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COMPUTER SIMULATION MODELS FOR CONSIDERATION OF SEASONAL TRENDS INFLUENCE ON THE STRUCTURAL DYNAMICS OF BRIDGES

Elimination of seasonality temperature trends in a structural health monitoring of bridges is considered in the article. On example of a beam bridge, eigenfrequencies are plotted against seasonal fluctuations of environmental temperature. Next, analysis of a time series, formed from a data of frequency changes in the bridge, was made. To describe the time series, two different methods were implemented: ARIMA model based on a statistical relationship between the data and LSTM model of a recurrent neural network.

Keywords: *computer simulation, seasonality elimination, structural health monitoring, time series, forecast, SHM, ARIMA, recurrent neural network*

1. Introduction

In general, long-term structural health monitoring of bridges can be described as a process of detecting damage and strategies for describing structures using mathematical models. Appearance of damages inevitably leads to a change in the dynamic response of an object, but this change can also be related to environmental factors (impacts of temperature, seasonal changes in soil characteristics and etc.) or even with dynamic loads (wind pressure, different types of transport), which also significantly affect the dynamics. For example, a daily or seasonal temperature change that deforms the contour of a bridge deck due to heating, or severe, stable wind that deflects the bridge deck. These changes may persist for a certain period of time before returning to normal condition. Standard instruments, such as accelerometers, can give only instant local vibration, but cannot detect stable deformation of the bridge deck, so an absolute displacement was left undetected. Such limitations in detecting an initial condition of the structure would lead to errors in modal parameter estimation. Studies of bridges show that environmental influence leads to deviation of the eigenfrequencies of the structures to 1.52% [1], which can mask the change in frequencies due to damage.

Therefore, before determining the presence of damage in a structure, it is necessary to evaluate an influence of environment on the dynamic response of a structure. The process of the damage identification, based on the operational modal analysis with the filtering of influence, is shown in Figure 1.

Parameter u_k represents "white noise", stationary Gaussian process across the entire frequency band, x_k is a response of a structure in time, u^{env}_k is an environmental impact, w_k is modal contribution from random loads, v_k is a noise from external sources, y_k is measured response of the structure, all arrows denote signal vectors, and k denotes discrete time index. The impact of environment and loads on the measured response is estimated based on the correlation dependence between them, for example, using the regression models [2]. In addition, influence of different types of excitation were studied (measured and controlled harmonic oscillations, hammer impact, recording of "white noise") for identification of damages [3].

There are monitoring systems in which an impact of wind speed and temperature are measured (Wind and Structural Health Monitoring Systems). As an example, a system is installed on the Stonecutters Bridge, Hong Kong, China [4]. Such long span bridges are often a subject to various aggressive environmental influences, such as ultra-high wind speed or uneven heating. To prevent detrimental effect on the results of the modal analysis, the characteristics of the wind flow and temperature of the heating of elements are fixed on the bridge. Further, using these data, the modal parameters are adjusted, as well as maximum displacements of the girder and pylons and forces in pylon basement. This approach is called "the model update method" - a process of iterative change in individual parameters of finite element model to minimize the difference between experimentally measured and calculated structural response [5]. However, some studies are aimed to eliminate the influence of environmental factors without their direct measurement. This will simplify the monitoring of objects by reducing the number of measured parameters.

2. Statement of the problem

Influence of environment, in particular the temperature changes that affect the eigenfrequencies of bridges, was considered in this paper. As an object for research was chosen an overpass - large road demountable bridge. The span of the structure has a length of 53.5 m and a width of 8.6 m, it consists of two main beams, assembled from six middle and two end sections,

