Structural Deterioration Detection Using Enhanced Autoregressive Residuals

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This paper presents a study on detecting structural deterioration in existing buildings using ambient vibration measurements. Deterioration is a slow and progressive process which reduces the structural performance, including load-bearing capacity. Each building has unique vibration characteristics which change in time due to deterioration and damage. However, the changes due to deterioration are generally subtler than changes due to damage. Examples of deterioration include subtle loss of steel-concrete bond strength, slight corrosion of reinforcement and onset of internal cracks in structural members. Whereas damage can be defined as major sudden structural changes, such as major external cracks of concrete covers. Herein, a deterioration detection method which uses structural health monitoring (SHM) data is proposed to address the deterioration assessment problem. The proposed novel vibration-based deterioration identification method is a parametric-based approach, incorporated with a nonparametric statistical test, to capture changes in the dynamic characteristics of structures. First, autoregressive (AR) time-series models are fitted to the vibration response time histories at different sensor locations. A sensitive deterioration feature is proposed for detecting deterioration by applying statistical hypotheses of two-sample f-test on the model residuals, based on which a function of the resulting *P*-values is calculated. A novel AR model order estimation procedure is proposed to enhance the sensitivity of the method. The performance of the proposed method is demonstrated through comprehensive simulations of deterioration at single and multiple locations in finite element models (FEM) of 3 and 20-storey reinforced concrete (RC) frames. The method shows a promising sensitivity to detect small levels of structural deterioration prior to damage, even in the presence of noise.

Keywords: Deterioration detection; autoregressive residual; structural health monitoring; Vibration-based method.

1. Introduction

Buildings play a vital role in supplying essential infrastructures needed for societies; however, many of these structures are deteriorating at an alarming rate due to a variety of adverse factors, such as ageing, environmental effects, and varying service loads. The changing characteristics of buildings due to deterioration along with inappropriate maintenance programs reduce their intended structural performance. Hence, it is crucial to evaluate the deterioration condition of structures to maintain their safety, to increase their life expectancy and to reduce their costs of maintenance and repairs. Numerous existing buildings are and will be in great need of repair and maintenance. A preventive maintenance plan usually cost less than repairing damage, but the current structural assessment methods often fail to identify deterioration prior to damage. Visual observations were the very first effort for evaluating and monitoring structures and infrastructures. The implementation of these methods were conducted before the 1960s but only limited to visible damaged parts. Structural health monitoring (SHM) is a useful process to identify changes in the dynamic characteristics of structures. This study aims to develop a useful method which provides useful information for engineers to plan proper preventive maintenance actions. The method will help to prevent major damage from happening and will assist with often inefficient and costly visual inspections.

Here, deterioration is defined as a slow and progressive changes to the material and the geometric properties of infrastructures. Each structure has a unique set of vibration characteristics which changes due to accumulated deterioration. Farrar et al.[1] asserted that the dynamic properties of a structure alter due to changes in the structure's mass, stiffness or energy dissipative characteristics. It is worth noting that the changes owing to damage are generally more significant than changes due to deterioration. Du et al.[2] concluded that the undamaged surface of a concrete structure does not confirm its healthy condition. As a result, deterioration is much more difficult to detect. It needs a more accurate and sensitive method than damage detection procedures. Therefore, a novel and accurate procedure for deterioration assessment of buildings is necessary. Monavari et al.[3, 4] attempted to develop time-series based deterioration detection methods. They estimated the optimal model order as a preliminary study of the current proposed method, but they did not verify their methods on a deteriorated structure. On the other hand, some researchers studied deterioration based on redundancy of structures[5-7], the vulnerability of structures under sudden and progressive damage[8], the vulnerability, robustness, and redundancy of structures[9, 10]. Finite element analysis approaches were used in these studies. Frangopol et al.[11] reviewed the common probabilistic models for deterioration assessment of structures. They concluded that no generally applicable approach has been proven.

One of the primary roles of using SHM data so far is identifying the exiting damage in structures[12], but not detecting deterioration. Doebling et al.[13], Carden and Fanning[14] and Chan and Thambiratnam[15] reviewed a large number of vibration-based SHM methods, and their works show that not much research has been done on deterioration assessment using vibration response data. Deterioration has, however, been evaluated in other approaches such as reliability-based methods[16, 17]. Therefore, there is a real need to develop a vibration-based deterioration assessment. The following sections are dedicated to review the existing vibration based assessment approach and most relevant methods as well as influential factors that could affect deterioration assessment.

The vibration structure of buildings changes due to accumulated deterioration and damage because of the correlation of the dynamic characteristics (natural frequencies, mode shapes, and damping properties) with the material and the geometric properties of structures. Consequently, damage and deterioration can be detected by capturing these changes in the vibration characteristics. However, as the changes because of deterioration are difficult to detect in comparison with those of damage, deterioration detection procedures need to be more accurate and sensitive to these changes.

In the vibration-based SHM techniques, ideal features in real structures are the ones that are sensitive to deterioration but not to the E&O variations. Vibration-based damage detection (VBDD) methods have been investigated in the past three decades[18, 19]. A summary review of VBDD can be found in Doebling et al.[13], Carden and Fanning[14], and Chan and Thambiratnam[15]. Besides, Farrar and Jauregui[20, 21] studied the sensitivity of some of the vibration based damage features to various levels of damage. These reviews reveal that the time-series analysis methods seem to be more sensitive and reliable to be used as deterioration feature among the existing VBDD methods[22]. Besides, some researchers, such as Pardoen 1983[23] and Kadakal and Yuzugullu 1996[24], discussed some advantages of using the time-series analysis modelling for ambient vibration over the usual frequency domain methods. The time-series analysis estimates mathematical models using statistical tools to describe and analyse data such as signals.

