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Long-term strain measurement on a jacket-type offshore structure and neural networks based prediction model

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ABSTRACT

Structural strain responses of a jacket-type offshore structure are analyzed and the prediction model is constructed based on the neural networks technique using long-term measurement data. Uldolmok tidal current power plant structure under severe tidal environments is utilized as an example structure. From the measurement data during normal operation, it is observed that strain responses are obviously fluctuated with M2 and M4 tidal constituent periods and also with relatively short period of about 11 min due to the peculiar tidal characteristics in the Uldolmok strait. The neural networks based prediction model is also constructed for the signal-based structural health monitoring system, and the predicted strain responses are well coincident with the measured data.

1. INTRODUCTION

Jacket-type offshore structures are exposed to high levels of external loads such as waves, wind, earthquakes, ship-berthing impacts, and many kinds of operational loads. Moreover, maintenance, repair, and rehabilitation works for offshore structures are much more difficult than for large land-based infrastructures due to the difficulty of access and the inherent characteristics of offshore harsh environments. Therefore, preventative management is very important for achieving a sufficient level of structural safety and operational serviceability for offshore structures, and structural health monitoring (SHM) systems with reliable sensors can play an important role in preventative management (Yi *et al* 2013).

In this study, static strain responses of a jacket-type offshore structure are investigated in light of environmental changes, mainly tidal variations. The results can be a useful public source of fundamental information for a structural health monitoring system for jacket-type offshore structures, especially in high tidal current environments. The neural networks based prediction model is also constructed for the signal-based

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structural health monitoring system, and the predicted strain responses are well coincident with the measured data.

2. STRAIN MEASUREMENT FOR A JACKET-TYPE OFFSHORE STRUCTURE

2.1 Target Structure and Measurement Setup

Korean south-west coast has been considered as a highly attractive candidate for power generation from tidal currents for a long time. Among the possible sites, the Uldolmok Strait is known as the most promising site owing to the distinctive tidal currents with very high speeds up to 4-6 m/sec. Recently the Uldolmok tidal current power plant (TCPP) was built as a pilot plant to promote research and development investment and speed up the commercialization of TCPPs (KORDI 2011). Uldolmok TCPP is located between Jindo Grand Bridge and Byeokpa Port in the east-west direction and also between the towns of Jindo and Haenam in the north-south direction, as shown in Figs. 1 and 2. Uldolmok TCPP was designed, fabricated, constructed, and operated according to the design guidelines for offshore steel jacket platform structures, in order to maintain the structure safely and economically under very high levels of tidal current loading. It is nevertheless very important to monitor structural responses to ensure structural integrity and also to establish load and response databases for further design of a commercialized TCPP farm.

The Uldolmok TCPP monitoring system tracks three categories of data: (1) power-related data including rotational speed and torque at the side of turbine; (2) structural responses including strain, acceleration, and dynamic tilts; and (3) environmental data including tidal current and temperature. This study focuses on the utilization of strain data for investigating the structural behaviors at the bottom of this jacket structure.

8 strain gauges were instrumented at the bottom part of jacket legs (i.e. DL-18m) by referring design report for Uldolmok TCPP as shown in Fig. 3. The strain gauges were attached when the structure was fabricated in the land-based working place at Byeokpa Port and they are protected by specially designed external casings from floating objects in the strait.