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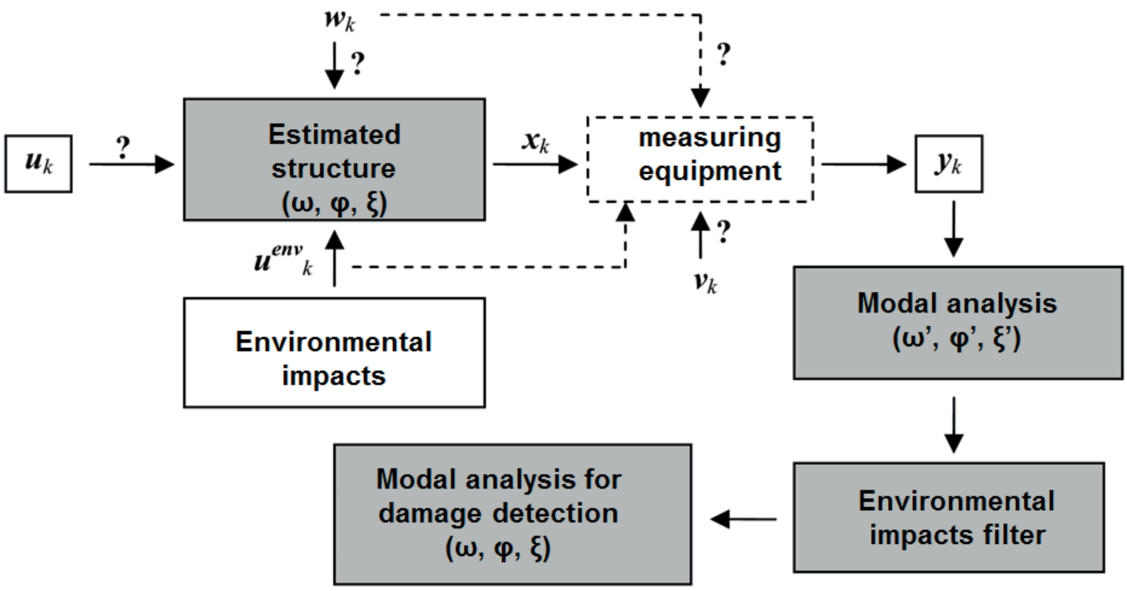

***Figure 1** Sequence of the operational modal analysis process for fault identification*

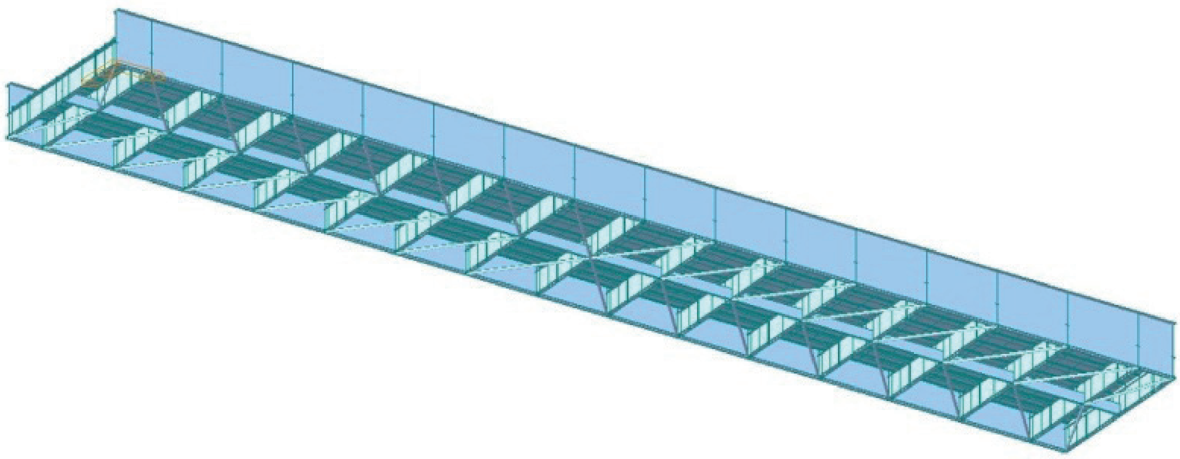

***Figure 2** Spatial model of the BARM road bridge, bottom view*

interconnected by transverse beams of the I-section. The deck lays on this system, made in a form of an orthotropic plate.

A spatial model of the structure was created using the Midas Civil software (Figure 2). The model is made up of beam elements in the form of I-beams for the main and transverse beams and I-beams ℓ14 for the flooring. The deck is represented by plate elements of a given thickness and is rigidly connected to the transverse beams. Eigenfrequencies and eigenvalues for the model were calculated.

