Chapter 9
Incorporating Uncertainty in Mechanics-Based Synthetic Data Generation for Deep Learning–Based Structural Monitoring

M. Cheraghzade and M. Roohi

Abstract This chapter presents a hybrid deep-learning methodology for seismic structural monitoring, damage detection, and localization of instrumented buildings. The proposed methodology develops mechanics-based structural models to generate sample response datasets by accounting for the uncertainty of model parameters that can highly affect the estimation of baseline model nonlinear responses. The mechanics-based models are developed considering uncertainties in the stiffness, strength, and geometry of the baseline numerical model's characteristics and elements. The baseline model is run multiple times with defined assumptions and variations in the selected parameters of the model. The uncertainty of model parameters is evaluated through the design of experiments methodology by employing the central composite design for sampling. A parameter effect analysis is used to assess the significance of the modeling input parameters on the selected structural output response, such as inter-story drifts. The generated sample response dataset is utilized for training a hybrid data-driven model for feature extraction. To select the damage-sensitive features, a convolutional neural network as the main feature extraction body of the network is used. In addition, wavelet packet–based nodal first temporal moments (energies) are also employed to boost the feature extraction power of the network as a complementary body. This data-driven model is designed to use global story-level noise-contaminated response measurements are employed as input for the data-driven model to perform damage detection and localization in a manner consistent with performance-based design criteria. The performance of the proposed methodology is studied in the context of numerical and experimental case studies developed based on the shake table testing of a concentrically braced frame subject to various input ground motion intensities at the E-Defense facility in Miki, Japan. The results show that the proposed methodology provides high accuracy in classifying and localizing various damage patterns.

Keywords Seismic monitoring · Deep learning · Model-based uncertainty · Wavelet packet transform · Central composite design

9.1 Introduction

Structural integrity and risk assessment of civil infrastructure assist decision-makers in the prior, during, and following extreme damaging events with maintenance, resource allocation, and planning. Risk and resilience assessment methodologies (such as FEMA P-58) and platforms [such as Interdependent Networked Community Resilience Modeling Environment (IN-CORE)] quantify physical damage, functionality, and consequences using probabilistic component and system-level fragility and vulnerability functions [1, 2]. On the other hand, structural monitoring systems provide near-real-time data and measurements (such as conventional vibration data and visual inspection data), which can be incorporated into structural integrity assessment procedures to improve the accuracy of physical damage assessment decision-making. Therefore, the accurate estimation of damage states as a critical element in loss estimation can be reliably achieved by adopting monitoring systems and methodologies.

The development of more feasible and practical SHM approaches will be enabled by recent advances in computational and big-data analytics methods, as well as low-cost sensors for data acquisition. Various vibrational methods for civil

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infrastructure have been proposed in the past two decades, including methods based on models, methods based on model-data fusion, and methods based on data [3–5]. Recent SHM initiatives have concentrated on creating data-driven (model-free) techniques that use machine learning algorithms such as deep learning (DL) to extract damage-sensitive characteristics exclusively from measured data that are hand-crafted or automated. Notably, practical uses of the DL approaches are seen in a variety of seismic monitoring projects. An image classifier model is used to quickly assess post-earthquake damage to structures by using convolutional neural network (CNN) deep models with transformed wavelet data as inputs [6]. Based on various evaluation matrices, the DL methods are used to predict structural and earthquake features used in performance-based and seismic design [7]. The estimate of responses and the computation of various structures have been the subject of substantial numerical and empirical models in previous years. With the aid of deep models for seismic monitoring, a time-series predictor is suggested to reconstruct the responses of nonlinear structural models [8]. Researchers have developed deep models to identify unknown damage patterns that can detect damage and stiffness loss with excellent generalization ability. For example, an application of CNN for detecting damage caused by unknown seismic excitations is conducted using wavelet-based transmissibility [9].

In the context of earthquake engineering and structural damage assessment, numerous studies have focused on the uncertainties of finite element (FE) models and damage localization models. Using a response surface, Monte Carlo sampling has been used to assess probabilistic collapse risk assessments and predict structural responses [10]. There is, however, a greater need to pay attention to variation and uncertainty in FE models since model-based uncertainty affects the evaluation of engineering demand parameters (i.e., inter-story drift) needed to perform collapse risk assessments more than other uncertainty sources. A comparison of the distribution functions of intact and damaged structures was used to evaluate the uncertainty of FE models for damage assessment using modal data such as frequencies and shapes [11]. FE model-based uncertainty has also been used for damage assessment using a comprehensive set of non-probabilistic methods, such as response surface models [12]. Existing literature that explores the significant influence of model-based uncertainty assessment does not sufficiently address the notable impact of model-based uncertainty assessment integrated with data-driven methods. As discussed previously, it is imperative to develop DL algorithms that can capture the FE modeling error and provide an accurate estimate of the structural damage.

