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Removing Environmental Influences in Bridge Health Monitoring and Copula Approaches

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ABSTRACT

This study aims to normalize operational and environmental influences in a long-term bridge health monitoring. After normalizing the operational and environmental influences, a copula-based feature sensitive indicator is proposed for the bridge health monitoring. Changes in the modal parameters with the time are identified by the copula statistical properties. A case study is carried out based on the observed vibration data collected from a steel plate girder bridge. The data including the temperature and acceleration for the past ten years is utilized to test the applicability of the proposed approach. Based on the results, the copula-based feature sensitive indicator and the selection of the best statistical model in removing operational and environmental influences are discussed.

1. INTRODUCTION

Maintenance of civil infrastructure including bridge structures has been keen technical issues not only for developed countries but also for developing countries. There exist potential risks due to the loss of structural integrity. Therefore, it is highly demanded to establish an efficient inspector or monitoring method. Bridge health monitoring (BHM) using vibration data has been recognized as one of these technologies for timely inspections on bridge structures.

In recent studies, many techniques which identify the hidden information of structural integrity from the vibration data are proposed to diagnose damage in bridge structures (Dilena and Morassi 2011), and are successfully applied to laboratory experiments. Sartor et al. (1999) investigated how short-term monitoring can be used to evaluate bridges when accident occurs. However, bridge health monitoring is usually a

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long-term task, and in the practice of long-term bridge health monitoring, bridge structures are suffering from changing environmental and operational conditions which influence significantly on observed vibration data. For example, the effects of temperature and vehicle weight lead to a statistical change in the measured vibration data (Peeters and De Roeck 2001) and therefore may lead to wrong decision making. The separation of these in-service environment influences from measured vibration data is an important technical issue. Kim et al. (2012) investigated the effects of temperature and traffic loading on structural health monitoring of a multi-span steel plate Gerber type bridge using the in-service vibration data as well as a damage-sensitive feature (DSF) derived from the coefficients of the autoregressive (AR) model. Kim et al. (2014) demonstrated that, in the Bayesian hypothesis testing utilizing long-term monitoring data from the healthy bridge, the damage of the bridge was judged as ‘barely worth mentioning’. Kim et al. (2013) also conducted other research works on long-term BHM and noticed that it is useful to use the Mahalanobis Distance (MD) to detect anomalies from the monitoring data in the multivariate time series data.

All these approaches are theoretically applicable only when the data from different sources are linearly dependent. However, nonlinear dependence is quite common in real sensor observations (Wah et al. 2017). In order to solve this problem, the regression method can be employed to remove the environmental effects contained in the time series. Moreover, accurate multivariate models are required to detect structural damage from multiple observations. Among the recent developments, the copula theory could provide a more efficient use of multivariate data in the structural health monitoring analysis (Zhang et al. 2015). Copula is a multivariate probability distribution whose marginal probability distribution are all uniform distributions. The copula model is used to analyze the statistical changes in the modal parameters. Also, it can be used to describe those dependencies between time series data. The changes in the modal parameters with the time can be identified by the copula statistical properties.

In this study, the copula-autoregressive integrated moving average (copula-ARIMA) model is utilized to remove environmental influences in the observed data for long-term BHM. Based on a case study of real bridge monitoring data, the use of copula-ARIMA model in long-term BHM is proposed.

2. Methodology

2.1 Copula model

Copula has been widely used in quantitative finance to model and minimize risks. Generally, copula is a model which could connect univariate marginal distributions to a multivariate distribution. It is much more flexible than traditional ones as it can describe various kinds of dependencies which include association concepts such as concordance, linear correlation and the related dependence measures. For any random variables with a joint cumulative distribution function, the copula function can be expressed as Eq. (1).

$$C : [0,1]^N \rightarrow [0,1] \text{ and } H(x_1, \ldots, x_n) = C(F_1(x_1), \ldots, F_n(x_n)) \quad (1)$$

where C: $[0,1]^N$ is an n-dimensional distribution function, $H(\cdot)$ is the cumulative joint distribution function and $F_i(\cdot)$ is the individual cumulative marginal distribution function for the i^{th} variable. Specifically, copula C is itself a cumulative distribution function which connects the one-dimensional probability distributions $F_1(x_1),\ldots,F_n(x_n)$ to a multivariate probability distribution $H(\cdot)$.

The most important characteristic in a copula model is the dependence structure. Recently, it has also been considered as an approach in BHM field (Zhang et al. 2017).