To study the effect of temperature on dynamic characteristics of the bridge, a table of average monthly air temperatures is compiled taking into account the number of sunny days (Table 1). For the temperature influence an assumption was made that during the sunny weather an additional solar heating of the span structure takes place, which was calculated according to the "Recommendations for calculating the temperature effects" [6].

Heat of hydration analysis was made for each month with and without additional heating. Further, additional stresses in the main beams of the model due to heating were determined. At the next step, those stresses were applied as initial conditions for calculating the eigenfrequencies of the bridge. As a result, obtained data on the example of fluctuations of first eigenfrequency of bridge can be represented in form of the graph in Figure 3. In the case of annual fluctuations in temperature of the beam, change of the first eigenfrequency will correspond to the graph of Figure 3.a. In order to trace the possible patterns Figure 3.b was constructed, corresponding to change of the first eigenfrequency for 3 years and the weighted moving average (marked red) was calculated.

3. Creation of the predictive models for the data set

Generated data is represented in form of time series - sequentially measured data describing a time-consuming process. The first thing that needs to be done when analyzing this type of data is to estimate the stationarity of the time series - the absence of a trend, seasonality, data releases, etc. According to the moving average (red in graph in Figure 3.b) there is a pronounced

Table 1 *Average temperature of air and bridge per year and additional influence of solar radiation*

month	sunny days in mounth	t air, C		additional solar heating	t of heated bridge, C
		min, night	max, day		
1	2	-10	-7.5	5.12	-2.38
2	2	-7.4	-4	2.73	-1.27
3	3	-5	-0.4	0.27	-0.13
4	8	2.7	9.6	6.56	16.16
5	15	10.7	20	13.66	33.66
6	14	13.3	22.7	15.50	38.20
7	17	15.3	25.1	17.14	42.24
8	19	14.1	23.8	16.26	40.06
9	9	8.9	15.7	10.72	26.42
10	6	3	6.9	4.71	11.61
11	6	-1.5	1.4	0.96	2.36
12	2	-5.9	-3.4	2.32	-1.08

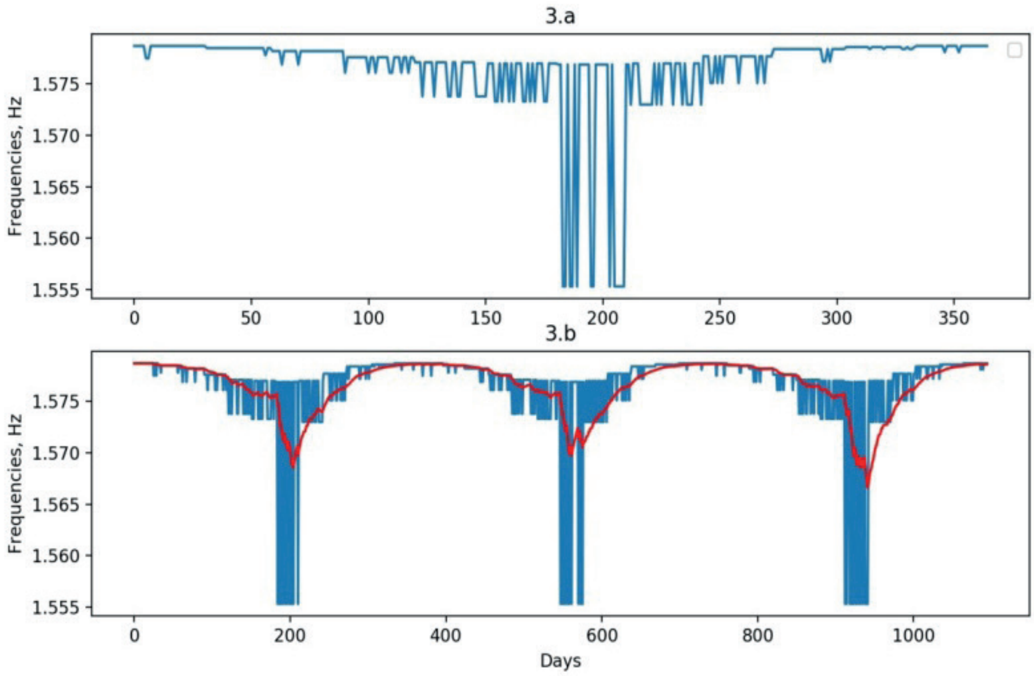

Figure 3 *Change in the first eigenfrequency of the bridge in a year (3.a) and in three years (3.b)*

