Convolutional neural network-based wind-induced response estimation model for tall buildings

Byung Kwan Oh¹ | Branko Glisic¹ | Yousok Kim² | Hyo Seon Park³

¹Department of Civil and Environmental Engineering, Princeton University, Princeton, NJ, USA
²Department of Architectural Engineering, Hongik University, Sejong, Korea
³Department of Architectural Engineering, Yonsei University, Seoul, Korea

Correspondence
Hyo Seon Park, Department of Architectural Engineering, Yonsei University, 134 Shinchon, Seoul 120-749, Korea.
Email: hspark@yonsei.ac.kr

Funding information
National Research Foundation of Korea, Grant/Award Numbers: Korea government (MSIP) 2011-0018360, 2018R1A5A1025137

Abstract
This study presents a convolutional neural network (CNN)-based response estimation model for structural health monitoring (SHM) of tall buildings subject to wind loads. In this model, the wind-induced responses are estimated by CNN trained with previously measured sensor signals; this enables the SHM system to operate stably even when a sensor fault or data loss occurs. In the presented model, top-level wind-induced displacement in the time and frequency domains, and wind data in the frequency domain are configured into the input map of the CNN to reflect the resisting capacity of a tall building, the change in the dynamic characteristics of the building due to wind loads, and the relationship between wind load and the building. To evaluate stress, which is used as a safety indicator for structural members in the building, the maximum and minimum strains of columns are set as the output layer of the CNN. The CNN is trained using measured wind and wind response data to predict the column strains during a future wind load. The presented model is validated using data from a wind tunnel test of a building model. The performance of the presented model is verified through strain estimation with data that were not used in the CNN training. To assess the validity of the presented input map configuration, the estimation performance is compared with a CNN that considered only the time domain responses as input. Furthermore, the effects of the variations in the configuration of the CNN on the wind response estimation performance are examined.

1 | INTRODUCTION

Structural health monitoring (SHM) identifies the conditions of structures, such as buildings, bridges, industrial machines, exposed to various uncertain loads, such as earthquakes and strong winds, and evaluates their safety (Amezquita-Sanchez & Adeli, 2016; Gao & Mosalam, 2018; Rafiei & Adeli, 2018; Shan, Shi, & Lu, 2016; Sigurdardottir, Stearns, & Glisic, 2017; Tsogka, Daskalakis, Comanducci, & Ubertini, 2017). SHM is also used to evaluate the safety of civil structures during construction and use (Amezquita-Sanchez & Adeli, 2015; Glisic, Inaudi, Lau, & Fong, 2013; Rafiei & Adeli, 2017; Shi, Shan, & Lu, 2012). Due to the scale of tall buildings, numerous sensors of various types are installed on such buildings to assess the lateral deformation (Li et al., 2018; Park, Sohn, Kim, & Park, 2008), modal parameters (Amezquita-Sanchez, Park, & Adeli, 2017; Li, Park, & Adeli, 2017; Park & Oh, 2018), and stress of major structural members (Xia, Ni, Zhang, Liao, & Ko, 2011). In addition, considering the service life of tall buildings, long-term monitoring might be included in the SHM strategy (Ni, Xia, Liao, & Ko, 2009).
There are several issues to consider regarding the field application and operation of SHM due to various unpredictable situations, such as the prevention of measuring structural responses due to faulty sensors in the installed SHM system, temporary inability to measure structural responses due to the instability of the power supply, and data loss during data transmission between a sensor node and receiver in the wireless sensing system (Lee, Kim, Sho, & Park, 2010; Zhang & Luo, 2017). For structures with a long service life, such as tall buildings, the permanent failure of sensors may occur at various stages of a building’s life, which can challenge structural safety evaluation based on measured responses (Oh, Kim, Kim, Park, & Adeli, 2017). If the top floor displacement measuring instrument and vibration measuring instrument are faulted, those can be replaced. However, the replacement of sensors such as strain sensors is meaningless because meaningful stress evaluation is possible only if the data reflect the strains generated by the dead loads accumulated from the construction stage of the building as well as live loads during the use of the building. Furthermore, strain sensors installed in reinforced concrete (RC) or steel reinforced concrete (SRC) columns, which are column types widely used in tall buildings, cannot be replaced even if they have a fault because they are embedded in concrete.

Therefore, many techniques have been developed for reconstructing structural responses in the event of data loss or missing measurements from some sensors in an SHM system. Zhang and Luo (2017) proposed a method to recover missing data from long-term measurements, considering the whole-life monitoring of structures. Their method analyzes the correlations of multiple strain sensors installed in a structure and restores the missing data by interpolating their relationships. They applied the proposed method to study a steel structure in a stadium building. Yang and Nagarajaiah (2016) proposed a recovery method for time history vibration data using an optimization technique. They verified the effectiveness of the proposed method by accurately estimating the randomly missing time history acceleration response in applications of high-rise buildings and large-scaled cable-stayed bridges. Yu, Han, Bao, and Ou (2016) introduced a signal compressive sampling technique to reconstruct lost data in a wireless sensor network, which is an alternative to Nyquist/Shannon sampling theory. This technique accurately recovers signals from smaller amounts of measurements than those required in general (Caione, Brunelli, & Benini, 2014). The proposed techniques were applied to bridges and verified through lost time history acceleration response recovery.

When a tall building structure that is sensitive to wind is designed, not only the structural safety but also the building serviceability caused by lateral deformation due to wind loads is considered. Unlike in the case of low-rise buildings, in the design of a tall building, a wind tunnel test that reflects the building site characteristics is performed with a miniature model, and the design is reviewed considering the test results. Thus, one of the most important factors influencing behavior of a tall building is the expected wind load, and the measurements of the wind load and wind-induced response are considered crucial factors in the design of an SHM system for a tall building (Kim & Adeli, 2005). Regarding the SHM data loss issue, when long-term monitoring of a tall building is considered, the wind load or wind-induced response measurements may be limited or not recorded. Thus, methods to evaluate the structural safety under wind loads have been developed for limited numbers of structural response measurements.