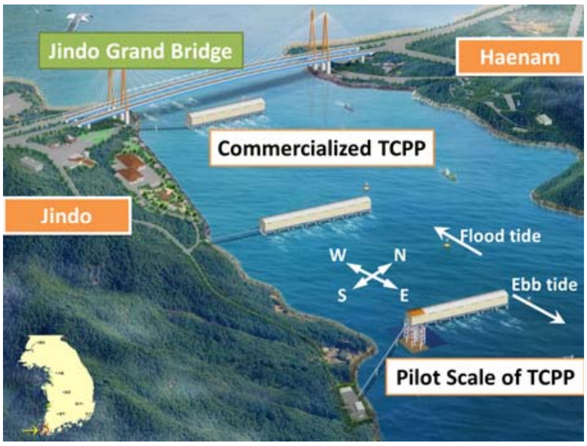


Fig. 1 Location of Uldolmok TCPP

Fig. 2 Jacket-type Uldolmok TCPP

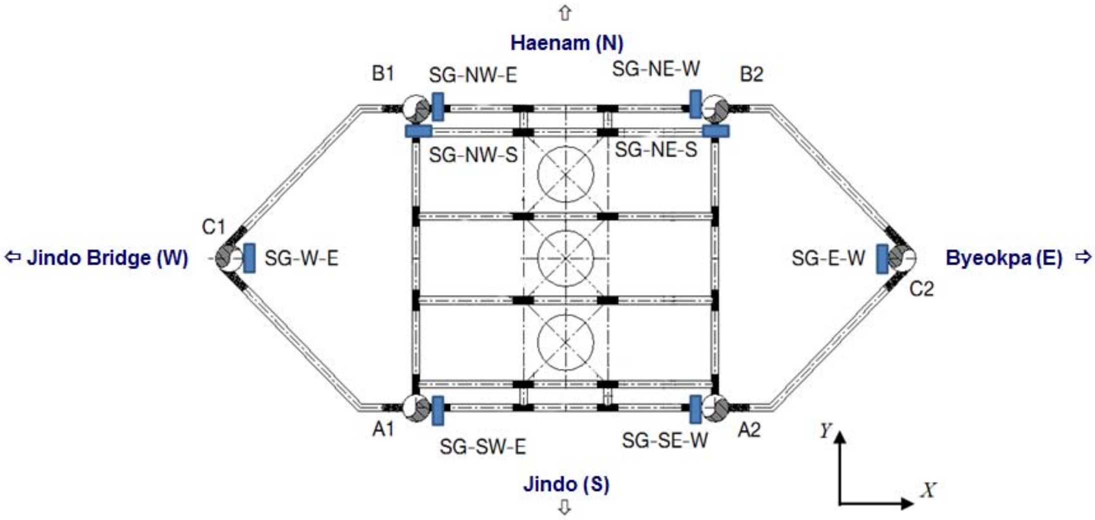


Fig. 3 Installation Locations of Strain Gauges

2.2 Strain Measurement Data

Fig. 4 shows the measured static strain data for three days from September 5 to 7, 2010 with tidal current speed and height. From the measurement data, it is observed that the strains in flood tides is relatively bigger than those in ebb tidal condition, and this is caused by the different characteristics in tidal flow in flood and ebb tides. As shown in this figure, the tidal current speed is up to about 1.6 m/sec in flood tides while the speed is just up to about 1 m/sec in ebb tides. This distinctive characteristic is due to the unique geological and bathymetric features in Uldolmok Strait; i.e. the tidal current in flood tides flows uniformly into the narrowest channel section in this strait while the tidal current bypassed just after the narrowest channel section flows out mainly along the center line in strait. It is also observed that the measured strains in still water conditions (i.e. no tidal current flow) are not the same; i.e. fluctuated as shown in the upper figure in Fig. 4, which is caused that there are some flowing tidal current components along the depth even the surface tidal speed is measured as zero at the measurement point.

From the above Fig. 4, it can be also observed that there is a fluctuation in strain data with a relatively short period. For more quantitative evaluation of this fluctuation phenomenon, the spectral analysis is carried out to identify the period of this fluctuation using long-term measurement data. Fig. 5 shows the spectral components of the measured strain data for six months from April 1 to October 1, 2011. It can be easily observed that the static strain data fluctuated with constant cycles of 1.343×10^{-3} cycles/min and 2.688×10^{-3} cycles/min, which corresponded to periods of 12.412 hours and 6.206 hours, respectively. These values are very close to the periods of modal properties (Yi *et al* 2013) and also with the M2 and M4 tidal constituent periods (i.e. 12.42 hours and 6.21 hours). From the spectral analysis results using static data in flood tides, it can be observed that there is fluctuating components with a relatively short period of 11.25 min, and this unusual periodic component can be also observed as short duration fluctuation in Fig. 4, and this phenomenon is due to the bottleneck feature which can be observed in a very narrow channel like the Uldolmok Strait.