This chapter presents a DL-based structural monitoring methodology that incorporates model-based sample generation with consideration of uncertainties in the process of data-driven monitoring. The performance of data-driven algorithms for structural monitoring is highly dependent on the availability and accuracy of training data, which is difficult to obtain from real-world structures due to the extensive instrumentation of various structures being impractical (primarily due to budget and maintenance constraints) and the low probability of high-consequence events like earthquakes. The performance of data-driven methods can be considerably enhanced by using robust numerical techniques that consider model-based uncertainty. As a result, the main objectives of this research are summarized as follows:

- Accounting for the uncertainty of model parameters that can highly affect the accuracy of dynamic response estimation and complimentary sample generation estimation using the baseline nonlinear structural model, which are developed based on highly idealized engineering assumptions which might not accurately represent the physical aspects of the actual structures and lead to various levels of modeling error
- Augmenting real-world measurements with simulated physics-based measurements to improve the robustness and accuracy of data-driven seismic monitoring

The experimental validation of the proposed approach demonstrates its capability and effectiveness in helping structural engineers make informed and swift decisions regarding post-earthquake assessment of critical instrumented building structures and improving earthquake resiliency of communities.

9.2 Methodology

In accordance with performance-based design objectives, this section proposes a hybrid DL-based approach for post-earthquake damage identification and localization of instrumented structures. The approach divides damage quantification into five steps, as shown in Fig. 9.1. By taking parameter uncertainty into account, mechanics-based structural models are first created in the first two steps. Each model is then examined while being subjected to a variety of ground movements, producing and augmenting a sample response dataset in the third step. The sample response datasets will then be used in the fourth and fifth steps to train a hybrid data-driven model for damage identification and localization utilizing global story-level