Due to the complexity of wind loads and the physical limitations involving the installation of wind pressure sensors, wind load estimation methods were developed for limited number of measurements from an SHM system of a tall building. Hwang, Kareem, and Kim (2011) proposed a wind load estimation method using wind tunnel test data for a miniature model of a slender 210-meter tall structure. Using a Kalman filter, they estimated the wind load from the measured top floor displacements, velocity, and acceleration structural responses. Ni and Li (2016) introduced a neural network (NN) to reconstruct the missing data of faulty wind pressure sensors and verified the proposed method by estimating the wind pressure of a 600-meter tall building during a typhoon. Dongmei, Shiqing, Xuhui, and Xue (2017) introduced a back-propagation NN to estimate the wind load acting on a high-rise building. In the proposed NN, the coordinates of the wind pressure sensor were set as inputs, and the mean, root-mean-square pressure coefficients, and time series of the wind-induced pressure were set as outputs. They verified the wind pressure estimation method by conducting a wind tunnel test on a miniature model of a high-rise building.

Not only wind load but also wind-induced responses have been estimated through limited measurements of structural responses in previous studies. Niu et al. (2015) proposed a method for simultaneously reconstructing the wind load and wind response of a high-rise building through operational modal analysis (OMA), finite element (FE) model updating, and Kalman filtering. They verified the proposed method by estimating the wind load and wind response using acceleration responses measured in a 600-meter tall building. Bani-Hani (2007) proposed a method using a NN to predict the wind response of a 306-meter tall 76-story building and the control force of an active tuned mass damper installed in the building. In their study, the previous and present measured wind-induced acceleration responses were used as inputs, and the future time series of the wind response and control force were used as outputs of the NN.

The abovementioned studies suggested various methods to estimate wind load and wind response for the structural safety evaluation of tall buildings considering limited numbers of measurements or data loss. Wind load estimation based on structural responses is meaningful for tall buildings,
because it is difficult or costly to measure wind loads using wind direction and speed data. However, because the structural responses to wind load are required to directly evaluate the structural safety of buildings, an additional technique is required to estimate wind responses using the wind load estimated in previous studies. The abovementioned previous studies on wind response prediction mainly focus on estimation of the acceleration response. Although important information on structural states can be derived from estimated acceleration responses, this approach has limitations in terms of the safety evaluation for structural members of tall buildings. For member safety evaluation, Oh et al. (2017) proposed a sensing model based on a NN for which the measured wind direction and speed data were inputs and the column stress of a tall building was output. In that study, the test data for training the NN were obtained using a relatively uniformly generated wind, excluding the turbulence effect that occurs in an actual wind load.

Wind is basically a load with severe fluctuations accompanied by turbulence; thus, the wind load-induced responses of buildings are complex. The wind load, which changes over time, causes a vortex effect and acts on a building both along the wind load and across the wind load direction, with considerably different characteristics depending on the speed, direction, and site characteristics of the building (Tanaka, Tamura, Ohtake, Nakai, & Kim, 2012). Furthermore, the inherent characteristics of the building, such as its natural frequency and damping change depending on the intensity of the wind load acting on the building (Tamura & Suganuma, 1996). Under a wind load, the changing unique characteristics of the building affect the building’s structural responses and change the response amplification and decaying characteristics. Therefore, for a more accurate and reliable estimation of wind responses, the interactions between the wind load and building in the frequency domain reflect the building’s structural response characteristics in the time domain for time-varying wind loads with turbulence, and the characteristics of the structure that change due to the wind load intensity must be considered.

Some of the abovementioned studies on the prediction of wind load and wind response introduced the use of NNs (Bani-Hani, 2007; Dongmei et al., 2017; Ni & Li, 2016). NNs have been widely used in various forms in engineering problems with high nonlinearity owing to their outstanding performance in calculating predictions. NNs have also been used actively in SHM research in the civil domain to address the considerable amount of data collected from large structures. Recently, the convolutional neural network (CNN) has been used in SHM (Gao & Mosalam, 2018; Li, Zhao, & Zhou, 2019; Lin, Nie, & Ma, 2017; Rafiei, Khushefati, Demirboga, & Adeli, 2017; Yang et al., 2018) besides image-related problems (Molina-Cabello, Luque-Baena, López-Rubio, & Thurnhofer-Hemsi, 2018; Wang & Bai, 2018). Lin et al. (2017) employed a deep CNN into a damage identification method with measured time-domain responses. By automatically extracting features with related damages, the presented CNN identified localizations and severities of damages in a beam structure. Gao and Mosalam (2018) presented a vision-based damage recognition method based on CNN and transfer learning. Through experiments with a number of images of structural damages, it successfully classified component type, spalling condition, damage level, and damage type from the images. Yang et al. (2018) presented a fully CNN to detect cracks of structures at pixel level. With no postprocessing or preprocessing, the fully CNN detected cracks accurately through training and validation of collected crack data set. Li et al. (2019) proposed a damage detection method for concrete structures based on a fully CNN. The fully CNN trained with a database of images including crack, spalling, efflorescence, and hole identified multiple damages in concrete structures. Most studies on SHM based on CNN have focused on damage detection and image-based crack detection. Considering the capacity of CNN to handle a large number of data, it can be utilized to extract features of measured time series data and predict structural responses. Unlike the conventional NN, a CNN does not require hand-crafted feature extraction (Koziarski & Cyganek, 2017) allowing for the input of many time series datasets given the nature of the input layer configuration and efficiently solving overfitting problems through convolution and a pooling operation (Ortega-Zamorano, Jerez, Gómez, & Franco, 2017). Thus, CNNs can be used for the SHM of large structures that require addressing a considerable amount of noisy data and that are being actively used in related studies.

In this regard, this study introduces a CNN to effectively address a considerable amount of data measured in tall buildings instead of using conventional NNs. In addition, this approach overcomes the limitation found in the literature focused on estimation of global dynamic responses through directly evaluating safety using strain values predicted from a CNN trained with wind and wind response sensor signals. The presented model involves wind data and top floor displacement, and strain measurements in the monitored major structural members. A CNN architecture is presented with wind and displacement data as inputs and strain as output, and the CNN is trained using measured data. If a loss of measured data from the structural members occurs in the future, the trained CNN predicts the wind-induced strain that is used for the structural safety evaluation of a tall building.