seasonality of the data - a regular frequency change that repeats over a period of time, in this case annually. Emissions and stable trends are absent - moving average does not change from year to year, since the eigenfrequencies remain unchanged. Therefore, further processing will be carried out with an emphasis on the removal of seasonality.

In general, two main methods for creating models for describing and predicting time series can be distinguished: mathematical methods based on statistical data processing and machine learning methods, such as, for example, recurrent neural networks. Each of them was analyzed separately.

3.1 Integrated model of autoregression moving average (ARIMA)

The ARIMA model belongs to the class of statistical models for analysis and prediction of the time series. The model name is an acronym, the capital letters of which literally means the following:

AR: Autoregression is the use of a link between current and some lagging observations;

I: Integrated - a process that uses the difference between the current and previous observation so that the time series is unchanged;

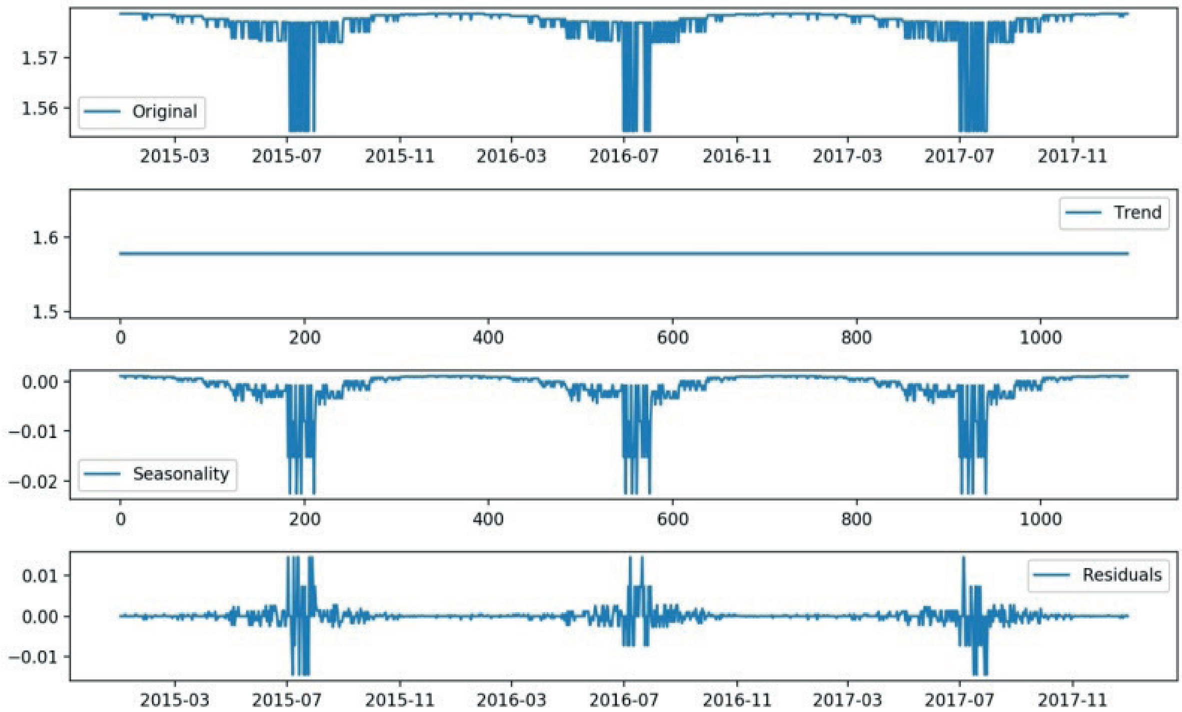

Figure 4 *Decomposition of the initial time series to the trend, seasonality and residuals*

MA: The moving average is a model where the relationship between observation and residual errors from the moving average model is used in relation to delayed observations.