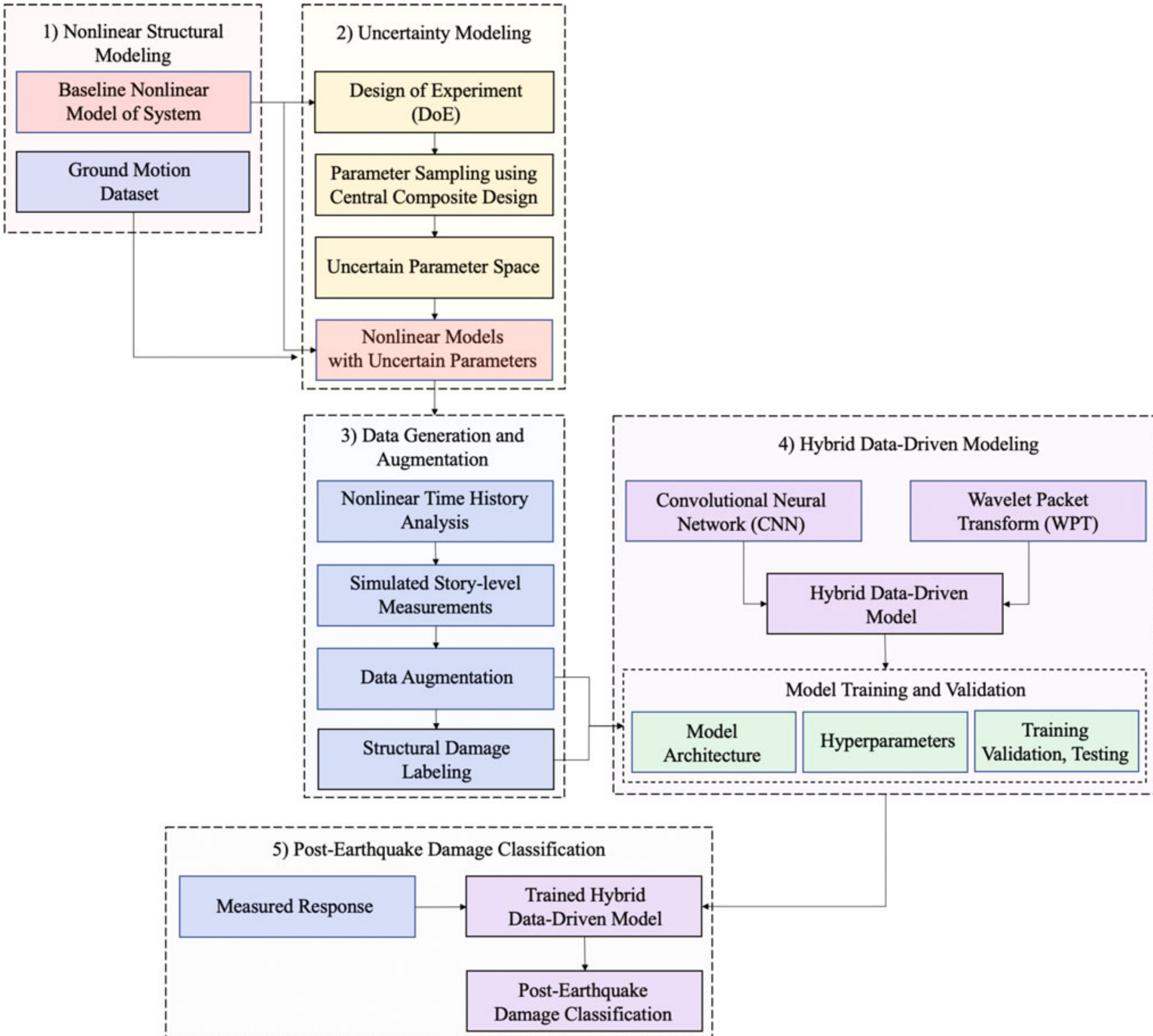

Fig. 9.1 Proposed methodology for deep learning–based structural monitoring

noise-contaminated response measurements. This research employs accelerometers as the preferred sensor because of their widespread usage, long lifespan, and dependability. It then applies a hybrid DL model for damage estimation based on code-based seismic performance levels to the recorded story-level acceleration responses. Interested readers are directed to [17] regarding further details about the proposed methodology and its application validated through numerical and experimental case studies.

9.2.1 Structural Modeling

The simulation of the nonlinear structural models and sample generation is the first step in putting the proposed methodology into practice. From the initial stages of damage to total collapse, the nonlinear structural models can effectively simulate all key modes of deformation and degradation in the structure. It is, therefore, important that these models encompass local and global inelastic behavior as well as the structure's actual behavior.

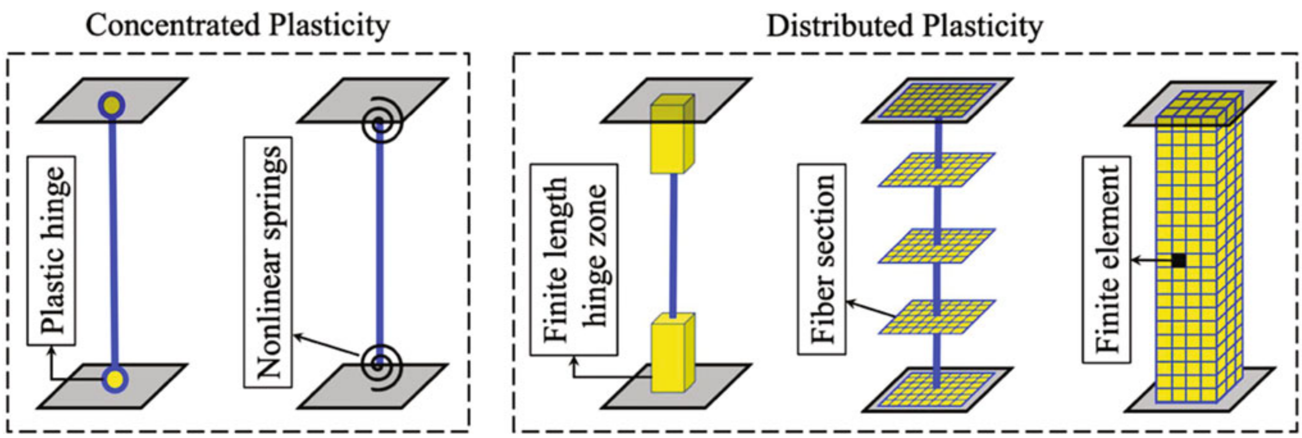

Fig. 9.2 Idealized nonlinear models for simulation of various structural elements. (Adopted from [13])

The modeling of non-linearity can generally be classified into concentrated and distributed plasticity. The concentrated plasticity models involve plastic hinge and nonlinear spring hinge models. On the other hand, the distributed plasticity models are also categorized as finite length hinges, fiber section, and finite element continuum models [13]. Figure 9.2 shows a comparison of five idealized model types for simulating the inelastic response of the structural frame. It is recommended to simulate nonlinear structural behavior using advanced structural modeling software (such as OpenSees [16]) that provides a wide range of nonlinear simulation material and element models, solution algorithms, data processing procedures, and distributed computing approaches.

9.2.2 Uncertainty Assessment and Data Augmentation

Several uncertainties can be considered, including those in the simulation models, measurements, or damage detection models. Specifically, this study focuses on assessing the uncertainty of baseline numerical model parameters, such as strength, stiffness, and geometry, which can strongly influence the simulated responses that are used for training data-driven models.