The input layer of the CNN requires three data types: (a) the time history displacement of the top floor of a tall building measured during a wind load to reflect the overall performance in resisting the deformation under that wind load; (b) the responses of the measured top floor displacement in the frequency domain to reflect the variations in the dynamic characteristics of the target building, which change
depending on the wind load and vary with time; and (c) the measured wind speed in the frequency domain to reflect not only the dynamic characteristics of the wind, but also the response amplification characteristics of the monitored building (considering the relation between the wind load and the building with the frequency domain responses as per point (b) above). In the output layer of the CNN, the maximum and minimum strains in the time history of the wind-induced strains measured in the structural members (e.g., columns), which can be used as indicators in the structural safety evaluation, are set. To validate the presented wind response estimation model using the CNN, a wind tunnel test was conducted on a small-scale model of a tall building. The CNN was trained using wind data and the wind-induced responses measured under turbulent wind, and the wind response estimation performance of the trained CNN was verified. In addition, the effectiveness of the CNN input layer composition presented in this study was evaluated through comparison with a CNN model that only uses the time domain structural responses. Furthermore, the estimation performance that depends on the architecture configurations, such as the input map size and depth of the layer in the CNN, was examined.

2 | WIND-INDUCED RESPONSE ESTIMATION MODEL

2.1 | Structural health monitoring

The wind-induced response estimation model for tall buildings presented in this study is based on the data collected by an SHM system. A CNN is introduced to estimate the wind-induced strain, and CNN training is required using complete data sets, that is, assuming that there is no data loss due to malfunction of sensors or data transfer channels. The measurement data used for configuring the CNN are the top floor displacement of a tall building, the wind data (wind speed), and the strain in its major structural members. The top floor displacement of a tall building can be measured using sensing technology such as a global position system (GPS) (Park et al., 2008). The wind data can be measured with an anemometer installed at the top of a tall building. For the structural member of the tall building monitored in this study, the columns of the lowest story in the building that have the largest stress among all the columns were selected, and it was assumed that the stresses of the columns are determined from strains measured by strain sensors, for example, fiber Bragg-grating (FBG) sensors installed in the columns. Figures 1a and 1b, respectively, show the SHM system required to obtain measurements in the presented model and the measured structural responses and wind speed data. In Figure 1b, the measurements of strain sensor 1 represent the strains of the surface of a column (column A) at the lowest story of the building, and the measurements of strain sensor 2 represent the strains of the surface of a column (column B) opposite to column A.

The measured data need to be processed to configure the input and output layers of the CNN for the presented model. First, as shown in Figure 1 all the measured data are divided into specific intervals (with a specific data length) of data with corresponding times. All the measured data in one interval become the dataset for CNN training. Furthermore, to consider the continuity of responses to the wind load, the dataset includes overlapping of data within the same intervals, as shown in Figure 2. The wind speeds, top floor displacements, and column strains within the same time interval are considered to be one dataset for CNN training and used for the input and output data of CNN.

2.2 | Convolutional neural network

The dataset obtained through the data processing described in Section 2.1 is used as the input and output data of the CNN. In the input layer of the CNN presented in this study, the measured data for wind speed and top floor displacement are set. As shown in Figure 3a, the top floor displacement and wind speed time history data from the same time interval are required for configuration of the input layer. Among these time history data, the time domain responses of the top floor displacement are directly used in the input layer. The top floor displacement of the time domain is used in the input layer to reflect the performance in resisting the deformation of the building under wind load.

The top floor displacement responses converted to the frequency domain are also used in the input layer. The dynamic characteristics, such as natural frequency and damping, of the structure change with the wind load, which changes with time. To reflect this in the CNN training, not only the time domain responses of the top floor displacement but also the frequency domain responses are used in the input layer. Furthermore, while the time domain responses of the top floor displacement contain unidirectional components (e.g., displacements in the x-direction), the frequency domain responses for corresponding components include the translational mode in that (e.g., x) direction and the translational mode in the direction perpendicular (e.g., y) to that direction (e.g., x). If the wind loads act along a direction (e.g., x), the peak at the natural frequency for the translational mode of the y-direction in the frequency domain is clearly visible while that of the y-direction has a smaller value. If the direction of the wind load changes to the direction perpendicular (e.g., y), the amplitude of the frequency response at the natural frequency for the mode of the y-direction increases while that of the x-direction decreases. Hence, the responses of the frequency domain can properly reflect the dynamic characteristics and structural response characteristics in the CNN training using only unidirectional displacement measurement. In this study, the singular value
FIGURE 1  (a) SHM system for estimating wind-induced responses and (b) measured data

FIGURE 2  Data overlapping in the construction of the training dataset

obtained from the singular value decomposition of the power spectrum density function of the time history displacement represents the responses of the frequency domain of the top floor displacement. Through Equations (1)–(3), the singular value of the time history signal can be obtained (Oh, Hwang, Kim, Cho, & Park, 2015).

\[
R_{x(k)\times l}(t) = \int_{-\infty}^{\infty} x_k(\tau)x_l(t + \tau)d\tau \tag{1}
\]

\[
S_{x(k)\times l}(\omega) = \int_{-\infty}^{\infty} e^{-i\omega t} R_{x(k)\times l}(t)dt \tag{2}
\]

\[
S(\omega) = U(\omega) \times SV(\omega) \times V(\omega) \tag{3}
\]

where \(x(t)\) and \(R_{x(k)\times l}(t)\) are the measured time history signal and correlation function of \(x_k(t)\) and \(x_l(t)\), respectively; \(S_{x(k)\times l}(\omega)\) is the cross power spectrum density value at the angular frequency \(\omega\) for \(x_k(t)\) and \(x_l(t)\); \(k\) and \(l\) are locations of measurements; \(SV(\omega)\) is a rectangular diagonal matrix indicating a singular value obtained by combining \(S_{x(k)\times l}(\omega)\); and \(U(\omega)\) and \(V(\omega)\) are complex unitary matrices representing singular vectors. For wind speed data, only the values of the frequency domain obtained from the time history data
are used in the input layer of the CNN. By using the data, both the dynamic characteristics of the wind load, which change with time, and the dynamic characteristics of the building, which change with wind load (affecting the structural response amplification and damping), are reflected. The wind data in the frequency domain represent the interactions between the structure and wind load, and this relationship is reflected in the CNN training. In this model, singular values for the time history of wind speed, which can be obtained from Equations (1)–(3), were used as the wind data in the frequency domain. Three types of data such as frequency response (singular value) of displacement, time history of displacement, and frequency response (singular value) of wind speed are established together in the CNN input, as shown in Figure 3c.