Wang et al.[25] used the enhanced AR coefficients to detect small levels of structural damage in the presence of measurement noise. Zheng and Mita[26-28] used the ARMA models to detect and locate damage, and the performance enhanced due to using pre-whitening filters. Wang and Ong[29] used the AR models and formulated three statistical hypotheses to detect damage. They used P-values of the tests to define the damage indicator. Tang et al.[30] experimentally verified that the time-series methods can be used for damage detection. Although time-series models, such as the AR models, have been used extensively among VBDD methods to detect and locate damage in structures[31-37], they have not been used for deterioration detection. The statistical time-series methods compare two main different conditions of a considered structure called baseline and assessment phases. The former is defined as the reference or healthy state of the structure, and the latter is defined as the current state. In each phase, the statistical time-series methods use random response signals from the structure to describe and to characterize its health state.

The time-series analysis may be classified into parametric and non-parametric methods. In the non-parametric methods, the statistic is formulated through non-parametric time-series models, such as frequency response function (FRF) and binned power spectral density (PSD)[38]. In other words, the changes in the dynamic characteristics of structures change the statistics. On the other hand, in the parametric methods, the statistic is formed via the parametric time-series models (e.g., AR models)[39], which means that the changes in time-series parameters identify a fault in structures. The parametric methods can be classified into model parameter-based: residual-based, and functional model-based methods[38].

This study aims to develop a novel deterioration detection procedure using the AR time-series models which have not been used in deterioration assessment. The study utilizes both the parametric-based approach and the nonparametric statistical test to capture the changes in dynamic characteristics of structures. Acceleration response data are first normalised through a 3-step process and then fed through an AR time series models assisted by a novel model order estimation scheme. Finally, the statistical hypotheses of a two-sample f-test are applied on the AR model residuals to derive deterioration-representative feature.

The layout of the remaining of the paper is as follows. First, the novel deterioration detection framework is discussed. Then, the details of the simulation investigation of the proposed method are next summarized, and the deterioration detection method is verified using two case studies. Finally, deterioration detection results are presented before the conclusion is made.

2. Methodology

The use of AR model is often associated with an assumption that the structural responses are stationary. However, this is not often the case for the data recorded under ambient excitation conditions. Therefore, the following data normalization procedure is designed. First, data is collected from the structure using each sensor (here acceleration response data is used) and standardized as follows:

$$\hat{x}_i = \frac{x_i - \overline{x}}{\sigma} \tag{1}$$

where x_i denotes amplitude of the measured acceleration response (see later sections for other details such as sample length); $\overline{x}$, σ and $\hat{x}_i$ are the mean, standard deviation (STD) and the standardized signal of x_i, respectively. Second, the data is filtered with a low-pass Chebyshev filter, which removes high-frequency content. This filter was chosen due to its speed. More information can be obtained from Smith[41]. Third, the following batch approach pre-whitening filter[40] is applied. This filter is capable of minimizing the cross-correlation among multiple excitations since most of the input excitations are mutually correlated. In this process, the *l*-dimension sensor signals $\boldsymbol{x}$ are pre-processed by using the following whitening transformation:

$$\boldsymbol{y} = \boldsymbol{W}\, x \tag{2}$$

where *l* is the number of sensors, $\boldsymbol{W}$ is the $l \times l$ whitening matrix, and $\boldsymbol{y}$ indicates the whitened signals. The matrix $\boldsymbol{W}$ is chosen so that the covariance matrix $E\{\boldsymbol{y}\,\boldsymbol{y}^T\}$ becomes the unit matrix $\boldsymbol{I}_l$. Hence, the components of the whitened signals $\boldsymbol{y}$ are mutually uncorrelated and they have unit variance, i.e.,

$$\boldsymbol{R}_{yy} = E\{\boldsymbol{y}\,\boldsymbol{y}^T\} = E\{\boldsymbol{W}\,\boldsymbol{x}\,\boldsymbol{x}^T\,\boldsymbol{W}^T\} = \boldsymbol{W}\,\boldsymbol{R}_{xx}\,\boldsymbol{W}^T = \boldsymbol{I}_l \tag{3}$$

In general, the recorded signals $\boldsymbol{x}$ are mutually correlated, which means that the covariance matrix $\boldsymbol{R}_{xx}$ is a full (not diagonal) matrix. It should be noted that the matrix $\boldsymbol{W}$ is not unique, and by multiplying an arbitrary orthogonal matrix to $\boldsymbol{W}$ from the left, a new $\boldsymbol{W}$ is generated and the equality (3) is still preserved.

$$\boldsymbol{W} = \boldsymbol{\Lambda}_x^{-1/2}\,\boldsymbol{V}_x^T = diag\{\frac{1}{\sqrt{\lambda_1}}, \frac{1}{\sqrt{\lambda_2}}, ..., \frac{1}{\sqrt{\lambda_l}}\}\boldsymbol{V}_x^T \tag{4}$$

or

$$\boldsymbol{W} = \boldsymbol{U}\,\boldsymbol{\Lambda}_x^{-1/2}\,\boldsymbol{V}_x^T \tag{5}$$

where $\boldsymbol{\Lambda}_x = diag\{\lambda_1, \lambda_2, ..., \lambda_l\}$ is a diagonal matrix with positive eigenvalues $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_l > 0$, $\boldsymbol{V}_x$ is an orthogonal matrix, and $\boldsymbol{U}$ is an arbitrary orthogonal matrix.