It is normal for modeling parameter values to vary from their intended values. It is important for the classification of post-earthquake damage to examine the randomness brought by these variations. The central composite design (CCD) sampling technique is used in this work to assess the consequences of modeling uncertainty using the criteria of design of experiments (DOEs) techniques. CCD contains a fractional factorial design $2k$ with ± 1 levels; $2k$ axial points with $\pm\alpha$ star points and n_0 center points. Different types of CCDs are proposed based on the value of α, namely, rotatable, spherical, face-centered, and practical. As a result of selecting α and n_0, the CCD is characterized by certain desirable properties. For rotatable designs, the α factor is calculated in Eq. (9.1).

$$\alpha = \frac{2^{k-f}\left(n_f\right)_{\frac{1}{4}}}{n_s} \tag{9.1}$$

where n_f is the number of replicates of rows in the original factorial design, n_s is the number of replicates at the axial points, f is the fractional factorial, and k is the number of parameters. Mechanic-based models are developed based on the variation of variables (i.e., modeling parameters such as f_y) within the DOEs criteria. Experimental and statistical studies can determine the amount of variation in baseline values. In other words, various samples for the baseline values should be statistically evaluated to determine the amount of mean, variance, and statistical distribution of the variables. Moreover, the CCD method determines the variation of parameters in each test which allows for the augmentation of data for various structural responses conducted in each sampling with different sets of modeling parameters. Additionally, the generated data are split into same-length sub-fragments of the raw samples, as shown in Fig. 9.3, as another approach for data augmentation.