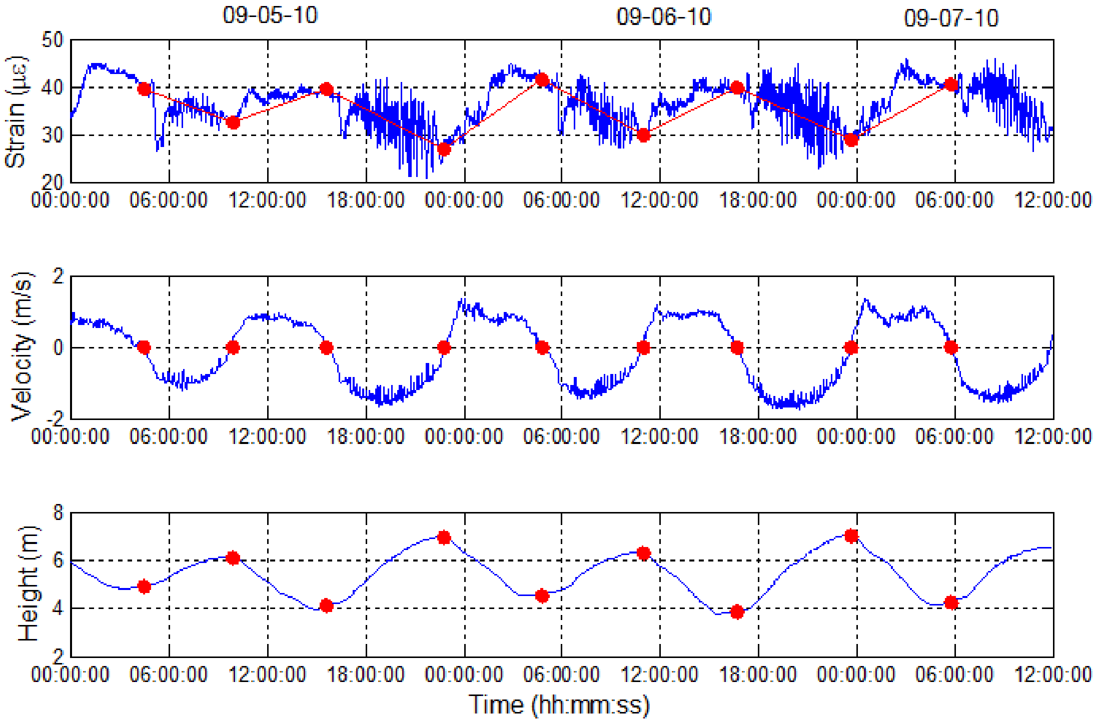
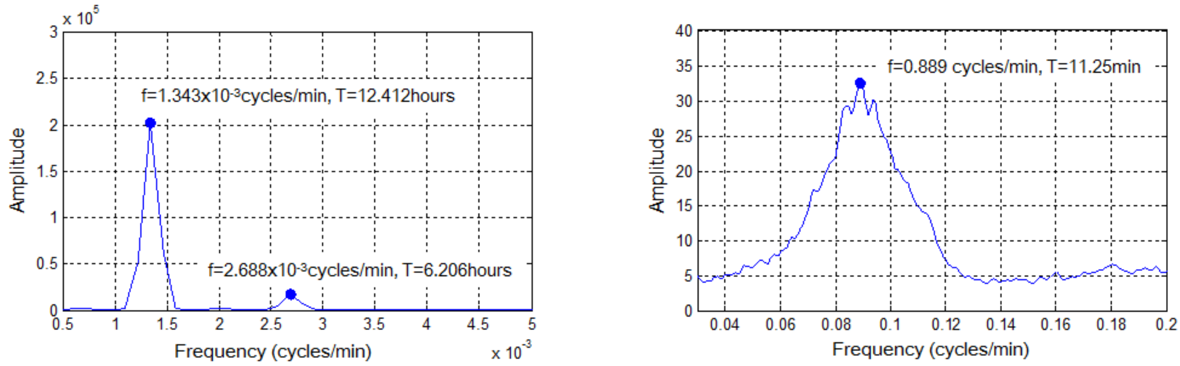


Fig. 4 Measured strain data from September 5 to 7, 2010
(● denotes the still water condition)