The number of data segments in the extraction process of singular values to obtain responses in the frequency domain is set to be equal to the time history data length of each training dataset, and the length of the frequency domain responses is thus half of the time history data length. Because two types of frequency domain data, namely, wind speed and displacement, are used, the total data length of the frequency domain is identical to that of the time history data length of the displacement. Therefore, the value used in the input layer corresponds to twice the time history data length of the displacement of a training dataset. In this study, the length of the time history of displacement was set as 800 which means 8 s with 100 Hz of sampling rate and the length of the frequency responses for displacement and wind speed were set to 400. Thus, the total data length of one input map was 1,600 which can be reshaped as 40 × 40. The time and frequency domain responses obtained in this way constitute the input layer of the CNN, as shown in Figure 3c.

In the CNN presented in this study, the strains measured in the columns of a building to be monitored for structural safety evaluation are set in the output layer. The important value in stress evaluation is the strain corresponding to the maximum or minimum stress. For a lateral force, such as a wind load, tensile and compressive stresses are generated in the column of the building. The maximum values of the absolute values of the tensile and compressive stresses are used in the structural safety evaluation of the column. Thus, instead of considering all the time history of the strain data as the output of the network as presented in previous researches on time series forecasting (Borovykh, Bohte, & Oosterlee, 2017; Torres, Galicia, Troncoso, & Martínez-Álvarez, 2018) and classification (Bagnall, Lines, Bostrom, Large, & Keogh, 2017; Wang, Yan, & Oates, 2017; Zhao, Lu, Chen, Liu, & Wu, 2017) based on neural networks including the CNN, the maximum and minimum values among the time history strains measured in the selected columns were extracted and used as the CNN output data, as shown in Figure 4a. As the tensile and compressive stresses change according to the wind direction, not only the maximum but also the minimum stresses were considered for monitoring purposes. The extracted strain values of the columns are set as output nodes, as shown in Figure 4b. In Figure 4b, only two columns are considered as monitoring targets. If the number of structural members considered for the SHM increases, the number of nodes in the output of the CNN increases with the number of monitoring targets or strain sensors.
FIGURE 4  Constitution of the output layer in the CNN: (a) data collection among time series of strain for output of the CNN, (b) output of the CNN

FIGURE 5  CNN architecture

TABLE 1  Description of the details of the CNN

| Layer               | Size      | Operator     | Size/strdie size |
|---------------------|-----------|--------------|------------------|
| Input layer         | 40 × 40   | —            | —                |
| Convolutional layer 1 | 22 × 22 × 20 | Kernel 1    | 19 × 19/1        |
| Pooling layer 1     | 11 × 11 × 20 | Subsampling 1 | 2 × 2/2          |
| Convolutional layer 2 | 3 × 3 × 40  | Kernel 2     | 9 × 9/1          |
| Pooling layer 2     | 3 × 3 × 40  | Subsampling 2 | 1 × 1/1          |
| Fully connected layer | 360 × 1 | —            | —                |
| Output layer        | 4 × 1     | —            | —                |

The total CNN architecture was configured using the input and output layers presented in Figures 3c and 4b. Figure 5 shows the CNN architecture presented in this study. The input map forms the convolutional layer through convolution using the kernel. The kernel size was set to approximately half of the size of the previous layer of the convolution layer. The convolutional layer forms a pooling layer through subsampling. Within subsampling size, mean value is collected. The depth
of the first convolutional and pooling layer was set to half of the input map size, and the depth of the second convolutional and pooling layer was set to twice that of the first convolutional and pooling layer. The size of kernel was set to a slightly smaller value of one-half of the map size in the previous layer. These layer and operator sizes were found by extensive analyses of the trained CNNs in advance. The detailed sizes of each layer and operator are listed in Table 1. The presented CNN architecture is trained using the dataset obtained from the measured structural responses, and the trained CNN is used to predict the strains using the inputs such as the top floor displacement and wind data measured when the strain sensors used for the output have failures or there are data losses.

3 | EXPERIMENTAL VALIDATION

3.1 | Wind tunnel tests

To validate the presented wind response estimation model based on a CNN, a wind tunnel test was performed on an experimental model of a tall building. In this experiment, to obtain a dataset for CNN training, the wind data and wind-induced response are measured while the wind speed and wind direction are changed in various ways using the wind generator and wind rotation table inside the wind tunnel test room. The experimental specimen, which is shown in Figure 6a, has five floors, a height of 1.0 m, and plan dimensions of 0.2 m × 0.2 m. In addition, there are eight perimeter columns (6 × 3 mm) and one core column (15 × 10 mm) at the center of the model, and there is an outrigger in the top floor. A mass is installed on each floor, and the specimen is made of aluminum, which has a tensile strength of 147 MPa and a yield strength of 78 MPa. To ensure that the specimen behaves similarly to a real building against the wind load, an outer cover was installed around the specimen.

Figure 6b shows the entire wind tunnel test setup. The wind tunnel test room is a closed boundary layer wind tunnel, the entire length of which is 78.5 m; the range of wind speeds that can be generated is 0.5–30 m/s. To replicate different wind speeds to obtain various CNN training datasets, the power of the wind generator was varied from 200 rpm to 400 rpm. The wind rotation table (labeled “E” in Figure 6b) was adjusted from 0 to 90° (Figure 7a) to change the wind direction. A total of 28 tests were performed while changing the rpm of the generator and angle of rotation table. Information of the 28 tests are listed in Table 2. Among the inputs of the CNN dataset, the top floor displacement of the building was measured with a motion capture system (MCS) (Oh et al., 2015) (labeled “A” in Figure 6b), and the wind speed was measured with a wind speed sensor (labeled “C” in Figure 6b) installed immediately in front of the specimen. In the authors’ previous work (Oh et al., 2017), the same specimen and experimental conditions were observed. However, the tests in the previous work were conducted using uniformly blowing wind loads while the tests represented in this study were performed with wind loads including turbulence effects that can be created by a wind generator. Thus, completely different wind data were obtained and utilized in this research to those of the previous work.

