Structural Damage Identification under Non-linear EOV Effects Using Genetic Programming

Mohsen Mousavi*
Faculty of Engineering and IT,
University of Technology Sydney
Sydney, NSW
mohsen.mousavi@uts.edu.au

Amir H. Gandomi†
Faculty of Engineering and IT,
University of Technology Sydney
Sydney, NSW
gandomi@uts.edu.au

Magd Abdel Wahab‡
Faculty of Engineering and
Architecture, Ghent University
Ghent, Belgium
magd.abdelwahab@ugent.be

CCS CONCEPTS

• Computing methodologies → Heuristic function construction; • Applied computing → Engineering.

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1 INTRODUCTION

The methods to perform long-term condition monitoring of structures can be generally divided into two main categories, i.e. output-only and input-output methods. The former seeks to detect any anomaly in the structural modal data caused by damage without knowing the cause. Input-output normalisation methods have been used for removing Environmental and Operational Variations (EOV) effects, some examples of which include multiple linear regression [1], artificial neural networks [4] and support vector regression [2].

All these methods, however, are either very complex, so that the basic rule behind their performance cannot be unfolded or they cannot deal with the case when there is a nonlinear dependency between the temperature and the structural natural frequencies. A typical example of such problems is the benchmark problem of the Z24 bridge [3]. In this paper, the genetic programming (GP) is used to deal with the nonlinear problem of condition monitoring of structures under EOV.

2 A GP-BASED CONDITION MONITORING METHOD

Figure 1 shows the pipeline of the proposed condition monitoring strategy. It is assumed that a couple of first natural frequencies of the healthy structure as well as the air temperature signals measured at some period of time are available in the first stage to train a GP model. The evolved GP model learn how to predict temperature using the natural frequencies as input. The absolute error of the prediction results in the secondary stage of the structure is considered as damage sensitive feature. Finally, the predicted errors are smoothed using a moving average sliding window and compared against a threshold to decide whether or not the structure has undergone a change that can be referred to as damage.

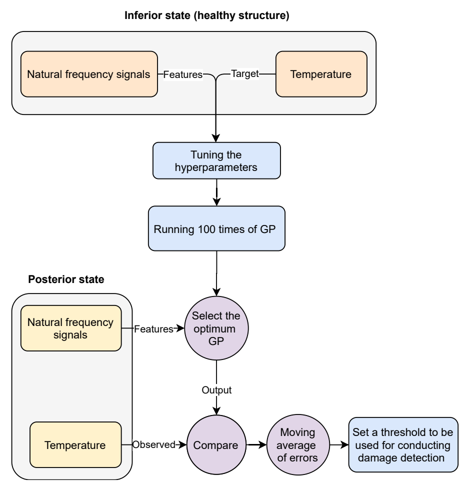

Figure 1: Flowchart of the proposed pipeline.

3 A THRESHOLD SETTING TECHNIQUE

Here we propose a method to specify a threshold for the damage detection purpose. The following steps are followed to this end,

(1) A moving average sliding window[1] is first used to smooth the curve of the prediction errors.
(2) The peaks in the resulting signal corresponding to the validation set are selected.
(3) An upper-bound confidence level for the expected value of the peaks is introduced as the threshold.

The following formula is, therefore, proposed to be used,

$$\bar{\epsilon}^{+} = \bar{\epsilon} + z_{1-\alpha/2}\left(\frac{s}{\sqrt{n}}\right), \tag{1}$$

*Dr. Mohsen Mousavi is a postdoctoral research associate at the data science institute, University of Technology Sydney.
†Prof. Amir H. Gandomi is a professor of data science at the data science institute, University of Technology Sydney.
‡Prof. Magd Abdel Wahab is a professor of mechanical engineering at Ghent University.

[1]The length of the sliding window is 100 records in the example of this paper.

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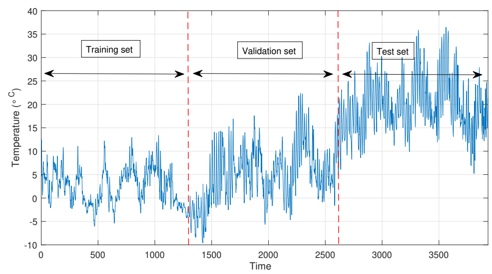

Figure 2: The environmental temperature recorded during the time of monitoring of Z24 bridge