2.2 ARIMA model

ARIMA model is widely applied in time series analysis. This model type is generally referred to as ARIMA(p, d, q), with the integers referring to the auto-regressive, integrated and moving average parts of the data set, respectively. ARMA model is the basic form of ARIMA model, the general formula of the ARMA model can be shown as Eq. (2).

$$X_t = a_1 X_{t-1} + \ldots + a_p X_{t-p} + b_1 \varepsilon_{t-1} + \ldots + b_q \varepsilon_{t-q} + \varepsilon_t \tag{2}$$

where ε_t is a Gaussian white noise with zero mean. The ARMA model comprises two parts, namely AR and MA. In the AR model, the current value of the process, X_t, is expressed as a finite linear regression of previous values of the process. In the MA model, the current value of the process, X_t, is a finite linear regression of previous values of the white noise, ε_{t-1}, ε_{t-2}, …, ε_{t-q}, plus the current value of the noise ε_t. In the ARMA model, X_t is expressed as a sum of finite linear regression of previous values of the process, and the past and current white noise inputs.

It should be noticed that in the ARMA model (Ho et al. 1998) the degree of differencing (d) is set as 0. Then, to ignore deterministic component, the lag operator L shown in Eq. (3) is taken into consideration.

$$(1 - L^k) X_t \equiv X_t - X_{t-k} \tag{3}$$

Then the AR model can be shown as

$$X_t = (1 + a_1 L + a_2 L^2 + \cdots)\epsilon_t = \theta(L)\epsilon_t \tag{4}$$

The MA model can also be shown as

$$\epsilon = (1 - b_1 L - b_2 L^2 - b_3 L^3 \ldots) X_t = b(L) X_t \tag{5}$$

Therefore, the ARIMA model can be expressed as

$$a(L) x_t = b(L)\epsilon_t \rightarrow (a(L)/b(L)) x_t = \epsilon \tag{6}$$

where the differencing is not equal to 0. Differencing a non-stationary process d times can transfer it to a nearly stationary process. For example, if y_t is non-stationary, through the following Eq. (7) we can turn it into a nearly stationary one.

$$x_t = (1 - L)^d y_t \tag{7}$$

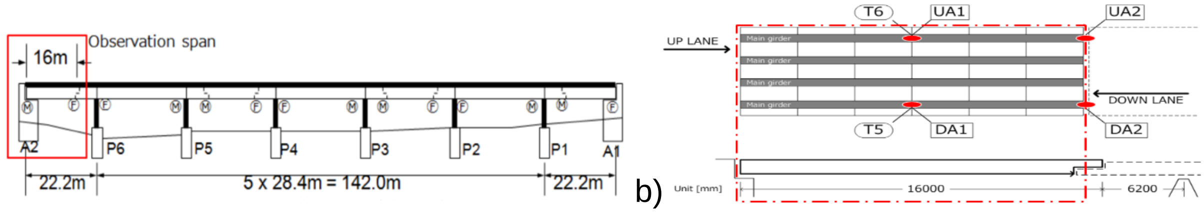
2.3 Copula-ARIMA model

Copula-ARIMA model is a compound model constructed based on ARIMA and copula model. Since the ARIMA model has normalization step, so that here the Gaussian copula will be taken into consideration. It will be utilized to judge the variation of bridge frequency during long-term monitoring.

3. LONG-TERM MONITORING ON AN IN-SERVICE STEEL PLATE-GIRDER BRIDGE

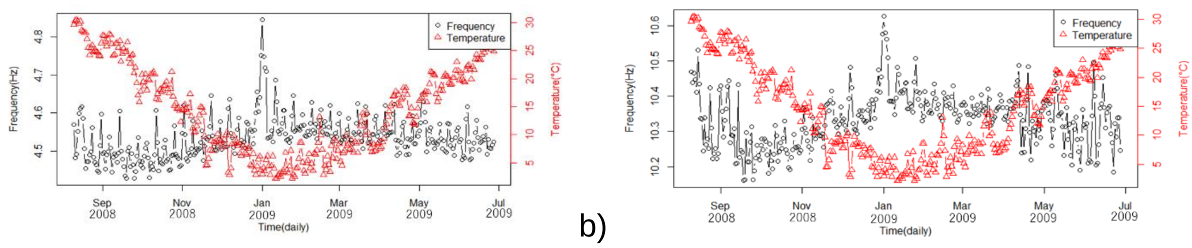
3.1 Observation bridge

A steel plate-girder bridge with Gerber system which is constructed in 1960 is monitored. It has a length of 187m with 7 spans and width of 8m. The bridge has been in service for over 55 years. The general layout of this bridge is illustrated in Fig. 1. The observation bridge experienced fatigue damage caused by higher percentage and volume of heavy trucks. A long-term monitoring for this bridge thus has been conducted since 2008 (Kim et al. 2018). The earliest observed period is considered as the time for the bridge in an intact condition. After normalizing the environmental influences, the data observed during this period can be considered as reference data which will then be compared with the newly observed data. Therefore, the main focus is to examine the first year's data, which is recorded from 6th August 2008 to 21st June 2009.