Fourth, assuming the structural response as stationary, the AR models are fitted to the data:

$$x_k = \sum_{i=1}^{p} \Phi_i^x x_{k-i} + e_k^x \tag{6}$$

where x_k is the measured signal at discrete time index k; e_k^x is residual error at the k^{th} signal value; p is the model order; x_{k-i} represents the $(k-i)^{th}$ previous response; Φ_i^x is the i^{th} AR coefficient. Figure 1, as an example, shows a dataset and the corresponding AR model, in which the model estimates the dataset well.

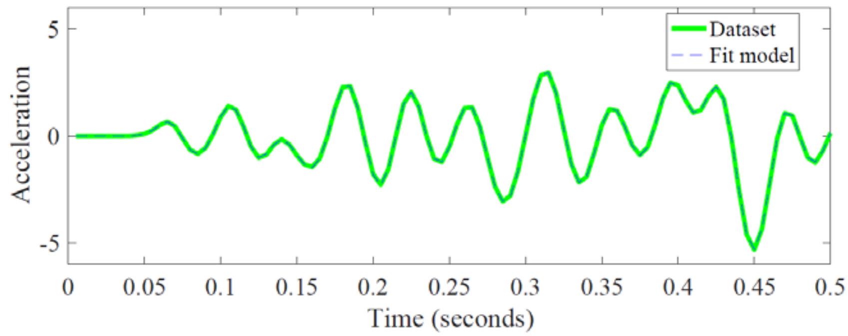

Figure 1. A dataset and the corresponding AR model

In order to enhance the sensitivity of the time-series analysis, the BMO technique is proposed in this study. It estimates the best-fit time-series model to the data considering its complexity to be generalized to other datasets. As the time-series models are well fitted to the data, the residual against baseline become very small and close to zero. The best-fit model order is the one with the least residual and suitable complexity, as a too simple fit will increase the residual while an overly-fitted model may not be generalized to the other datasets[42]. The proposed BMO technique satisfies both the minimum residual and the simplicity of the model.

This technique enhances the sensitivity of the time-series based features to detect even slight changes in the vibration characteristics of buildings. It is worth noting that most of the current structural health monitoring procedures are suitable for detecting damage but not deterioration. The changes in the response of structures due to deterioration are much smaller than those caused by damage. Hence, although the current techniques for estimating the model orders are widely used in damage detection, they cannot be used in deterioration detection. As a result, estimating the best model order is essential for obtaining a sensitive feature to identify deterioration.

The BMO technique is specifically developed to enhance the sensitivity of the proposed deterioration detection method. It requires some datasets in the baseline state. For a reasonable estimation, different datasets should be selected from different operational states, time as well as temperature. Undoubtedly, the more datasets in the baseline, the more accurate the result.

Step 1: Obtain AR models using different model orders (p is limited to a high enough model order) for the first dataset.

Step 2: Feed another dataset and predict it using the obtained AR models in step 1.

Step 3: Calculate the residuals of time-series models in step 2.

Step 4: Calculate STD of the residuals in step 3.

$$FR_{(i,j)} = \sigma(e_{(i,j)}) \tag{7}$$

where $i = 1,2,\dots,n$; n is the number of datasets in the baseline state; $j = 1,2,\dots,m$; and m is a high enough limitation for the model order.

Step 5: Calculate C parameter using the following equation to obtain the changes ratio in the residuals of different models and datasets.

$$C_{(i,j)} = \frac{FR_{(i,j)} - FR_{(i,1)}}{FR_{(i,1)}} \tag{8}$$

Step 6: Repeat steps 2-6 for the number of datasets in the baseline state (m). $\boldsymbol{C}$ is the $n \times m$ matrix.

Step 7: Calculate root mean square (*RMS*) of the residuals in step 3 as follows:

$$RMS_{(i,j)} = \sqrt{\frac{1}{k}\sum_{l=1}^{k}(e_{(i,j)})^2} \tag{9}$$

Step 8: Obtain $\boldsymbol{\alpha}$ criterion which is the mean value of the vectors $\boldsymbol{RMS}_i$ and estimate the minimum required model order[42, 43] to ensure the AR models capture the dynamic characteristics of structures.

$$\alpha_i = \mu(\boldsymbol{RMS}_i) \tag{10}$$

Step 9: Use the following equation and calculate $\boldsymbol{\beta}$ criterion. The minimum value of this criterion corresponds to the model order with a higher sensitivity to the changes in data, including the changes in data due to deterioration. This equation shifts the mean line to the left by two standard deviations indicating that about 95% of data values are within two standard deviations of the mean. It makes the $\boldsymbol{\beta}$ criterion sensitive to the changes in either the mean or the standard deviation. The minimum value of $\boldsymbol{\beta}$ criterion is corresponding to the model order which is not sensitive to the E&O variations but the structural changes.

$$\boldsymbol{\beta} = \boldsymbol{M} + 2 \times \boldsymbol{S} \tag{11}$$

where $\boldsymbol{S}$ and $\boldsymbol{M}$ are the matrices of STD and mean of the vectors $\boldsymbol{C}_j$ ($j = 1,2,\dots,m$), respectively. $\boldsymbol{C}_j$ is the $n \times 1$ vector of the C parameters for the j^{th} model order with n different datasets.