The strain of the column used for collecting output data was measured using FBG strain sensors. As shown in Figure 7a, two FBG sensors were installed at the bottom of the columns where the largest stress was generated. The FBG sensor installation and locations are shown in Figures 7b and 7c, respectively.

3.2 | Results

The dataset for CNN training was created during the wind tunnel tests by measuring the structural responses and wind speeds for the variety of wind-load scenarios, including different wind speeds and directions. One dataset was formed from the top floor displacement of the specimen measured from the MCS and the wind speed measured with a wind speed sensor as the input data and the strains measured from two FBG sensors installed in the specimen as the output data. As explained in Section 2.1, a specific range or a specific length of measured data were used to generate the training dataset. The sampling rate of every measuring instrument was set to 100 Hz, so the specific range was 8 s, that is, a data length of 800 was used for each training dataset. The data overlap interval was set to 1 s. When the power spectrum density function was formed to obtain the frequency domain responses of the top floor displacement and the frequency domain values of the wind speed, which are the input data, the number of data segments in the frequency domain was set to the time domain data length, which is 800. Thus, singular values with data lengths of 400 were obtained for the displacement and wind speed, respectively. Consequently, a total of 1,600 data points consisting of time domain top floor displacements with a data length of 800, frequency domain top floor displacement responses with a data length of 400, and frequency domain wind speeds with a data length of 400 comprised the 40 × 40 CNN input map. For one training dataset, among the time history strain data with a data length of 800, measured from the FBG sensors, the maximum and minimum values were used in the output layer. Because the two FBG sensors are objects of monitoring, a total of four strain values comprised the output layer. A total of 2,100 training datasets were obtained from the experiments, and 2,000 were randomly selected among them for use in the CNN training. In addition, the 100 datasets that were not used in training were used for validation. The CNN architecture described in Section 2.2 was applied to the training. The activation function of the convolution layer was set as a sigmoid function, and the average pooling was used for...
**FIGURE 6** (a) Experimental specimen and (b) wind tunnel test

**FIGURE 7** (a) Perspective view, (b) FBG installation, and (c) FBG sensor location

**TABLE 2** Information on wind tunnel tests (✓: used test, -: not measured)

| Wind speed (m/s) | 0  | 10 | 20 | 30 | 40 | 45 | 50 | 60 | 70 | 80 | 90 | Number of test |
|------------------|----|----|----|----|----|----|----|----|----|----|----|----------------|
| 5.0              | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | 11             |
| 7.5              | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | 11             |
| 8.75             | ✓  | -  | -  | ✓  | -  | ✓  | -  | -  | -  | -  | -  | 4              |
| 10.0             | -  | -  | -  | -  | -  | -  | ✓  | -  | -  | -  | ✓  | 2              |
the pooling type. During the training, the batch size was set to 100, and the terminating condition was set to 3,000 epochs.

The wind response estimation results of the trained CNN are shown in Figures 8 and 9. The strain estimation results of FBG sensor 1 and FBG sensor 2 (Figure 7c) for the 2,000 datasets used in the training are shown in Figures 8a and 8b, respectively. The root-mean-square error (RMSE) of the estimation results was 10.8145 (\(\mu\varepsilon\)), and the average absolute difference was 7.9503 (\(\mu\varepsilon\)). The estimated wind-induced strain of the two columns of the specimen showed good agreement with the reference values.

The strain estimation results of FBG sensor 1 and FBG sensor 2 for the 100 datasets that were not used for training are shown in Figures 9a and 9b, respectively. The RMSE and the average absolute difference of the estimation results were 12.7261 (\(\mu\varepsilon\)) and 9.1796 (\(\mu\varepsilon\)), respectively. Although the average absolute difference was greater than that of the estimation results for the training dataset, it is still a relatively high degree of agreement considering that these wind responses were not used in the CNN training and have very complex characteristics.

The strain estimation results for the test datasets were examined in terms of the wind direction and wind speed, which are shown in Figures 10a and 10b, respectively. As shown in Figure 7a, if the wind direction is 0\(^\circ\), the column surface on which the FBG sensor is installed can be regarded as the reference for the along-wind direction, and the column surface is governed by flexural behavior in this case. In general, when the wind direction is in the range of 0–30\(^\circ\), the column shows flexural deformation characteristics. Considering the surface on which the FBG sensor is installed, tensile stress is recorded at FBG sensor 1, and compressive stress is recorded at FBG sensor 2. In contrast, if the wind direction is 90\(^\circ\) or approximately 90\(^\circ\) (between 70\(^\circ\) and 90\(^\circ\)), the column surface on which the FBG sensors are installed can be regarded as the reference for the across-wind direction. The column surface on which the FBG sensor is installed shows very large fluctuations, alternating between tensile and compressive stresses. Figure 10a shows the average absolute difference of the datasets for a specific wind direction among the 100 verification sets. In this figure, the estimation errors for the wind directions between 0\(^\circ\) and 30\(^\circ\), in which range the columns show flexural behaviors, are relatively low. In contrast, for the wind direction between 70\(^\circ\) and 90\(^\circ\), which corresponds to the wind blowing across the column surface on which the FBG sensors are installed, the strain is estimated with a relatively high error. Figure 10b shows the absolute errors for the wind speeds of the 100 test datasets. In general, the error increases with the wind speed. There are 16 datasets whose absolution error is greater than 30 \(\mu\varepsilon\), which is estimated to be a large error; a majority of these datasets (68.75\%) were for the across-wind direction. For the purposes of this study, across-wind direction represents the worst-case scenario, and large error is a result of lack of sensitivity of sensors installed on given columns for that direction of wind. In real-life settings, the accuracy of prediction can be improved by adding a pair of sensors installed in across-wind direction.

### 3.3 Comparative study

The main characteristic of the wind response estimation model presented in this study is the use of not only the time history wind responses but also the frequency domain responses and the wind speeds in the frequency domain. To verify the validity of the presented input map configuration method, another CNN model was composed using only the time history wind responses, excluding the frequency domain responses and wind speed frequency domain values, and the response estimation performances were compared. The CNN presented in this study was named “CNN_TF,” and the CNN using only the time history wind responses for comparison was named “CNN_T.” The input map configuration of CNN_T is shown in Figure 11. Whereas CNN_TF used the unidirectional time domain of the top floor displacement only, CNN_T used the bidirectional time domain of the top floor displacement, as shown in Figure 11a. These two time history datasets comprise the input map, as shown in Figure 11b. The output layer of CNN_T was set as the maximum and minimum wind-induced strains of the column, in the same manner as that of CNN_TF.