(a) Spectra for long period components (b) Spectra for short period components

Fig 5. Spectral analysis for strain measurement data

2.3 Strain Prediction Model Using Neural Networks for Signal-Based Monitoring

It is generally required to build an appropriate strain prediction model for successful model-based or signal-based SHM system. Recently many researches are being carried out to develop signal-based SHM methods as well as model-based methods such as model updating techniques. In the cases of model-based methods, it is available to estimate the damage type, location and severity as well fundamentally based on the quantitative inverse analysis using numerical simulation model, however it should be also noticed that it is very difficult to consider various different boundary conditions, external loading condition, and also non-structural members in the numerical model, and they act as modeling errors in these methods. On the contrary, it is possible to detect the time of damage occurrence and damage locations by looking at the abrupt changes in the measurement strain responses without consideration of modeling errors in the cases of signal-based methods. However, it is also noticed that the reference (i.e. intact or baseline) signal is necessary to detect the abrupt changes due to damage and also environmental effects due to loading and temperature changes need to be studied forehand for successful strain signal-based SHM.

For the construction of fundamental background of signal-based SHM using measured strain data, the neural networks model is utilized to predict the oncoming strain in this study. Tidal information including tidal current speed and tidal height and strain information for the past time from $(i-N_m)$ to i are used as input data, while the strain for the future time step of $(i+1)$ is used as output data to be predicted for multi-layered back-propagation neural networks as shown in Fig. 6. In this figure, N_m represents the model order, which is an equivalent value with the model order in an autoregressive model (Sohn *et al* 1999) given as

$$y(i+1)=\sum_{j=0}^{N_m} a_j y(i-j)+\varepsilon \tag{1}$$

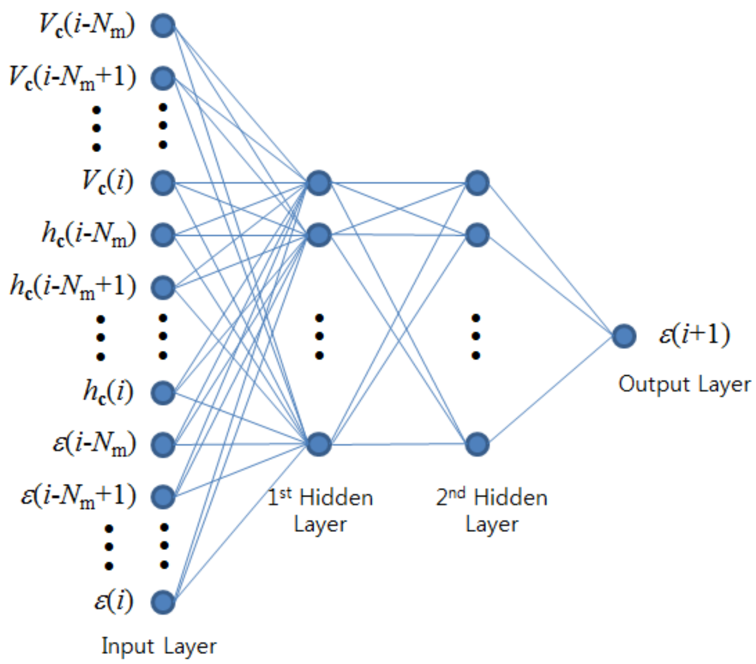


Fig. 6 Strain Prediction Model Using Neural Networks

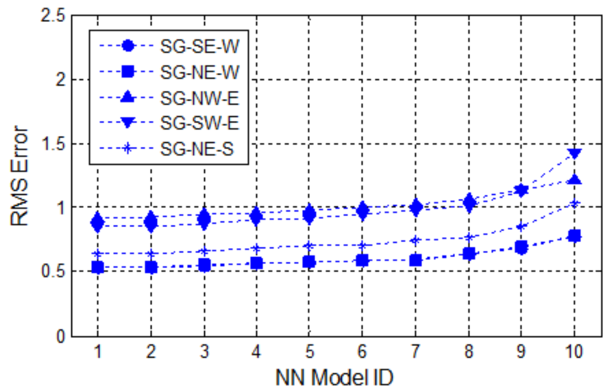
10 different models are introduced with $N_m = 0,1,2,\cdots,9$ to investigate the effect of past data. The model order for the neural network model 1 (i.e. NN model 1) is set as 9, and the model or for the NN model 10 is set as 0, which means that the NN model 1 uses the longest time series (i.e. 10 time step data) while the NN model 10 uses the