Step 10: The best model order is equal to the model order corresponding to the minimum value of $\boldsymbol{\beta}$ criterion higher than the estimated model order in step 8. The minimum model order obtained in step 8 ensure the minimal of residuals and the minimum $\boldsymbol{\beta}$ criterion ensures that the model could be generalized to the other datasets.

As the data were normalized, it could be assumed that the residuals come from normal distributions. When structures deteriorate, their vibration characteristics change. The changes in the vibration characteristics alter the structural response data. As a result, the residual error increases and the variances changes. The statistical hypothesis of two-sample f-test, which is a procedure to distinguish the differences in the variances of two datasets, was conducted on the residuals of the baseline and the assessment states of structures. Therefore, this hypothesis is able to detect deterioration through the changes in the variances between two populations with normal distributions. A function of the resulting *P*-values was then used to define the deterioration feature. The *P*-values of the test is a scalar of the probability that how an observing value is similar to the observed value under the null hypothesis. Small *P*-values reject the null hypothesis. The relevant details can be found in statistics literature such as the one by Gibbons and Chakraborti[44]. The following equation defines the deterioration indicator (*DI*) feature:

$$DI = \frac{P_A - P_B}{P_B} \tag{12}$$

where P is the *P*-values of the two-sample f-test; A is the assessment condition and B is the baseline condition of structures. As *P*-values illustrate the small changes in data, the defined *DI* well represents the changes in dynamic characteristics of structures in time.

3. Case studies

3.1. Case study 1: the 3-storey RC frame

In this study, a finite element model (FEM) of a three-storey reinforced concrete (RC) frame was designed and used to demonstrate the performance of the proposed deterioration detection method. Figure 2 shows the 3-storey RC frame building designed and then modelled by computer program IDARC[45]. Dimensions of all the columns and beams were $350 \times 350 mm^2$ and $300 \times 300 mm^2$, respectively. Table 1 shows the natural frequencies f_e.

Table 1. Natural Frequency in Hz

Mode	f_e (Hz)
1st	2.16
2nd	7.68
3rd	15.75

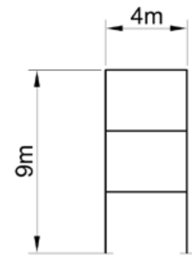

Figure 2. The designed 3-storey RC frame

Sanchez et al.[46] defined four cases representing the health cases related to deterioration of the reinforcement and the concrete cover: 1) a structure in its baseline state with full concrete cover and reinforcement area (FCFR), 2) a deteriorated structure with full cover but deteriorated reinforcement (FCDR), 3) a deteriorated structure with deteriorated cover but full reinforcement (DCFR), and 4) a deteriorated structure with both deteriorated cover and deteriorated reinforcement (DCDR). Some researchers defined deterioration as a continuous loss of cross-sectional area in time[6]. Barone et al.[47] considered annual deterioration rate (ADR) for a cross-sectional area to be equal to 2×10^{-3} in a single component subjected to an increasing axial force. In this case study, the health case of FCDR was considered for the 50-year period. During this period, the cross-sectional area of the left columns' bars was gradually reduced to simulate deterioration. The simulation was conducted for the three deterioration cases which are shown in Table 2. The annual deterioration rate (ADR) for the cross-sectional area was also considered equal to 2×10^{-3}. The deterioration rate (DR) of each year can be obtained by multiplying the ADR to the duration of deterioration (DOD) process (in year).

Fifty hours of the response data of a real structure under ambient vibrations[48] with a sampling frequency of 2000Hz and sample size of 120000 data points (sample length was $12000/2000 = 60$ seconds) were used as input ambient excitations to simulate the 50 years of deterioration simulation. For each year, the FEM frame structure was analysed using 60 different datasets of 60 seconds. The real structure is the recently constructed building (P-block building) at the Gardens Point campus of Queensland University of Technology (QUT), Australia. It has achieved 5-star Green Star rating from the Green Building Council of Australia, costing around AU$230M. As the input data was recorded from a real-world structure, it contains the E&O variations and a high level of noise.

$$\mathrm{ADR} = \left\{1 - \frac{Reduced\ cross\ sectional\ area}{Reference\ cross\ sectional\ area}\right\}_{year} \tag{13}$$

$$\mathrm{DR} = \mathrm{ADR} \times \mathrm{DOD} \tag{14}$$

Table 2. Deterioration cases

Case	Storey 1	Storey 2	Storey 3
1	deteriorated	non	non
2	non	deteriorated	non
3	non	non	deteriorated

In each case study, only one column was deteriorated. In the first case, the left column at the first storey experienced deterioration for 50 years. Besides, at the age of 21 years old, this column experienced a slight damage. The slight damage was simulated as a sudden reduction in the cross-sectional area equal to 5 years of deterioration. In the second case, the left column at the second storey was deteriorated for 50 years. In addition, at the age of 33 years old, a preventive maintenance was conducted on this column to simulate maintenance effect. The preventive maintenance was also simulated as a repair of the deteriorated columns equal to 5 years of deterioration. In order to simulate this preventive maintenance action, the cross-sectional area of the deteriorated columns increased equal to a reduction of cross-sectional area in five years of deterioration. In the last deterioration case, the left column at the third storey experienced 50 years of deterioration. It was assumed that the structure in this period experienced no damage and there were no maintenance actions. The effect of the deterioration on the dynamic characteristics and frequency content is depicted in Figure 3. Welch-based cross-spectral density (CSD) magnitude was computed for the structure with the healthy state and 50 years of deterioration.