To compare the performance between the two CNNs, they were trained and verified under the same conditions. As presented in Section 3.2, the CNN architecture and training conditions were configured identically, excluding the input map of the input layer. Furthermore, the number of datasets used for training and the number and type of datasets used for verification were identical. The training results of the two CNNs are plotted as convergence curves in Figure 12.

CNN_TF converged more quickly than CNN_T, especially in the early stage of training. CNN_TF also has a lower loss function value in the final convergence, which suggests that its training result was better. The wind-induced strain estimation results of the two CNNs were examined. Figure 13 shows the strain estimation results of the two CNNs for a verification dataset that generated the largest strain among the representative cases of the along-wind and across-wind directions. Figure 13a,b shows the strain estimation results for a case that generated the largest strain among the test datasets for which the wind direction was either 0\(^\circ\) or 30\(^\circ\) in the along-wind direction. CNN_TF estimates strains with high accuracy, compared to the performance of CNN_T. For example, for the strain estimation of FBG sensor 1 installed in the column that generated a tensile stress in Figure 13a, CNN_TF resulted in an absolute error of 3.20 \(\mu\varepsilon\), whereas CNN_T resulted in an absolute error of 27.58 \(\mu\varepsilon\). Figure 13c,d shows the strain estimation results for the case where the largest strain occurred in
the verification dataset with wind directions of 80° or 90° in the across-wind direction. In this case, the two CNNs showed similar wind response estimation performances. In a specific case, CNN_T showed a slightly better estimation performance than that of CNN_TF. For example, regarding the strain estimation of FBG sensor 2 in Figure 13d, CNN_TF resulted in an absolute error of 35.94 με, whereas CNN_T resulted in an absolute error of 23.16 με. A comparison of the performance confirmed that overall CNN_TF, which considers the frequency responses presented in this study, estimated the wind response more accurately than CNN_T, which considers only the time history responses when the column shows flexural behavior subject to the lateral force.

The estimation performances of the two CNNs were further examined according to an increase in the number of trainings. Figure 14 shows the average absolute difference
between the training and verification sets for a specific number of trainings of CNN_T and CNN_TF. The figure shows that the performances of CNN_TF are better than those of CNN_T for both the training and verification sets, which agrees with the above analysis. In the case of CNN_TF, as the number of trainings increased, the errors of both the training and test datasets decreased. In contrast, CNN_T showed decreasing errors for the training dataset, but the error of the test dataset increased after a specific number of trainings (blue arrow in Figure 14). For further detail, the strain estimation performances of the two CNNs were examined for the training and test datasets at specific number of trainings, including 1,000, 2,000, and 3,000 epochs, which are shown in Figure 15. In Figure 15a–c, for the training dataset, both CNNs were trained well, as the estimated value approached the reference value as the number of trainings increased. For the verification dataset, as shown in Figure 15d–f, as the number of trainings increased, the estimated value of CNN_TF approached the reference value. In contrast, for CNN_T, as the number of trainings increased, some estimated values scattered away from the reference value (pink dotted circle in Figure 15e,f). As confirmed in Figures 14 and 15, because the estimation result for the training dataset improved and the estimated result for the verification set worsened with an increase in the number of trainings of CNN_T, overfitting occurred in the training process of CNN_T. For the problems addressed in this study only, the CNN trained using both the time domain and frequency domain responses showed a higher performance in wind response estimation than the CNN trained only using the time domain wind responses.

3.4 | Effect of parameters in the CNN

The CNN performance was examined considering the changes in the input map configuration of the CNN architecture for wind response estimation in this study. As mentioned in Section 3.2, the presented CNN has an input map of $40 \times 40$. In other words, the measurement data for 8 s are used in one training dataset. When the lengths of the measured data are set to 0.5 s and 2 s, the input map size changes to $10 \times 10$ and $20 \times 20$, respectively. The wind response estimation performances of CNNs with different input map sizes were compared. The CNNs with different input map sizes were trained under the same conditions (number of training datasets, number of test datasets) as those for the CNN training described in Section 3.2. However, the kernel size was adjusted as the input map size decreased. The kernel size was set to approximately half of the previous layer’s kernel size. The wind response estimation errors of the CNNs with different input map sizes are shown in Figure 16a. This figure shows that as the input map size increased, the wind response estimation error decreased. Compared to the CNN with an input map size of $10 \times 10$, the CNN with an input map size of $40 \times 40$ showed performance improvements of 44.48% and 35.97% for the training and test datasets, respectively.
FIGURE 13 Comparison of the estimation results between CNN_TF and CNN_T: (a) 0° wind direction, (b) 30° wind direction, (c) 80° wind direction, and (d) 90° wind direction.

FIGURE 14 Comparison of the average absolute differences between CNN_TF and CNN_T

In addition, the effect of the depth of the layer in the CNN on the estimation performance was examined. The estimation results of three CNNs with different layer depths and the same input map size (10 × 10) were compared. The depths of the first convolutional layer of the three CNNs were 10, 20, and 30, and the depths of their second convolutional layers were twice the depth of the first layer. As shown in Figure 16b, the errors increased with layer depth for both the training and verification sets. The CNN with the largest depth showed a decrease in the strain performance of 10.43% and 8.87% for the training and verification sets, respectively, compared to the CNN with the smallest depth. Considering the substantial additional computational costs of the CNN with the larger depth, it is considered that an increase in depth in the CNN architecture is inefficient in terms of both accuracy and calculation time for the problem addressed in this study.