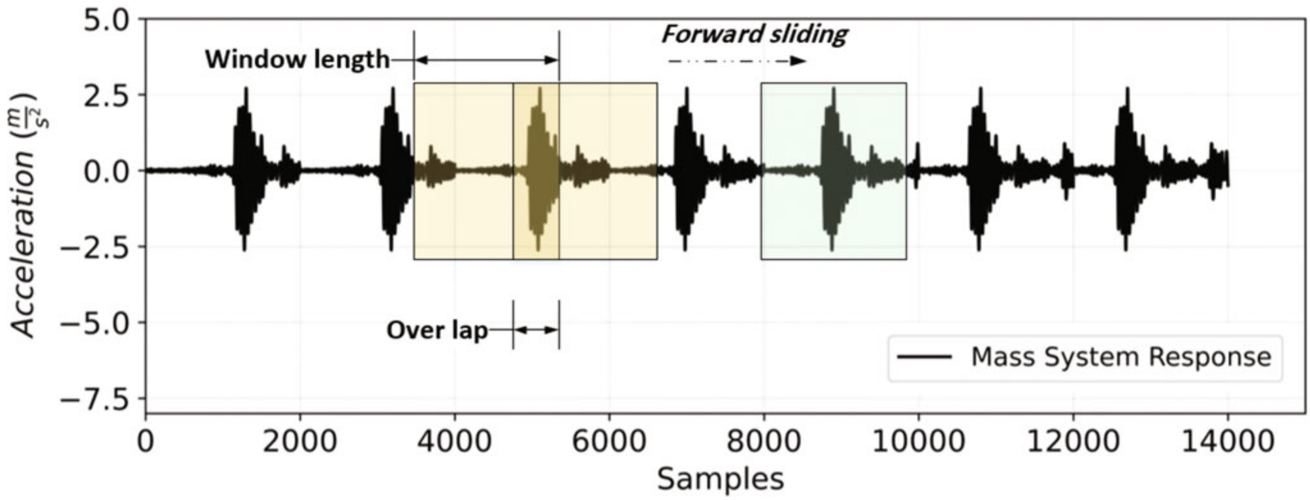

Fig. 9.3 Sliding window strategy for data augmentation on generating samples

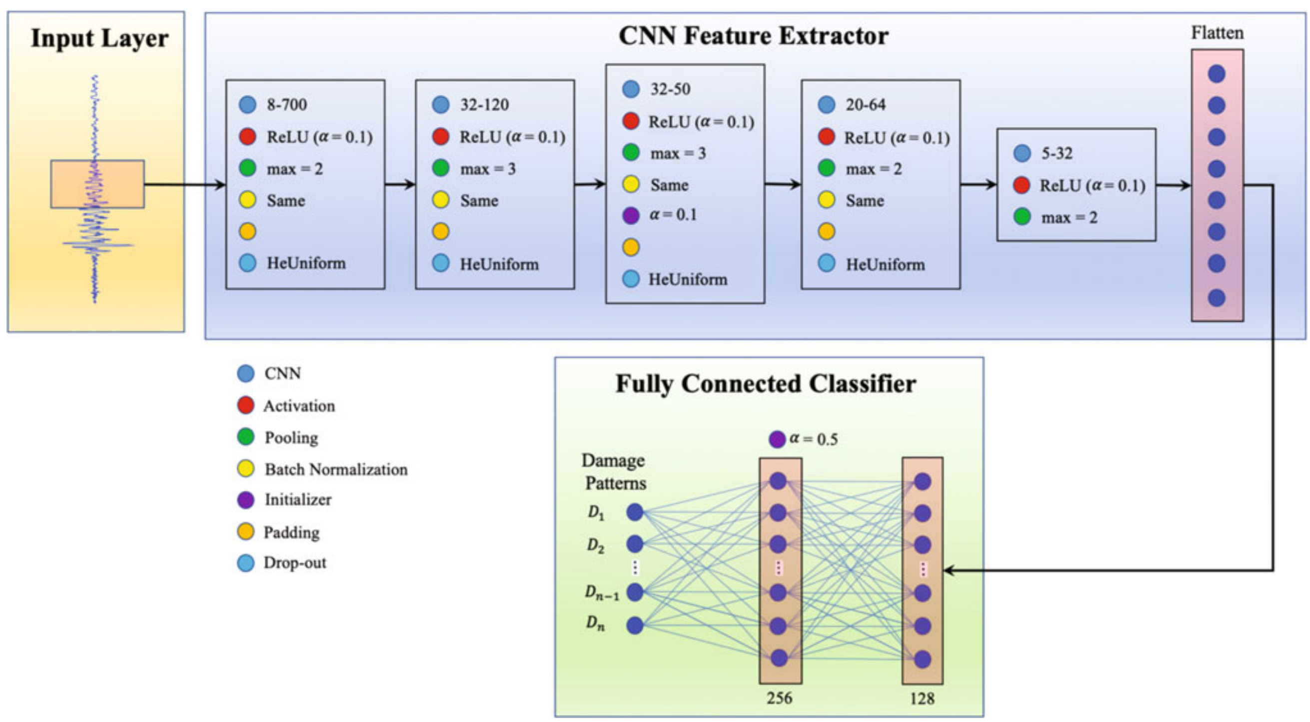

Fig. 9.4 Proposed CNN architecture for damage state classification

9.2.3 Damage State Classification

For reliable feature extraction, a hybrid classifier composed of a CNN and a wavelet packet transform (WPT) is suggested in this study. The last flattened layer of the CNN model and the WPT nodal energies are combined in the hybrid model to feed the fully connected classifier, as shown in Fig. 9.4. In order to improve classification outcomes, retrieved features from the CNN and WPT modules are employed as numerous inputs for the fully connected layers. In comparison to a CNN model, it is anticipated that the hybrid model will require fewer training iterations, making network convergence simpler.

CNNs are the commonly used type of deep neural network for automatic pattern recognition (i.e., mapped feature extraction). These networks use learnable units called kernels or filters for abstracting detail extraction in vector or grid form through the convolution procedure as element-wise multiplications. The mathematical operation of convolution is a well-known and regularly used function defined in Eq. (9.2).

$$f(i) = \int_{-\infty}^{+\infty} x(n)k(i-n)\, d_n \tag{9.2}$$

The filter function k slides over the input data x element-by-element through different convolutional layers, and the results are added up. Interested readers are referred to [17] for further detail regarding the background theories of CNN and other associated algorithms.

In order to assess the architecture of the suggested model, many hyperparameters need to be tested. To do this, many factors, including the CNN network's learning rate and the number of layers, are assessed via sensitivity try-and-error analysis. With hyperparameters chosen at random, nearly 40 networks are built. An Intel i7-10750H CPU, 16GB of RAM, and Nvidia GeForce RTX 2060 graphics cards are used for the numerical calculations, which are performed simultaneously.

9.3 Case Study of Experimental Concentrically Braced Frame

9.3.1 Experimental and Numerical Modeling

A full-scale single-story chevron concentrically braced frame (CBF) structure, as shown in Fig. 9.5, was used as a test case in this section to demonstrate the effectiveness of the proposed damage assessment methodology. This study utilizes seismic test data, such as acceleration responses, despite the fact that the structure was also exposed to other monotonic loads. For mass system and shake table acceleration response measurements, eight accelerometers with sample rates of 1000 samples per second (i.e., 1000 Hz) are used with four sensors on the shake table and four sensors on the mass system. For the 12%, 14%, 2 × 28%, 42%, and 70% amplification levels, respectively, the acceleration response data of the East-West component of the JR Takatori seismic motion are measured and accessible. For further information on the shaking table testing of the case study framework, the readers are directed to [14].

The experimental responses from the shaking table test are used to validate the numerical modeling for further data generation for DL model training and validation. The shaking table model's numerical CBF specimen with a single-story, single-span configuration is created first, as shown in Fig. 9.6. The model is developed using the OpenSeesPy python library of the open system for earthquake engineering simulation (OpenSees [16]). The validation results for various structural

