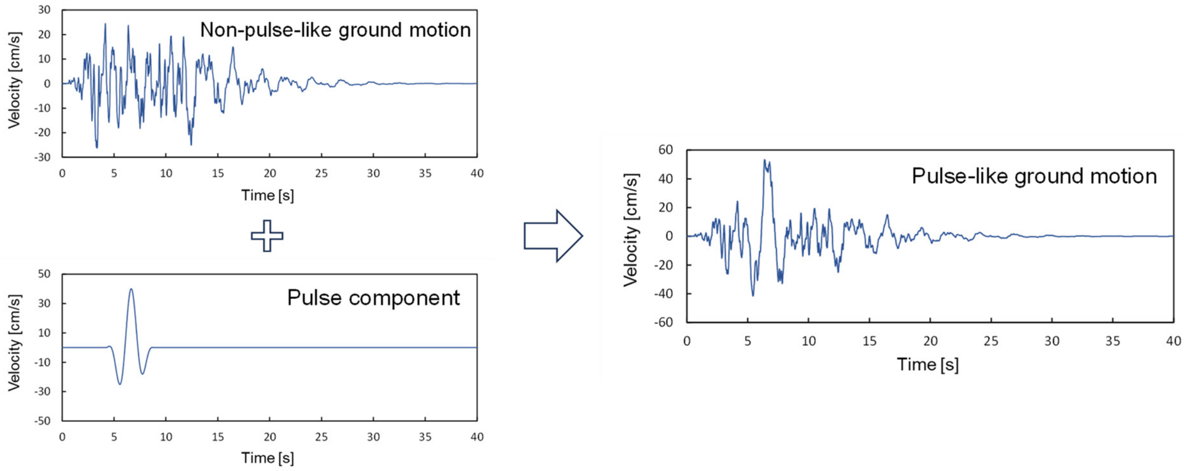


Figure 7: Method for generating pulse-like simulated ground motions

To test the performance of the trained damage classifier, seismic ground motion records are used as input. The classification accuracy is evaluated using two records observed by NIED, as listed in Table 1. Figure 8 shows the acceleration response spectra for these two records.

Table 1: Seismic ground motion records to test the damage classifier

Earthquake name	Date	Magnitude	Observation point	Component	Pulse
The largest aftershock of the Tokachi-Oki earthquake	9/26/2003	7.1	K-NET Urakawa	NS	Included
Kumamoto earthquake	4/16/2016	7.3	KiK-net Mashiki	EW	None

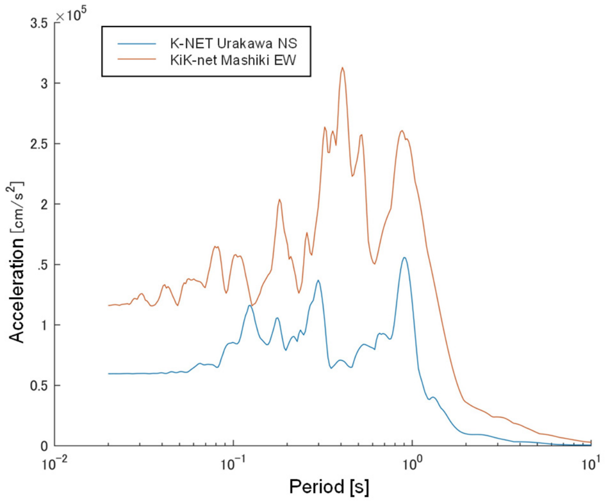


Figure 8: Acceleration response spectra of the records (damping ratio: 5%)

To generate models with various levels of damage, the input records are scaled by different amplitude factors. The scaling factors are determined using the same method as in Chiba et al. [3]. As with the training data, the test data are preprocessed, labeled, and selected according to the procedure described in Section 2.2.