4 CONCLUSIONS

In this study, a wind-induced response estimation model for tall buildings using a CNN was presented. The presented wind response estimation model was verified through a wind tunnel test of a reduced-scale model of a tall building. The CNN trained with experimental test data accurately estimated the maximum and minimum strains. From the comparative study to another CNN (CNN_T) that used only the time domain wind responses as input data, it was confirmed that the CNN_T overfitted and showed poorer results for strain estimation compared to those of the presented CNN. Furthermore, for the problem addressed in this study, it was confirmed that an increase in the input map size and decrease in the depth of layer improved the CNN estimation performance.
FIGURE 15 Comparison of the estimation results between CNN_TF and CNN_T: (a) in 1,000 epochs for training datasets, (b) in 2,000 epochs for training datasets, (c) in 3,000 epochs for training datasets, (d) in 1,000 epochs for test datasets, (e) in 2,000 epochs for test datasets, and (f) in 3,000 epochs for test datasets.

FIGURE 16 Estimation results according to the (a) input map size and (b) depth of the layer.

Because of the uncertainties in the material and geometric properties and stiffness contribution of non-structural elements in real tall building structures, it is difficult to construct a refined finite element model. The difficulty in measurements of dynamic loads such as wind loads also prevents an accurate estimation of structural responses in an FE model. Thus, the machine-learning-based presented model with measured responses including such uncertainties can be utilized to overcome the current model-based method for estimating structural responses and assessing safety. Moreover, safety monitoring and evaluation technology based on a CNN has the potential to become a breakthrough technology used to overcome the current dependence on sensor durability, requiring that sensors have a service life longer than that of the structures they monitor.

In the practical implementation of SHM in tall buildings, there is no change in the configuration of the CNN input layer because the presented model requires measurements of displacement and wind speed at the top floor. As the number of output nodes in the CNN increases with the number of structural members to be monitored, there is no observable change in the configuration of output layer. In addition, during long-term monitoring of tall buildings in practice, much more measured data would be produced compared to those of the experiments in this study. In this case, a method for cumulative training for the previously trained CNN with measurements for a specific period is expected to be an alternative solution to employ such big data.
Furthermore, the estimated strain can be converted to stress with material information and utilized to measure the real stress ratio with a value of allowable stress in the elastic range. If the system of the building is identified to be changed based on the investigation of variations in modal frequency, a CNN needs to be newly trained with data from the point where the system is changed.

ACKNOWLEDGMENTS

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIP) (No. 2011-0018360 and No. 2018R1A5A1025137).

REFERENCES

Amezquita-Sanchez, J. P., & Adeli, H. (2015). Synchrosqueezed wavelet transform-fractactal model for locating, detecting, and quantifying damage in smart highrise building structures. Smart Materials and Structures, 24, 065034.

Amezquita-Sanchez, J. P., & Adeli, H. (2016). Signal processing techniques for vibration-based health monitoring of structures. Archives of Computational Methods in Engineering, 23(1), 1–15.

Amezquita-Sanchez, J. P., Park, H. S., & Adeli, H. (2017). A novel methodology for nodal parameters identification of large smart structures using MUSIC, empirical wavelet transform, and Hilbert transform. Engineering Structures, 147, 148–159.

Bagnall, A., Lines, J., Bostrom, A., Large, J., & Keogh, E. (2017). The great time series classification bake off: A review and experimental evaluation of recent algorithmic advances. Data Mining and Knowledge Discovery, 33(3), 606–660.

Bani-Hani, K. A. (2007). Vibration control of wind-induced response of tall buildings with an active tuned mass damper using neural networks. Structural Control and Health Monitoring, 14(1), 83–108.

Borovykh, A., Bohte, S., & Oosterlee, C. W. (2017). Conditional time series forecasting with convolutional neural networks. arXiv preprint: 1703.04691.

Caione, C., Brunelli, D., & Benini, L. (2014). Compressive sensing optimization for signal ensembles in WSNs. IEEE Transactions on Industrial Informatics, 10(1), 382–392.

Dongmei, H., Shiqing, H., Xuhui, H., & Xue, Z. (2017). Prediction of wind loads on high-rise building using a BP neural network combined with POD. Journal of Wind Engineering and Industrial Aerodynamics, 170, 1–17.

Gao, Y., & Mosalam, K. M. (2018). Deep transfer learning for image-based structural damage recognition. Computer Aided Civil and Infrastructure Engineering, 33(9), 748–768.

Glisic, B., Inaudi, D., Lau, J. M., & Fong, C. C. (2013). Ten-year monitoring of high-rise building columns using long-gauge fiber optic sensors. Smart Materials and Structures, 22(5), 055030.

Hwang, J. S., Kareem, A., & Kim, H. (2011). Wind load identification using wind tunnel test data by inverse analysis. Journal of Wind Engineering and Industrial Aerodynamics, 99(1), 18–26.

Karim, F., Majumdar, S., Darabi, H., & Chen, S. (2018). LSTM fully convolutional networks for time series classification. IEEE Access, 6, 1662–1669.

Kim, H., & Adeli, H. (2005). Wind-induced motion control of 76-story benchmark building using the hybrid damper-tuned liquid column damper system. Journal of Structural Engineering, 131(12), 1794–1802.

Koziasri, M., & Cyganek, B. (2017). Image recognition with deep neural networks in presence of noise – dealing with and taking advantage of distortions. Integrated Computer-Aided Engineering, 24(4), 337–350.

Lee, H. M., Kim, J. M., Sho, K., & Park, H. S. (2010). A wireless vibrating wire sensor node for continuous structural health monitoring. Smart Materials and Structures, 19(5), 055004.

Li, Q., He, Y., Zhou, K., Han, X., He, Y., & Shu, Z. (2018). Structural health monitoring for a 600 m high skyscraper. Structural Design of Tall and Special Buildings, 27(12), e1490.

Li, S., Zhao, X., & Zhou, G. (2019). Automatic pixel-level multiple damage detection of concrete structure using fully convolutional network. Computer-Aided Civil and Infrastructure Engineering, 34(7), 616–634.

Li, Z., Park, H. S., & Adeli, H. (2017). New method for modal identification and health monitoring of super high-rise building structures using discretized synchrosqueezed wavelet and Hilbert transforms. The Structural Design of Tall and Special Buildings, 26(3), e1312.

Lin, Y. Z., Nie, Z. H., & Ma, H. W. (2017). Structural damage detection with automatic feature-extraction through deep learning. Computer-Aided Civil and Infrastructure Engineering, 32(12), 1025–1046.