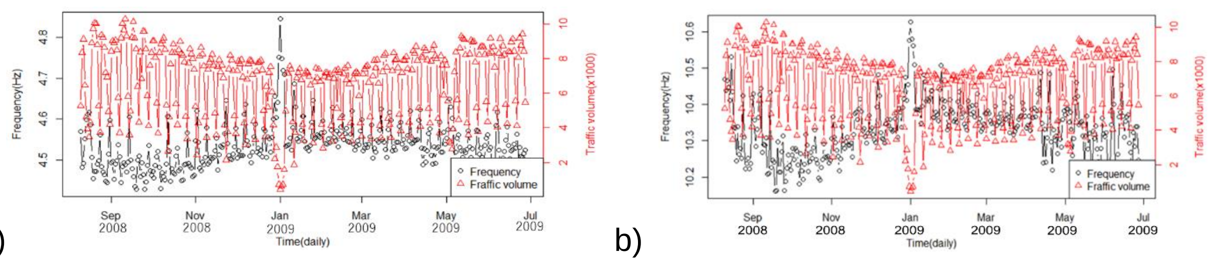
a) b)

Fig. 1 Target bridge a) General layout and b) Sensors location.



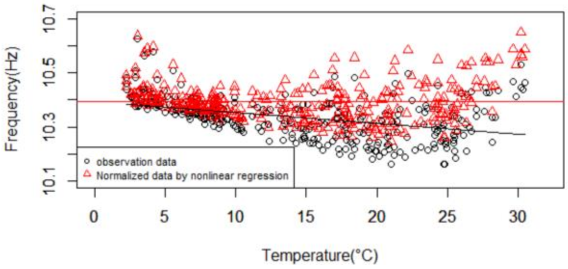
a) b)

Fig. 2 Frequencies and temperature during the first monitoring year: a) 1st bending mode and b) 2nd bending mode.

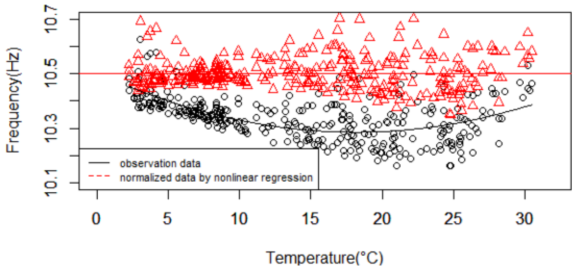


a) b)

Fig. 3 Frequencies and traffic volume during the first monitoring year: a) 1st bending mode and b) 2nd bending mode.



a)



b)

Fig. 4 Regression analysis considering dependency between frequency and temperature: a) linear regression and b) nonlinear regression.

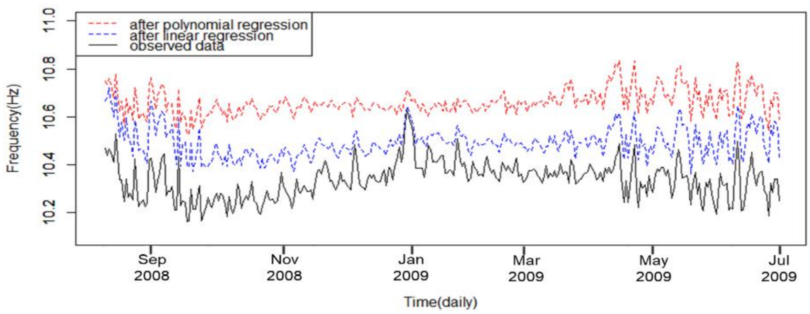


Fig. 5 Comparison of observed data to data after being normalized by linear and polynomial regressions.