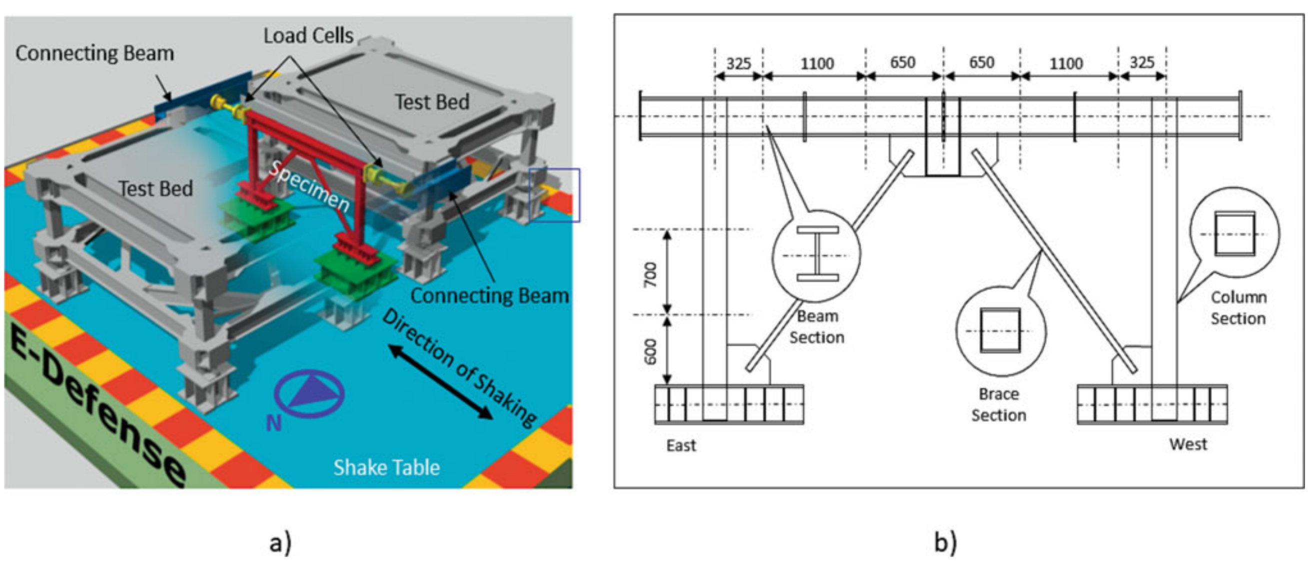

Fig. 9.5 (**a**) Schematic figure of the shake table test bed; (**b**) Schematic figure of the frame geometry (Adapted from [14])

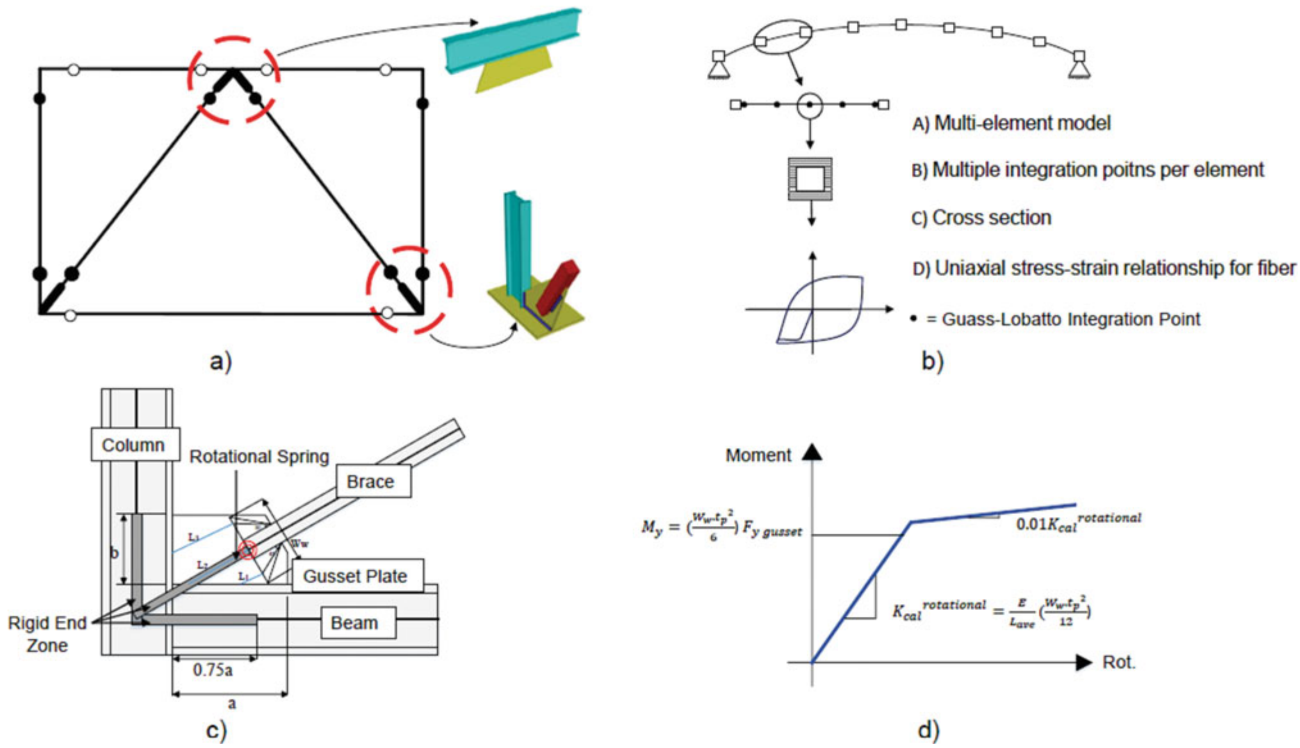

Fig. 9.6 (**a**) Schematic figure of the simulated model validated with experimental data; (**b**) Methodology toward modeling of the braces; (**c**) Modeling of gusset plates with concentrated hinges; and (**d**) Nonlinear modeling of the hinges