Molina-Cabello, M. A., Luque-Baena, R. M., López-Rubio, E., & Thurnhofer-Hemsi, K. (2018). Vehicle type detection by ensembles of convolutional neural networks operating on super-resolved images. Integrated Computer-Aided Engineering, 25(4), 321–333.

Ni, Y. Q., & Li, M. (2016). Wind pressure data reconstruction using neural network techniques: A comparison between BPNN and GRNN. Measurement, 88, 468–476.

Ni, Y. Q., Xia, Y., Liao, W. Y., & Ko, J. M. (2009). Technology innovation in developing the structural health monitoring system for Guangzhou New TV Tower. Structural Control and Health Monitoring, 16(1), 73–98.

Niu, Y., Fritzen, C. P., Jung, H., Buehle, I., Ni, Y. Q., & Wang, Y. W. (2015). Online simultaneous reconstruction of wind load and structural responses-theory and application to Canton tower. Computer Aided Civil and Infrastructure Engineering, 30(8), 666–681.

Oh, B. K., Hwang, J. W., Kim, Y., Cho, T., & Park, H. S. (2015). Vision-based system identification technique for building structures using a motion capture system. Journal of Sound and Vibration, 356, 72–85.

Oh, B. K., Kim, K. J., Kim, Y., Park, H. S., & Adeli, H. (2017). Evolutionary learning based sustainable strain sensing model for structural health monitoring of high-rise buildings. Applied Soft Computing, 58, 576–585.

Ortega-Zamorano, F., Jerez, J. M., Gómez, I., & Franco, L. (2017). Layer multiplexing FPGA implementation for deep back-propagation learning. Integrated Computer-Aided Engineering, 24(2), 171–185.

Park, H. S., & Oh, B. K. (2018). Real-time structural health monitoring of a supertall building under construction based on visual modal identification strategy. Automation in Construction, 85, 273–289.

Park, H. S., Sohn, H. G., Kim, I. S., & Park, J. H. (2008). Application of GPS to monitoring of wind-induced responses of high-rise buildings. Structural Design of Tall and Special Buildings, 17(1), 117–132.

Rafiei, M. H., & Adeli, H. (2017). A novel machine learning-based algorithm to detect damage in high-rise building structures. Structural Design of Tall and Special Buildings, 26(18), e1400.
Rafiei, M. H., & Adeli, H. (2018). A novel unsupervised deep learning model for global and local health condition assessment of structures. *Engineering Structures, 156,* 598–607.

Rafiei, M. H., Khushesfati, W. H., Demirboga, R., & Adeli, H. (2017). Supervised deep restricted Boltzmann machine for estimation of concrete compressive strength. *ACI Materials Journal, 114*(2), 237–244.

Shan, J., Shi, W., & Lu, X. (2016). Model-reference health monitoring of hysteretic building structure using acceleration measurement with test validation. *Computer-Aided Civil and Infrastructure Engineering, 31*(6), 449–464.

Shi, W., Shan, J., & Lu, X. (2012). Modal identification of Shanghai World Financial Center both from free and ambient vibration response. *Engineering Structures, 36,* 14–26.

Sigurdardottir, D. H., Stearns, J., & Glisic, B. (2017). Error in the determination of the deformed shape of prismatic beams using the double integration of curvature. *Smart Materials and Structures, 26*(7), 075002.

Tamura, Y., & Suganuma, S. Y. (1996). Evaluation of amplitude-dependent damping and natural frequency of buildings during strong winds. *Journal of Wind Engineering and Industrial Aerodynamics, 59*(2), 115–130.

Tanaka, H., Tamura, Y., Ohtake, K., Nakai, M., & Kim, Y. C. (2012). Experimental investigation of aerodynamic forces and wind pressures acting on tall buildings with various unconventional configurations. *Journal of Wind Engineering and Industrial Aerodynamics, 107–108,* 179–191.

Torres, J. F., Galicia, A., Troncoso, A., & Martínez-Álvarez, F. (2018). A scalable approach based on deep learning for big data time series forecasting. *Integrated Computer-Aided Engineering, 25*(4), 335–348.

Tsogka, C., Daskalakis, E., Comanducci, G., & Ubertini, F. (2017). The stretching method for vibration-based structural health monitoring of civil structure. *Computer-Aided Civil and Infrastructure Engineering, 32*(4), 288–303.

Wang, P., & Bai, X. (2018). Regional parallel structure based CNN for thermal infrared face identification. *Integrated Computer-Aided Engineering, 25*(3), 247–260.

Wang, Z., Yan, W., & Oates, T. (2017). Time series classification from scratch with deep neural networks: A strong baseline. *International Joint Conference on Neural Networks,* 1578–1585.

Xia, Y., Ni, Y. Q., Zhang, P., Liao, W. Y., & Ko, J. M. (2011). Stress development of a supertall structure during construction: Field monitoring and numerical analysis. *Computer-Aided Civil and Infrastructure Engineering, 26*(7), 542–559.

Yang, X., Li, H., Yu, Y., Luo, X., Huang, T., & Yang, X. (2018). Automatic pixel-level crack detection and measurement using fully convolutional network. *Computer-Aided Civil and Infrastructure Engineering, 33*(12), 1090–1109.

Yang, Y., & Nagarajaiah, S. (2016). Harnessing data structure for recovery of randomly missing structural vibration responses time history: Sparse representation versus low-rank structure. *Mechanical Systems and Signal Processing, 74,* 165–182.

Yu, Y., Han, F., Bao, Y., & Ou, J. (2016). A study on data loss compensation of wifi-based wireless sensor networks for structural health monitoring. *IEEE Sensors Journal, 16*(10), 3811–3818.

Zhang, Z., & Luo, Y. (2017). Restoring method for missing data of spatial structural stress monitoring based on correlation. *Mechanical Systems and Signal Processing, 91,* 266–277.

Zhao, B., Lu, H., Chen, S., Liu, J., & Wu, D. (2017). Convolutional neural networks for time series classification. *Journal of Systems Engineering and Electronics, 28,* 162–169.

How to cite this article: Oh BK, Glisic B, Kim Y, Park HS. Convolutional neural network-based wind-induced response estimation model for tall buildings. *Comput Aided Civ Inf.* 2019;34:843–858. https://doi.org/10.1111/mice.12476