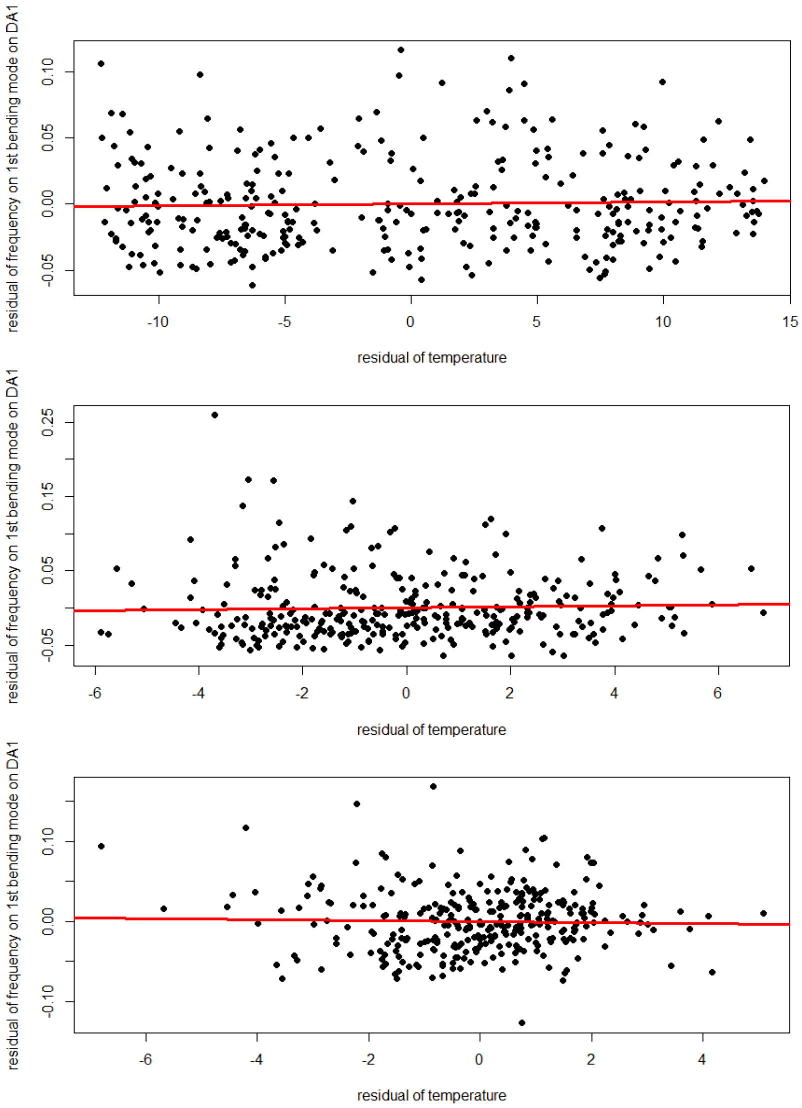
3.2 Data dependency

The correlation of frequency and environmental influences such as temperature and traffic will be investigated. Here, as an example, this study focuses on the frequency measured at the sensor located span center on the outbound lane. Frequency and temperature were plotted as shown in Fig. 2, which shows that the frequency and temperature in the first monitoring year has a negative correlation with each other. Following the same approach, it can be observed existence of the negative correlation between frequency and traffic volume, as shown in Fig. 3. From the observation between identified frequencies and temperature and daily traffic, it is clear that environmental factors are affecting the identified frequencies of the bridge.

3.3 Normalizing environmental influences by regression

Many techniques were developed to identify the hidden information of structural integrity based on the assumption of linear dependence. However, it is not always enough to idealize seasonal fluctuations of identified frequencies utilizing linear regressions. Therefore, both linear and nonlinear regressions are considered to normalize environmental influences. First, a linear regression to the temperature-frequency model is considered, and those results are shown in Fig.4a). Black circles show the observed data and red triangles show the data after the linear regression. Next, a polynomial regression as a nonlinear regression is applied to model the relationship between frequency and temperature as shown in Fig.4b). Unlike the linear regression, there are few limitations on the way that parameters can be used in the functional part of a nonlinear regression model. The nonlinear regression can produce good estimates of the unknown parameters in the model with relatively small data sets.

The frequency time series after normalizing the effect of both temperature and traffic at the same time is shown in Fig. 5. After normalizing environmental influences, the mean frequency was shifted to the upper side. One reason for the shift might exist on the observations of sharp peaks (seasonal outliers) due to drastic changes in traffic during major holidays such as New Year in January, Golden Week in May and OBON in August.



a) $y = k_1x + b_1$
$k_1 = 0.0001326$
$b_1 = -1.314e\text{-}18$

b) $y = k_2x + b_2$
$k_2 = 0.0006125$
$b_2 = 1.577e\text{-}18$

c) $y = k_3x + b_3$
$k_3 = -0.0005546$
$b_3 = -0.0001169$

Fig. 6 Comparison of correlation of temperature and frequency residual: a) linear regression, b) polynomial regression and c) ARIMA model.