Each of these components is explicitly specified as a model parameter. The standard notation used in the ARIMA (p, d, q), where each of the parameters is replaced by numbers in order to quickly specify the model being used. Model parameters mean:

p - the number of delayed observations contained in the model, also known as the order of lags;

d - number of order of difference of time series;

q - the size of the sliding-middle window (the order of the moving average).

In the case of the ARIMA type models, two main methods are distinguished in order to remove seasonality and trend in the time series: differentiation and decomposition [7]. In the generated data, trend is absent, so it is preferable to use the decomposition method, so trend would be represented as a horizontal line. In that case it is convenient to use the abstraction when the time series decomposes into several components: the remainder (the average value in a series), trend, seasonality and noise (random variation in a series). The first three components refer to systematic components of the time series that are consistent or repeatable and can be described and modeled. Noise, in turn, refers to the non-systematic component - it cannot be modeled directly.

According to Figure 3.b, it can be seen that seasonality has the same frequency and amplitude (width and height of cycles), that is, the linearity of the seasonal component. Then it seems possible to use an additive model describing the components of the time series, where the changes over time are consistently produced by the same amount:

$$y(t) = Residuals + Trend + Seasonality + Noise \quad (1)$$

After the decomposition is performed (Figure 4), the next step is to construct a mathematical model describing a stationary remainder of the time series. Building a model based on the ARIMA requires calculation of the parameters p, d, q, which can be performed in several ways. This article uses the method of iterative search for the best model by iterating through all of the basic combinations of parameters; the models are evaluated using the Akaike Information Criterion (AIC). This criterion measures how well the model fits the data, taking into account the overall complexity of the descriptive function.

A model that accurately describes data using multiple functions will have a larger AIC indicator than a model that uses fewer functions to achieve the same accuracy. Therefore, it is necessary to choose a model that gives the lowest value of the criterion. After iterative search, coefficients (0, 2, 0) gave the minimal result AIC:-7965,1. Figure 5 shows a graph of the time series and residuals description using the generated model ARIMA (0, 2, 0).

3.2 Model based on recurrent neural networks

From all the types of neural networks, the long-term memory (LSTM) is allocated to work with time series; it is well suited to learning on tasks of classification, processing and forecasting of time series in cases where important events are separated by time lags with indefinite duration and boundaries [8]. This recurrent network is trained using the back propagation in time - an algorithm that is used to update weights with all the network parameters taken into account. Use of a neural network can be rephrased as a question of constructing the regression dependence.