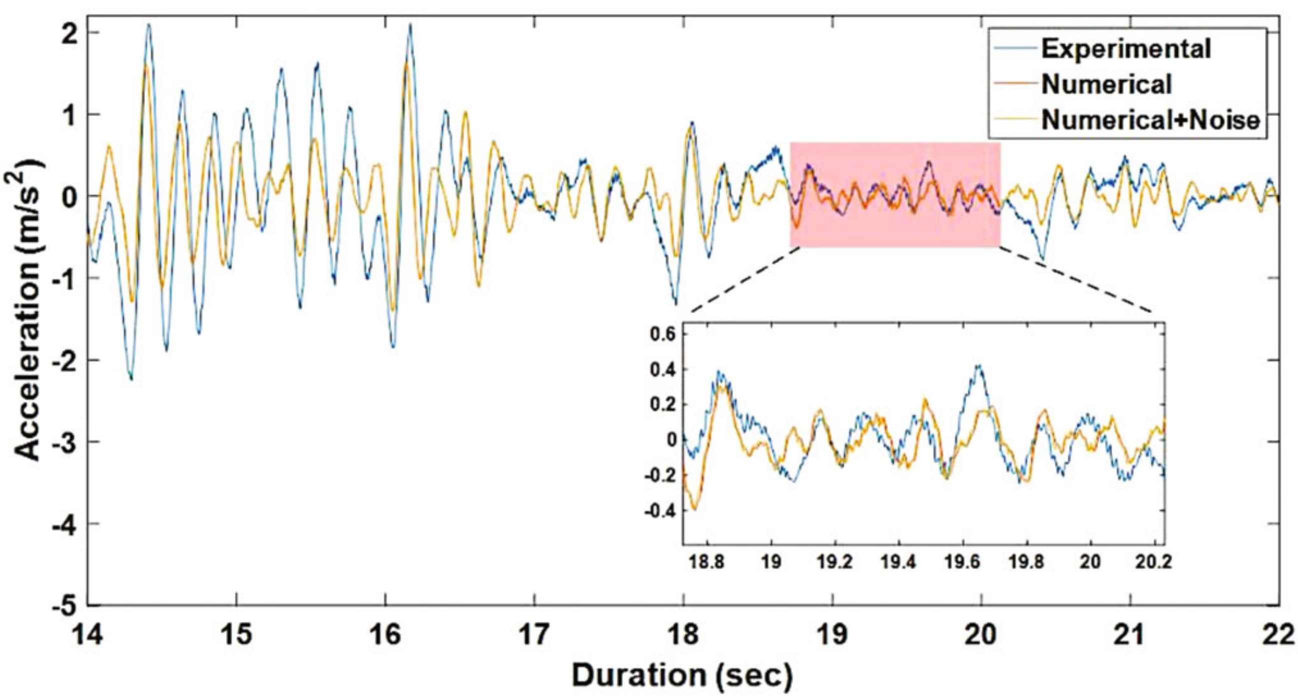

Fig. 9.7 Validation result for acceleration response simulation of 42% amplification level of the Takatori earthquake for numerical modeling

responses were captured. As shown in Fig. 9.7, the acceleration as a high-frequency response is simulated and is compared to experimental data for the 42% amplification level of the Takatori earthquake.

Table 9.1 Damage state labeling for classification

Damage state	Amplification level (%)	Performance label	Damage description
D_1	14	No damage	No damage and nonlinear behavior have been observed during the test
D_2	28	Slight damage	A small out-of-plane displacement occurred
D_3	42	Moderate damage	A residual out-of-plane displacement occurred near the mid-length of the left brace
D_4	70	Extensive damage	Both steel frames fractured near their mid-length due to low-cycle fatigue