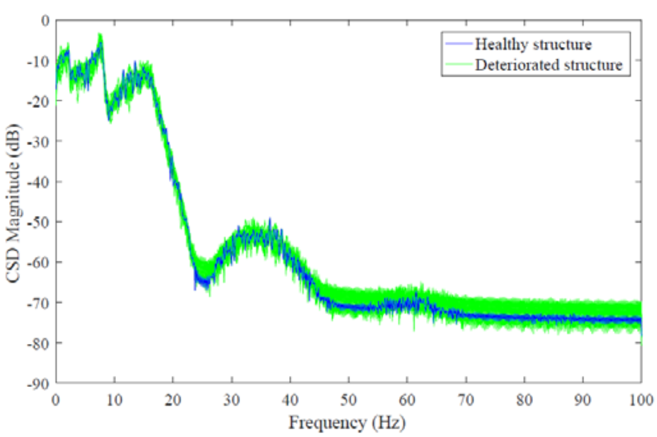

Figure 3. Welch-based cross-spectral density (CSD) magnitude

The response acceleration data of the simulated structure with the mentioned deterioration cases were utilized as input data for the AR models. First, a factor of ten was used to decimate the recorded data, which reduced the original sample frequency of 2000Hz down to 200Hz. A white Gaussian noise with the signal-to-noise ratio per sample of 10 (10% white Gaussian noise) was then added to the data. The added noise simulates the actual captured sensor data which is contaminated with noise. Hence, it can be ensured that the considered case study tests the applicability of the proposed method in real-world condition. In the developed method, a data normalization procedure including the following three steps was employed. First, data standardization was applied. Second, all data were filtered by employing a twelve-order Chebyshev type II low-pass filter with a cut-off frequency of 50. Third, the pre-whitening filter was applied. Then, the BMO technique was utilized to estimate the best model order. In the next step, the acceleration response data were modelled as AR time-series. Finally, the statistical hypothesis of two-sample f-test was conducted on the residuals of time-series models, and the *P*-values of the hypothesis test were used to define the deterioration indicator. This deterioration detection method was carried out using MATLAB. The statistical time-series methods compare two main different conditions of a structure called the baseline and the assessment phases. It was assumed that the structure was not deteriorated in the first year. Hence, the first 60 datasets indicate the healthy state of the structure (For each year, the FEM frame structure was analysed using 60 different datasets). The first 12 datasets were chosen as the baseline datasets and the other datasets were used as the assessment ones. The novel BMO technique was applied to these 12 datasets of each sensor to obtain the best model order for each sensor data in this case study. The best model order was chosen among a range of model orders from 1 to 40. Figure 4 (a) shows $\boldsymbol{C}$ parameter in the BMO technique which the horizontal axis indicates dataset number and the colours depict the $\boldsymbol{C}$ values corresponding to each of the 40 different model orders. This figure indicates that $\boldsymbol{C}$ parameter differs with different model orders. The best model order is the one which results similar $\boldsymbol{C}$ parameter for different datasets at the same health state. To achieve the best model order, $\boldsymbol{\beta}$ criterion is developed, in which the minimum value of $\boldsymbol{\beta}$ criterion is corresponding to the model order least sensitive to the E&O variations. Therefore, the minimum value of $\boldsymbol{\beta}$ criterion is corresponding to the optimal model order. However, the best model order must be high enough to address the minimum complexity of time-series models since a too simple fit will increase the residuals.

In order to find the minimum model order, the $\boldsymbol{\alpha}$ criterion is plotted as a function of the model order. The minimum required of the AR order can be achieved by minimizing the $\boldsymbol{\alpha}$ values (indicated as minimized $\boldsymbol{\alpha}$ criterion in Figure 4 (b)). Figure 4 (b) shows the mean of $\boldsymbol{\alpha}$ values for the AR models with different model orders (from 1 to 40) in all considered baseline datasets (12 datasets). $\boldsymbol{\alpha}$ criterion is minimized and almost constant with model orders higher than ten (see Figure 4 (b)), which satisfies the minimum complexity of time-series models. This suggests that AR models of orders higher than ten would fit the time history well. The best model order is corresponding to the minimum $\boldsymbol{\beta}$ criterion higher than the estimated the minimum model order using $\boldsymbol{\alpha}$ criterion. For instance, in this case study, Figure 4 (c) shows the result of $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ criteria. The red box shows the minimum required model order estimated using $\boldsymbol{\alpha}$ criterion and the minimum $\boldsymbol{\beta}$ criterion in this range (the red bar) is corresponding to the best model order. The best model order in here was 14 (see Figure 4 (c)). It is important to note that the best model order should be separately estimated for each sensor. The best model orders for the simulated structure were 14, 10 and 9 for the first, second, and third stories, respectively.

The result of the deterioration assessment is presented in Figure 5. This figure shows that the proposed method clearly detected the simulated deterioration, damage and maintenance actions in the frame. *DI* is zero when the frame was just built (time=0). By increasing the structural deterioration in the 50-year period, *DI* increases. In the first case, the structure started deterioration and experienced a slight damage at the age of 21, which the method detected both deterioration trend and the damage. Damage can be seen with a sudden increase in the *DI* at the age of 21 years. In the second case, the structure started deterioration, and a preventive maintenance action was performed at the age of 33 on the second storey. The method detected and depicted deterioration trend and the maintenance action. This can be seen as a sudden decrease in the *DI*. In the last case, the method showed a progressive and steady deterioration trend as was simulated. Besides, it was evident that deterioration in each storey affects the other stories *DI*'s results. However, in each case, the greater *DI* value was obtained from the corresponding deteriorated storey.