3.4 Normalizing environmental effects by utilizing ARIMA model

The time series model will be taken into consideration since the seasonal outliers may can be removed automatically during the prediction. Correlation of residuals of frequency and temperature is shown in Fig. 6, where x-axis denotes temperature residuals. In Fig.6 a), the y-axis shows the residual of frequency which has been normalized by the linear regression. In Fig.6 b), the y-axis shows the residual of frequency which has been normalized by the polynomial regression. In Fig.6 c), the y-axis shows the residual of observed data by applying the ARIMA model directly. The flatter the relation is, the better the regression is.

From k_1, k_2 and k_3 values in Fig.6, the k_1 value is the smallest which means that the linear regression performs best when normalizing environmental effects. However, as shown in Fig.5 the frequency after normalizing environmental effects shift to upside, which means that the linear regression will be affected easily by the outliers. This study also utilizes Akaike information criterion (AIC) which is a measurement for the relative quality of statistical models (Akaike 1974) and serves as a useful tool for model selection to judge the goodness of fit with these three approaches. The AIC value of ARIMA model was -1050.61, while the AIC values of linear and nonlinear regressions were -844.4535 and -854.6544 respectively. The better the independent variables of this model are in predicting the dependent variable, the smaller the AIC becomes. Compare to other two regression methods, the ARIMA model resulted in the smallest AIC value so that the monitored data by the ARIMA model is used in long-term monitoring.

3.5 Applying Copula-ARIMA model in long-term monitoring

The acceleration responses monitored at the DA1 and DA2 shown in Fig. 1 are investigated. DA2 locates at the internal hinge where fatigue cracks were observed, and DA1 locates at the span center. The joint probability distribution of the identified frequencies at DA1 and DA2 is considered to judge the bridge health condition.

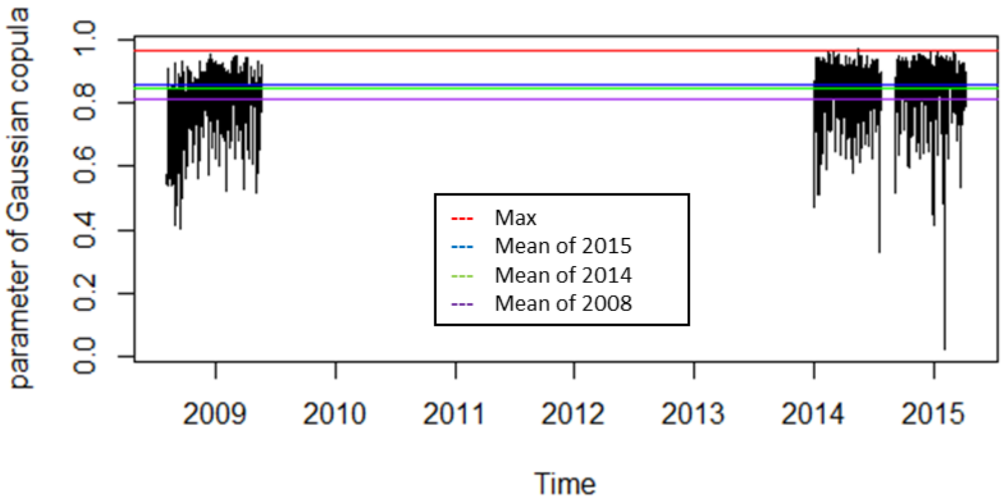
In applying the copula-ARIMA model, the ARIMA model was applied to observation data for normalizing environmental effects. The best fit ARIMA models for the frequency for the first bending mode were both following ARIMA (2,1,1). For the copula model, there are basically two families of copulas, Gaussian copula and Archimedean copula. In this study, since normalization will be applied on the observation data, the fundamental Gaussian copula which can be utilized in normal distribution was selected. The Gaussian copula can be written as Eq. (8).

$$C(u_1, \dots, u_N; \rho) = \Phi_\rho(\Phi^{-1}(u_1) + \cdots + \Phi^{-1}(u_N)) \tag{8}$$