shortest time series (i.e. just 1 time step data). Therefore the number of input data are simply given as 30, 27, …, 3 for NN models 1, 2, …, 10, respectively. Two hidden layers are used herein and the numbers of nodes in the first and second hidden layers are specified as 20 and 10, respectively. Then the total numbers of synaptic weights (i.e. unknowns to be decided by training) are 841 (= (30+1)x20 +(20+1)x10+(10+1)x1) and 301 (= (3+1)x20+(20+1)x10+(10+1)x1) for the NN models 1 and 10, respectively. For training NN models, 4000 training patterns are prepared using the measured data from September 5 to September 7, and 3100 data sets are used for the testing patterns. It is notable that the number of training patterns (i.e. 4000) is reasonable in the sense that the number of training patterns is about 5 times more than the number of synaptic weights (i.e 801 in the case of the NN model 1). Generally twice of the number of synaptic weights is recommended as the minimum required number of training patterns to build a neural network model with reasonable generalization capability.

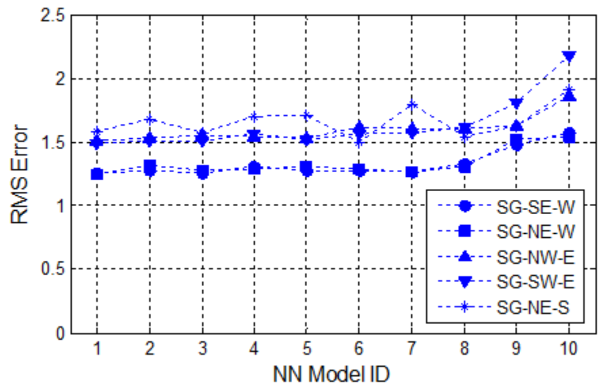
Table 1 and Fig. 7 show the training and testing errors in RMSE (root mean squared error) unit, and it is found that the training error is gradually increased as model order, N_m, is decreased and the training error is less than 1 $\mu\varepsilon$ for NN models 1 to 6. On the other hand, the testing error is slightly larger than training error and it is grossly less than 1.7 $\mu\varepsilon$ for NN models 1 to 6. It is also observed that the strain data measured from the sensors SG-NE-W and SG-SE-W are least for both cases, which means that the strain data measured from these sensors are more reliable and highly correlated with tidal variations. One can decide the NN model 1 is the optimal NN model because the training and testing errors for the NN model 1 are least as shown in the figure, however in the sense of generalization capability, it is more desirable to use less input information when the number of available training patterns is limited like this study. Therefore the NN model 6 with $N_m = 4$ is decided as the optimal NN model herein.

Table 1. Estimation Errors of Neural Networks Model

NN Model ID		1	2	3	4	5	6	7	8	9	10
$N_m^{1)}$		9	8	7	6	5	4	3	2	1	0
Number of Input Data		30	27	24	21	18	15	12	9	6	3
SG-SE-W	$E_{training}$	0.642	0.646	0.664	0.684	0.706	0.709	0.746	0.771	0.855	1.031
	$E_{testing}$	1.581	1.676	1.577	1.704	1.716	1.496	1.796	1.544	1.621	1.911
SG-NE-W	$E_{training}$	0.530	0.536	0.553	0.566	0.575	0.583	0.590	0.641	0.689	0.777
	$E_{testing}$	1.240	1.314	1.281	1.286	1.308	1.288	1.261	1.303	1.520	1.538
SG-NW-E	$E_{training}$	0.917	0.929	0.943	0.959	0.975	0.998	1.020	1.064	1.136	1.213
	$E_{testing}$	1.511	1.527	1.549	1.545	1.534	1.612	1.609	1.606	1.628	1.863
SG-SW-E	$E_{training}$	0.531	0.532	0.544	0.570	0.574	0.584	0.598	0.638	0.684	0.779
	$E_{testing}$	1.260	1.274	1.257	1.308	1.280	1.274	1.268	1.330	1.474	1.568
SG-NE-S	$E_{training}$	0.852	0.848	0.878	0.907	0.914	0.944	0.985	1.012	1.131	1.426
	$E_{testing}$	1.490	1.509	1.508	1.561	1.516	1.560	1.578	1.613	1.808	2.181



(a) Training Errors



(b) Testing Errors

Fig 7. Training and Testing Errors of Neural Networks Based Strain Prediction Models

Fig. 8 shows the measured and predicted strain time histories and it can be obviously observed that the predicted strains are quite well coincident with the measured data and the estimation errors in the period for testing data sets are slightly larger than those for training data. It is expected that the performance of the neural network model can be enhanced by using more measurement data as training patterns and it is also notable that the temperature effect needs to be considered when longer or seasonal variant annual data are utilized in the further study. By considering the temperature effect at the same time, it can be enabled to monitor the structural changes due to damage by using the neural network based strain prediction model.