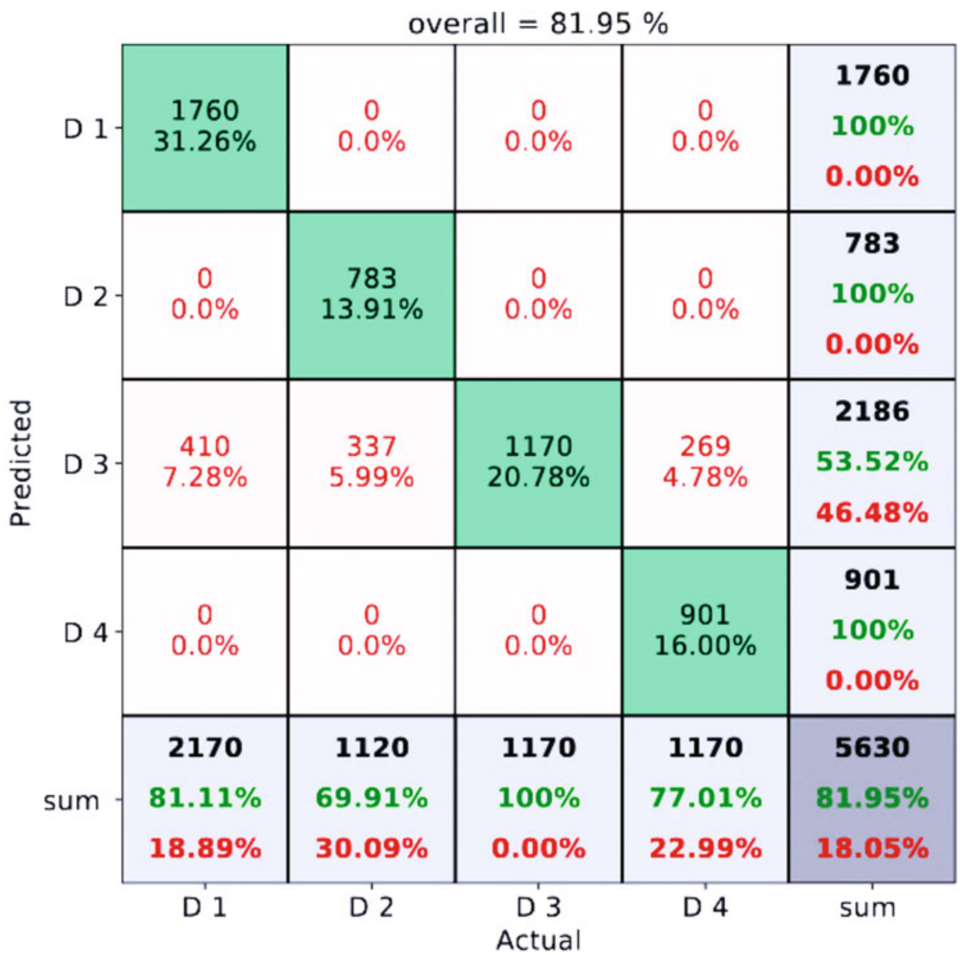

Fig. 9.8 The confusion matrix for the incorporated experimental and numerical trained hybrid model tested with the experimental datasets

9.3.2 Damage Classification

Incorporating numerical and experimental data into the proposed methodology, the performance of the data-driven hybrid model is assessed in this section. The proposed method is examined for damages associated with various Takatori earthquake amplification levels, as shown in Table 9.1. The numerical model is applied to four distinct Takatori earthquake amplification levels, with 14%, 28%, 42%, and 70% with consideration of noise effects, respectively. The recorded simulated responses for various modeling parameters [i.e., the module of elasticity (E), yield stress (f_y), and geometry of brace (thickness (t))] in different test sets in accordance with CCD sampling are generated and augmented for training and validation. Additionally, a significant parameter analysis is also conducted to evaluate the significance of every parameter in structural response, such as story drift ratios. This study utilizes the ground truth damages associated with the experimental response as a test dataset in the hybrid model.

On experimental test data, the hybrid model achieves an overall accuracy of 82%, as shown in Fig. 9.8. The hybrid model can successfully classify damage patterns corresponding to various amplification levels.

9.4 Conclusions

This chapter presents a deep learning–based structural monitoring methodology that incorporates uncertainty in mechanics-based models to generate synthetic data and train hybrid data-driven models. The implementation of the proposed methodology starts by developing nonlinear simulated models that account for model-based parameter uncertainty. The developed models with determined sets of parameters analyzed through parameter significant analysis produce and augment sample response datasets using central composite design sampling by subjecting them to various sets of ground motions within the criteria of design of experiments. Hybrid DL-based models are then trained using noise-contaminated global story-level response measurements as generated sample response datasets. This hybrid model includes convolutional neural networks and wavelet packet transforms for damage-sensitive feature extraction. Damage feature extraction and classification are achieved in this methodology by utilizing and incorporating robust numerical models for training and validation with experimental data as test datasets. The numerical model used in this study for sample generation is validated with experimental responses recorded from shaking table concentrically braced frame test data conducted at E-Defense, Miki, Japan, analyzed for various ground motions. Afterward, the proposed hybrid data-driven model is trained based on the sample dataset for assessing post-earthquake damages. The proposed methodology is verified and validated using global dynamic response measurements, demonstrating that the proposed approach can detect and localize structural post-earthquake damage patterns.

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