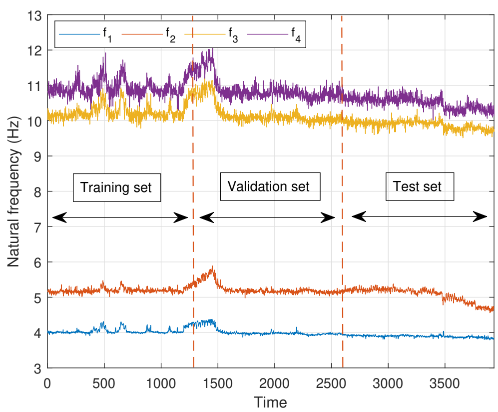

Figure 3: Obtained natural frequencies of the Z24 bridge from vibration data during the monitoring period.

where $z_{1-\alpha/2}$ represents the $(1-\alpha/2)$ quantile of the z-distribution where α is the significance level. $\bar{\epsilon}^{+}$ is the upper-bond confidence level of the expected value of the prediction errors regarding the peak points obtained from the errors of the validation set, i.e. $\bar{\epsilon}$. n represents the number of data samples in the validation set, and s is the sample standard deviation.

4 EXPERIMENTAL VALIDATION (Z24 BRIDGE)

In this section, the long-term condition monitoring problem of the Z24 bridge is studied as a benchmark problem. Figures 2 and 3 show respectively the air temperature and the first four natural frequencies of the bridge signals recorded during one year prior to the bridge dismantlement.

The introduction of damage starts at slightly before the record number 3500 of the obtained signals. A fraction of 1/3 of the dataset is used for training, 1/3 for validation and 1/3 for testing. Note that that the training and validation datasets, therefore, correspond to the healthy structure.

4.1 Training a GP model

The evolved GP program obtains a formula that outputs the value of the air temperature given the values of the frequency signals as

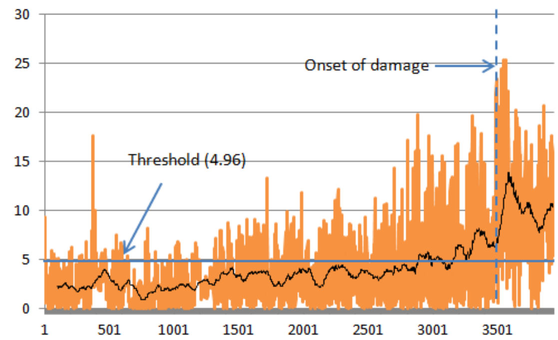

Figure 4: The calculated errors corresponding to the whole data set.

inputs. The following formula for the prediction of the temperature T using the frequencies at each time instant is derived as follows,

$$T = \left(\left(\frac{c_2}{f_4^2} \right) \times (c_2 - f_1) \times (Exp(f_2) + c_1) \right)^3, \qquad (2)$$

where $c_1 = 11.76$ and $c_2 = 4.25$. f_1, f_2 and f_4 indicate respectively the first, second and forth natural frequencies of the Z24 bridge at each time instant. It can be noted from (2) that the third natural frequency f_3 has not been used for the prediction.

Regarding the test set, the value of the temperature at each time instant given the values of the frequencies has been calculated using (2). The predicted values have been then compared against the observed values of the temperature. Figure 4 shows the calculated errors of the entire dataset (3932 records). It can be seen from the figure that the specified threshold can detect the time of the damage occurrence accurately.

5 CONCLUSIONS

A method has been proposed for long-term condition monitoring of civil infrastructures using the air temperature and a couple of lowest structural natural frequencies identified at some time instants over a long period of time. GP was selected as a technique to obtain an equation that can predict the value of the temperature given the structural natural frequencies as input. The prediction errors of the temperature was introduced as damage sensitive feature. We showed that the prediction errors exceed the specified threshold when the damage occurs in the benchmark problem of the Z24 bridge.

REFERENCES

[1] JM Ko and Yi Qing Ni. 2005. Technology developments in structural health monitoring of large-scale bridges. *Engineering structures* 27, 12 (2005), 1715–1725.
[2] Rolands Kromanis and Prakash Kripakaran. 2013. Support vector regression for anomaly detection from measurement histories. *Advanced Engineering Informatics* 27, 4 (2013), 486–495.
[3] Haichen Shi, Keith Worden, and Elizabeth J Cross. 2018. A regime-switching cointegration approach for removing environmental and operational variations in structural health monitoring. *Mechanical Systems and Signal Processing* 103 (2018), 381–397.
[4] HF Zhou, YQ Ni, and JM Ko. 2010. Constructing input to neural networks for modeling temperature-caused modal variability: mean temperatures, effective temperatures, and principal components of temperatures. *Engineering Structures* 32, 6 (2010), 1747–1759.