3.4 Performance test results

(1) Evaluation index

The performance of the damage classifier on the test data is evaluated using accuracy, which is calculated based on the confusion matrix shown in Table 2.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FN + FP} \tag{5}$$

Table 2: Confusion matrix (Considering unsafe as positive)

		Damage classification result	
		Safe	Unsafe
True value	Safe	True negative (TN)	False positive (FP)
	Unsafe	False negative (FN)	True positive (TP)

(2) Hyperparameter setting using RSM

As described in Section 2.1, RSM is used to determine the hyperparameters. The three factors considered are: (1) the number of LSTM units x_1, (2) the number of nodes in the first dense layer x_2, and (3) the learning rate x_3. The response variable is the accuracy on the validation data obtained after training the classifier with simulated earthquake ground motions. To ensure high fitting accuracy of the response surface, CCD is employed for DoE. The lower, middle, and upper levels of the three hyperparameters are set as shown in Table 3.

Table 3: Range of hyperparameters

Hyperparameter	Lower level	Middle level	Upper level
Number of LSTM units	64	128	256
Number of nodes in the first dense layer	8	16	32
Learning rate	0.0001	0.001	0.01

CCD with two levels is employed, and the normalized values of each factor are presented in Table 4. In this design, the axial point value is set to $\sqrt{3} \approx 1.732$, as there are three factors. The number of replicates at the center point is set to four, a commonly used value in practice due to the absence of a statistically definitive guideline [2]. The normalized values in Table 4 are then converted into actual factor values.

For the three hyperparameters considered in this study, it is appropriate to express their values in exponential form. Therefore, normalization is performed based on the exponents at the midpoint values, and the upper, middle, and lower levels are determined by adjusting the values on a logarithmic scale. Following the hyperparameter ranges shown in Table 3, DoE is constructed as presented in Table 5 in which also lists the corresponding accuracies.

Table 4: Normalized factor values

Number of experiment	x_1	x_2	x_3
1	−1	−1	−1
2	1	−1	−1
3	−1	1	−1
4	1	1	−1
5	−1	−1	1
6	1	−1	1
7	−1	1	1
8	1	1	1
9	−1.732	0	0
10	1.732	0	0
11	0	−1.732	0
12	0	1.732	0
13	0	0	−1.732
14	0	0	1.732
15	0	0	0
16	0	0	0
17	0	0	0
18	0	0	0

Table 5: Details of DoE and corresponding accuracies

Number of experiment	x_1	x_2	x_3	Accuracy [%]
1	64	8	0.0001	97.57
2	256	8	0.0001	98.68
3	64	32	0.0001	97.63
4	256	32	0.0001	98.57
5	64	8	0.01	97.34
6	256	8	0.01	91.35
7	64	32	0.01	96.83
8	256	32	0.01	86.98
9	38	16	0.001	97.74
10	425	16	0.001	99.48
11	128	5	0.001	99.09
12	128	53	0.001	99.05
13	128	16	0.0000185	97.11
14	128	16	0.0540	54.87
15	128	16	0.001	99.03
16	128	16	0.001	99.10
17	128	16	0.001	99.13
18	128	16	0.001	98.97

From the results in Table 5, a second-order polynomial was fitted with the least squares method to create the response surface. The combination of hyperparameters that maximized the response is shown in Table 6. At this point, the maximum response predicted that the accuracy on the validation data was 98.48%. Subsequently, the damage classification using test data is performed with the hyperparameters listed in Table 6.

Table 6: Optimal hyperparameter combination estimated by RSM

Number of LSTM units	Number of nodes in the first dense layer	Learning rate	Accuracy
128	16	0.0001	98.48%

(3) Damage identification using test data

Damage classification is performed using the test data described in Section 3.3. The results are shown in Table 7. Furthermore, the test data are divided into two groups by ground motion, and the classification results for each corresponding group are presented in Table 8.