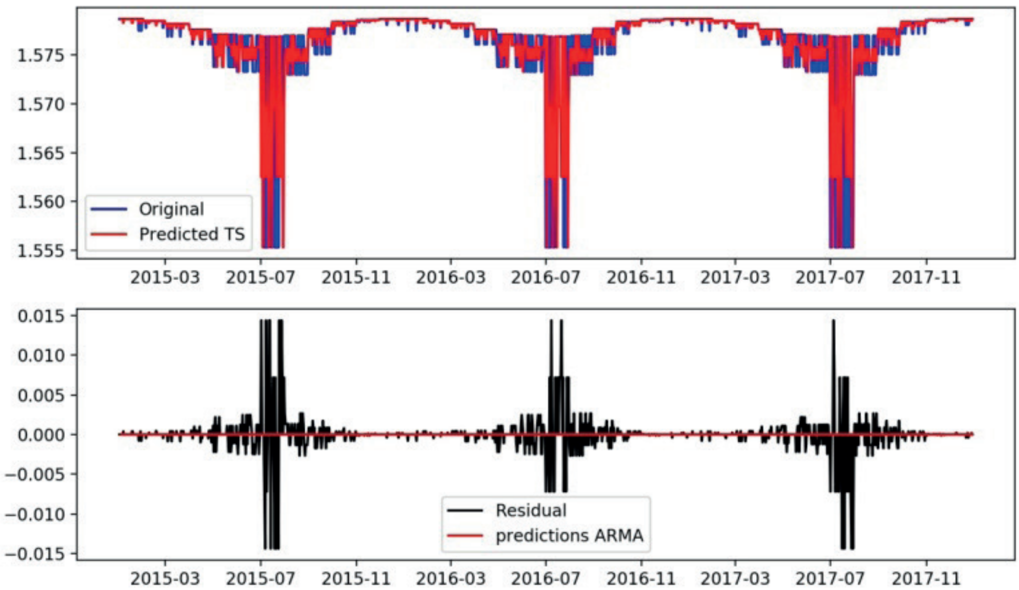

Figure 5 *Description of the original time series and residuals by the ARIMA model*

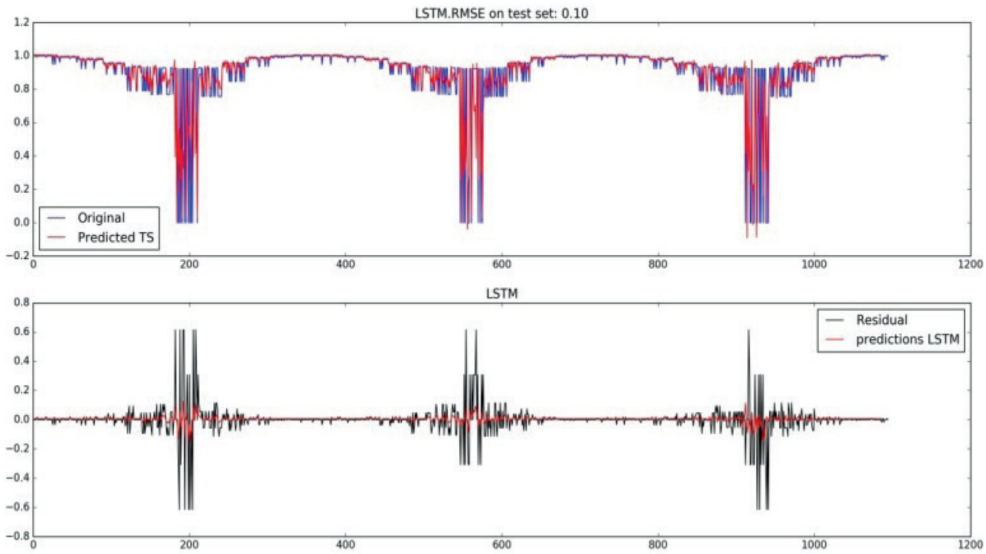

Figure 6 *Description of the original time series and residues by the LSTM model*

When using the time series, it is important to follow the order of using the values. The simplest method to use is to split an ordered set of data into a training and test data sets. The data was divided into a training data set with 67% of observations that can be used to train the model, leaving the remaining 33% for testing the model.

After the original data is modeled and the accuracy of the describing model is estimated by the training sample, one needs to get an idea of the predictive ability of the model with the new test data. For regression, this was done by using the cross-validation.

Form a network in which there is a visible layer with 1 input signal, a hidden layer with 4 LSTM blocks or neurons and an output level that makes one prediction value. For LSTM blocks, the default sigmoid activation function is used. Figure 6 presents a graph of the time series and remainder description using the generated model.

4. Conclusion

The article examines two main models of detrending and forecasting the time series. For the model building process a general data set was used, containing information about the dynamic response of the structure during the temperature fluctuations. Development of the two models, allowing to predict the influence of environment on the dynamic behavior of a structure, is an urgent task in the field of monitoring of artificial structures. Its solution would lead to reduction in the number of parameters that require direct measurement and, consequently, to simplifying the monitoring systems and reducing their costs.

Both models give a good descriptive ability, the root-mean-square error is within acceptable limits. Constraints on the predictive ability of models are introduced in connection with the correlation of the data of the numerical experiment; in the future, with long-term monitoring of real objects, this can be avoided.

Further investigation in this direction would be to combine the two models and construct one predictor based on the method of voting (ensemble learning). This combination would improve the predictive ability, eliminate errors arising due to appearance of emissions and align the flaws of each model.

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