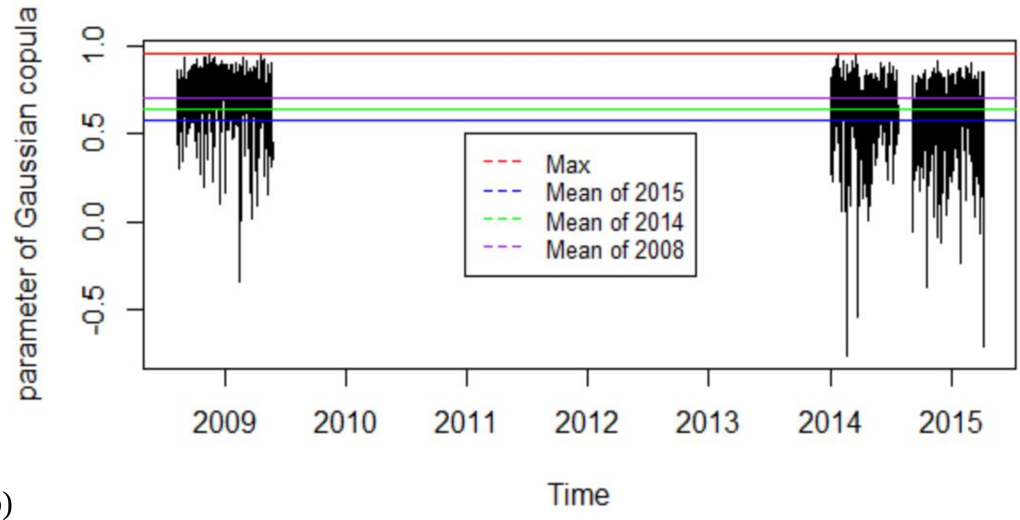
where ρ denotes a correlation coefficient matrix; $\Phi_\rho(\cdot)$ and $\Phi^{-1}(\cdot)$ denote the standard multivariate normal distribution function and the inverse function of standard normal distribution function respectively.

For two variables, the Gaussian copula has only a single parameter ρ. It conveniently incorporates the correlation into a function that combines each of the marginal distributions to produce a bivariate cumulative distribution function. Considering the bivariate dependence, there are some measurements like Pearson correlation coefficient, Spearman's rho and Kendall's tau. These three methods are utilized to judge the relationship between residues without utilizing copula model. They can only judge whether the correlation is strong or weak, but they cannot show the variation in long term monitoring. Therefor here the parameter of Gaussian copula will be utilized to judge the variation of the joint probability distribution of the frequency identified from accelerations measured at DA1 and DA2 sensors.

After applying the copula-ARIMA model in long-term monitoring, the variation of the joint probability distributions for the first and second bending modes are shown in Fig. 7, Table 1 and Table 2. Here the parameter of Gaussian Copula is considered as indicator to detect the potential change in the bridge integrity. Fig.7 demonstrated that the mean value of the parameter of first bending mode keeps increasing while the mean value of the parameter of second bending mode keeps decreasing during observation years. This may due to the change in structural conditions of the bridge.



a)



b)

Fig. 7 Long-term variations of parameter of Gaussian copula: a) first bending mode; b) second bending mode.

Table 1 Parameter of Gaussian copula of first bending mode in different years.

Year	Min.	Median	Mean	Max.
2008	0.4038	0.8142	0.7968	0.9539
2014	0.3310	0.8445	0.8263	0.9716
2015	0.0255	0.8570	0.8357	0.9630

Table 2 Parameter of Gaussian copula of second bending mode in different years.

Year	Min.	Median	Mean	Max.
2008	-0.3384	0.7334	0.7033	0.9462
2014	-0.7604	0.6701	0.6414	0.9583
2015	-0.7112	0.6112	0.5805	0.9186

4. CONCLUSIONS

Feasibility of normalizing the environmental effects in long-term bridge health monitoring such as temperature and traffic volumes by means of linear and polynomial regressions and ARIMA model is investigated utilizing long-term monitoring data of the steel plate girder bridge. Observations showed that the nonlinear regression model resulted in better regression than the linear regression model. However, the mean frequency was shifted to the upper side after normalizing environmental influences, which might be caused by seasonal outliers due to drastic changes in traffic during major holidays. However, in terms of AIC, the ARIMA model led to the best model.

A copula-ARIMA model showed that the mean value of parameter of the Gaussian copula was increasing for the first bending mode while the parameter was deceased for the second bending mode during the monitoring. This may due to changes in bridge integrity, although the mechanism of increasing and decreasing trends is not clear yet. The next step for this study is further investigations considering higher frequencies and other damage sensitive feature, and other copulas.

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