Table 7: Confusion matrix and accuracy (K-NET Urakawa and KiK-net Mashiki waves)

		Damage classification result	
		Safe	Unsafe
True value	Safe	6713	545
	Unsafe	71	5468
Accuracy		95.19%	

Table 8: Confusion matrix and accuracy for each wave

(a) K-NET Urakawa wave

		Damage classification result	
		Safe	Unsafe
True value	Safe	3694	126
	Unsafe	29	2836
Accuracy		97.68%	

(b) KiK-net Mashiki wave

		Damage classification result	
		Safe	Unsafe
True value	Safe	3019	419
	Unsafe	42	2632
Accuracy		92.46%	

As shown in Table 8, the method achieves high accuracy for both non-pulse-like and pulse-like ground motions. Additionally, because the misclassification rate for unsafe data is low, the proposed damage classifier effectively reduces the risk of users overlooking the possibility of building collapse, demonstrating its high practical value.

4 CONCLUSIONS

This study proposed introducing RSM to construct a damage classifier based on LSTM using acceleration responses as input data, with the aim of improving the accuracy of structural health monitoring systems through the theoretical determination of hyperparameters. The optimal combination of hyperparameters was explored through experimental design and fitting to the response surface, and the classification accuracy was verified using test data. By utilizing RSM to estimate the optimal hyperparameters (the number of LSTM units, number of nodes in the first dense layer, and learning rate), this study presented a method to theoretically enhance the classification accuracy of the damage classifier. The classification accuracy of the damage classifier on test data using the K-NET Urakawa NS component wave from the 2003 Tokachi-Oki earthquake and the KiK-net Mashiki EW component wave from the 2016 Kumamoto earthquake was 95.19%.

Future challenges include the development of a damage classifier that uses acceleration responses obtained from layers other than the first and second floors considering scenarios where maximum deformation occurs in multiple layers and verification of the effectiveness of the proposed method when applied to different target buildings.

REFERENCES

[1] Hochreiter, S. and Schmidhuber, J. Long short-term memory. *Neural Computation*. (1997) **9**(8):1735–1780.

[2] Myers, R.H., Montgomery, D.C. and Anderson-Cook, C.M. *Response Surface Methodology: Process and product optimization using designed experiments*, 4th ed., Wiley, (2016).

[3] Chiba, S., Kohiyama, M. and Yamashita, T.: Damage classification method for a wooden building based on hysteresis loop using CNN. *J. Jpn. Assoc. Earthq. Eng.* (2025) **25**(6) (in press, in Japanese).

[4] Mizobuchi, R., Kohiyama, M. and Yamashita, T. Improvement of damage classifier accuracy for wooden buildings considering pulse-type earthquakes, *J. Jpn. Assoc. Earthq. Eng.* (2025) **25**(4):97–108 (in Japanese).

[5] Nakagawa, T. Development of collapse analysis method for wooden frame houses under large earthquake ground motions, *Building Research Data* (2010) No. 128 (in Japanese).

[6] Nakagawa, T., Ohta, M., Tsuchimoto, T. and Kawai, N. Collapsing process simulations of timber structures under dynamic loading III: Numerical simulations of the real size wooden houses, *J. Wood Sci.* (2010) **56**(4):284–292.

[7] National Institute for Land and Infrastructure Management and Building Research Institute: *2020nenban Kenchikubutsu no Kouzou Kankei Gijutsu Kijun Kaisetsusho* (Commentary on the Structural Standards of Buildings, Year 2020 Edition), Official Gazette Co-operation of Japan (2020) (in Japanese).

[8] Martin Abadi, et.al.: TensorFlow: Large-scale machine learning on heterogeneous systems (2015) https://www.tensorflow.org/ (Accessed: 14 January 2024).

[9] National Research Institute for Earth Science and Disaster Resilience. Experiment on the Design method verification of a three-story wooden frame construction, *E-Defense Experiment Data Archive (ASEBI)* (2010) https://doi.org/10.17598/nied.0020 (Accessed: 31 January 2025).