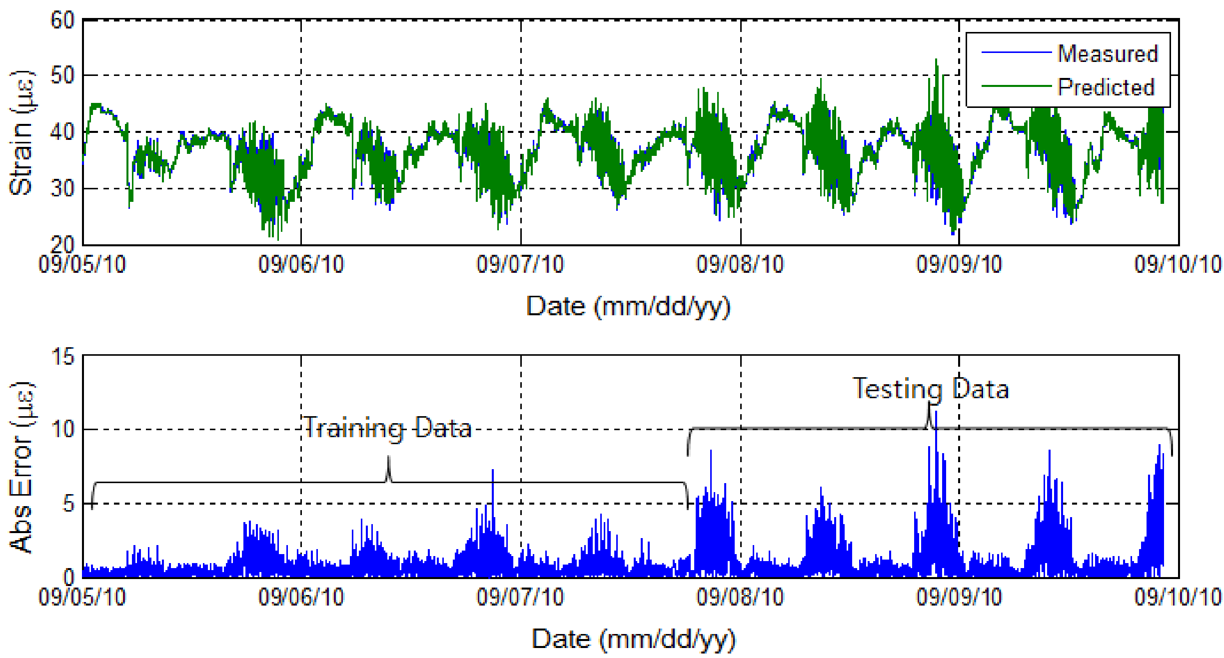


Fig. 8 Measured and Predicted Strain Time Series and Errors between Two Data

4. CONCLUSIONS

In this study, the structural strain responses were measured for the Uldolmok tidal current power plant. In particular, this study focused on the utilization of strain data for investigating the structural behaviors at the bottom of this jacket structure and also constructing the neural networks based strain prediction model for signal-based SHM system. The research also investigated the tidal effects on the modal properties in detail. The following conclusions were made from this study:

First, the measured static strains were also fluctuated and they were found to have same periods of 12.42 hours and 6.41 hours which are corresponding with M2 and M4 periods of tidal components. It was also found that the strains are fluctuated with a short duration with 11.25 min of period, which is due to the bottleneck phenomenon in a narrow channel.

Second, the neural networks based prediction model is also constructed for the signal-based structural health monitoring system, and the predicted strain responses are well coincident with the measured data.

Even though, it is revealed that the static strain data are highly associated with tidal changes and these observations can be very helpful for understanding the structural behavior in strong tidal areas, it is still required to investigate the relationship between the structural responses and structural damages for a successful SHM system. Therefore further studies are being carried out for eliminating these environmental effects with temperature compensation.

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