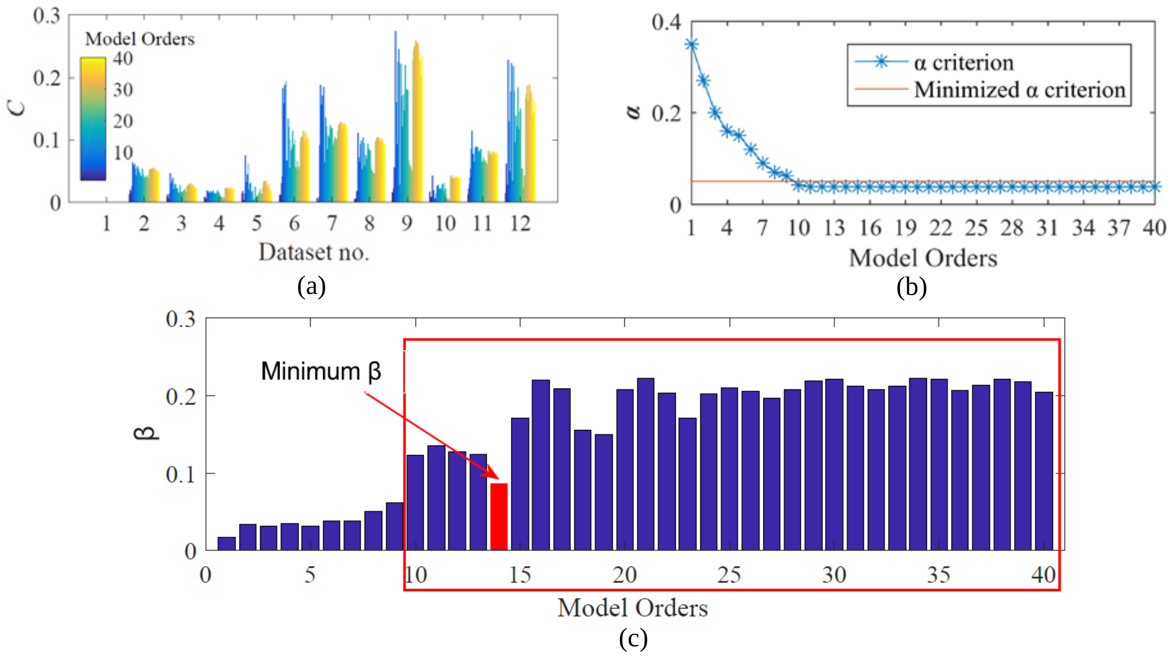

Figure 4. BMO technique: (a) ***C*** parameter, (b) ***α*** criterion (c) ***β*** criterion

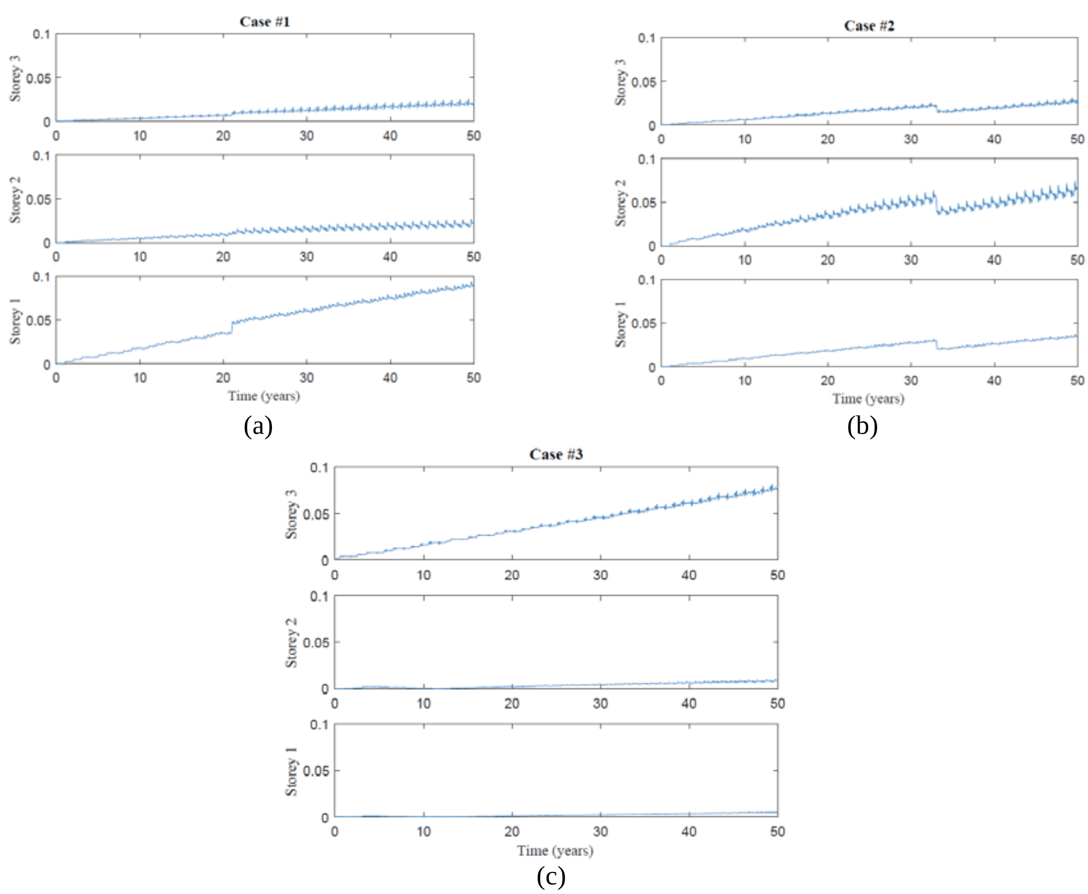

Figure 5. Deterioration identification (a) Case #1; (b) Case #2; (c) Case #3

3.2. Case study 2: the 20-storey RC frame

A FEM of a 20-storey RC frame was used to verify the performance of the proposed deterioration assessment method. Table 3 shows dimensions of the 20-storey RC frame building with 4 spans (Figure 6) designed and then modelled by the computer program IDARC[45]. For simplicity, all the columns, as well as the beams, have similar sections in each floor. Table 4 shows the first seven natural frequencies f_e .

The health case of FCDR was considered for the 50 years of deterioration. The deterioration rate (ADR) for the cross-sectional area was also considered equal to 2×10^{-3}. The cross-sectional area of the left columns' bars at levels 3, 8, 14 and 20 was gradually reduced to simulate deterioration. At the age of 32 years, a slight preventive damage maintenance was simulated and thereafter deterioration continued for 50 years.

Table 3. Dimensions of columns and beams

	Beam		Column	
Storey	Dimensions (mm)	Steel area (mm^2)	Dimensions (mm)	Steel area (mm^2)
16-20	400*400	900	400*400	4560
11-15	450*450	900	500*500	7385
6-10	500*500	900	600*600	9646
1-5	550*550	1000	700*700	9646

Table 4. The first seven natural Frequencies in Hz

Mode	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**
(Hz)	0.54	1.5	2.5	3.8	5	6.45	8.04

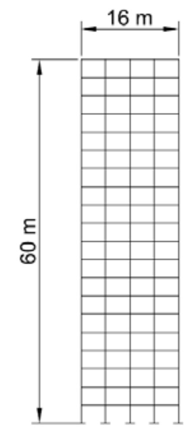

Figure 6. 20-storey RC frame

Similar to the previous case study, the response data of the real structure (P-block building at QUT) under ambient vibration with the sampling frequency of 2000Hz and the sample size of 120000 data points was used as input ambient excitation[48]. The response acceleration data of the simulated deteriorating structure was utilized as input data for the proposed method. Moreover, white Gaussian noise with the signal-to-noise ratio per sample of 10 was added. Then, the data normalization procedure was employed. The best model orders were estimated using the proposed BMO technique, and the acceleration response data was modelled as the AR time-series. Finally, the *P*-values of the statistical hypothesis of two-sample f-test were used to define the deterioration indicator.

The results of the assessment of the simulated deterioration are presented in Figure 7. It shows that the proposed method is able to detect deterioration at the multiple deterioration locations. *DI* is zero when the frame was just built (time=0). By the time the structure experienced deterioration, the *DI* increases over time. At the age of 32, slight preventive maintenance actions were performed, which the method clearly detected.

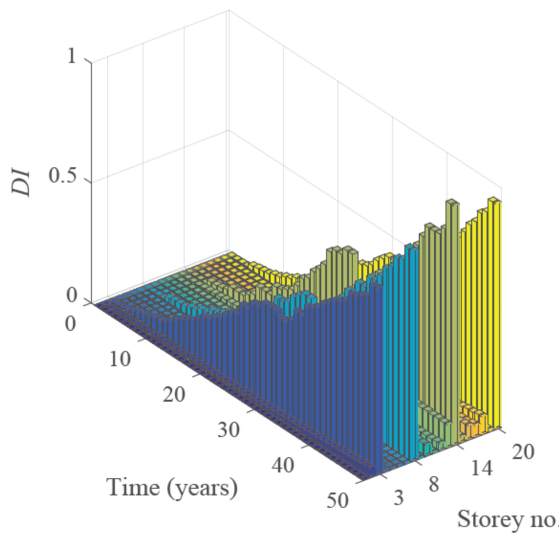

Figure 7. Deterioration identification

4. Results and Discussions

As mentioned earlier, a data normalization procedure was proposed in this study, including data standardization, applying a low-pass Chebyshev filter as well as a pre-whitening filter. The effect of the proposed data normalization procedure on *DI* is shown in Figure 8. As can be seen in this figure, the proposed procedure cancels all the false peaks and gives a smooth curve which is closer to the deterioration simulation.

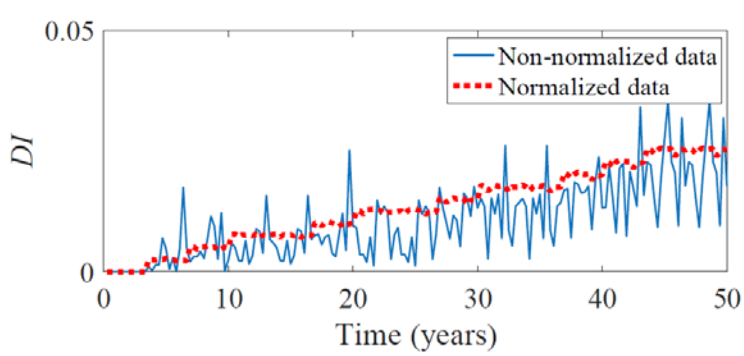

Figure 8. Effect of normalization procedure on *DI*

In order to enhance the sensitivity of time-series analysis, the BMO technique was proposed in this study. It increases the sensitivity of the deterioration detection method to slight structural changes by minimizing the residuals and optimizing the simplicity of the model. The effect of different model order on *DI* is shown in Figure 9. This figure illustrates the importance of the best model order for a precise deterioration detection. In this example, the BMO technique estimated the best model order for these datasets equal to 14. This figure shows that a higher model order (e.g. 30) increases the residuals and results in false positive and negative values. For instance, the model order of 30 cannot detect deterioration for the first 35 years and *DI* is almost zero. From the year 35 to 50, *DI* increases in time, however, it fluctuates. This contradicts the simulation of 50 years deterioration. On the other hand, a lower model order (e.g. 10) fails to identify deterioration. Therefore, having a suitable model order is crucial in this deterioration detection method.

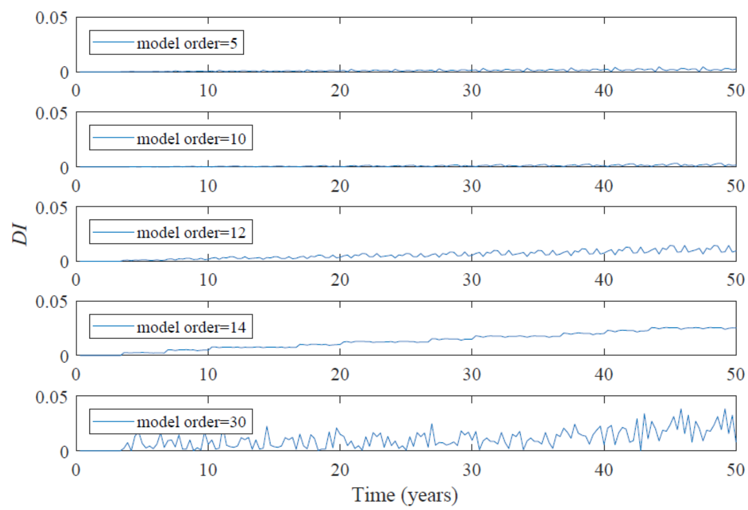

Figure 9. Effect of different model order on *DI*

All the results of this study were based on the sample length of 60 seconds. To study the effects of sample length on the results of deterioration detection, different sample lengths were chosen to be used for time-series models. As mentioned earlier, data with the sampling frequency of 200Hz and the sample size of 12000 data points (sample length of $1200/200=60$ seconds) were used. Herein, different sample lengths of 360, 180, 120, 60, 30 and 10 seconds with similar sample frequency were tested.

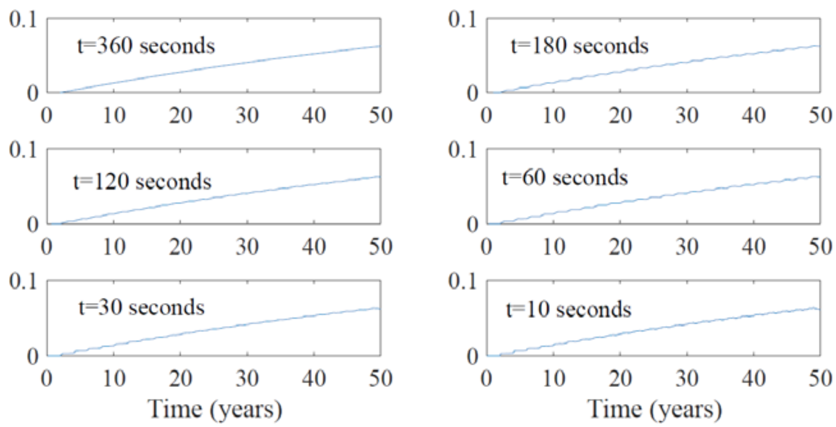

Figure 10. Deterioration identification with different sample lengths

5. Conclusion

This study developed a novel method to detect small adverse changes in structures known to be deterioration in an effort to address a significant research gap in the SHM research field. The method was applied to 3-storey and 20-storey RC frames under excitations recorded in a real structure. The responses of these frames during 50 years of deterioration simulation with the added Gaussian noise were fitted using the AR models. In order to assign the time series residuals to the deterioration trend, two-sample f-test was used. The enhanced time-series based method was able to detect multiple deterioration locations even in the presence of noise. In addition, the results proved that the proposed method is capable of detecting changes due to preventive maintenance actions and damage. Analyses also showed that it is crucial to select the best model order for vibration response data and the BMO developed in this research is an excellent tool to assist in this task.

The proposed method does not require data from the deteriorated states beforehand, and is capable of dealing with noise content. These are the key features of the proposed method which make it practically efficient to be used in real structures. However, it might face some challenges (as follows) that are highly recommended to be addressed in future studies. Due to the high level of uncertainty and noise in highly complex real-world asymmetric in plan and in elevation structures, it might be necessary to develop the method further in order to estimate a cost-effective number and location of sensors for obtaining precise deterioration detection results. Moreover, although this method can detect deterioration, it cannot localize and quantify deterioration. Finally, while the results of this method can be used to plan proper preventive maintenance actions, this study needs to be further developed to predict the occurrence of damage, which can make a considerable contribution to the industry to plan preventive maintenance actions**.**

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