Comparative study of output based identification methods for damage diagnosing of transmission towers

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ABSTRACT
Structural damage detection in large-scaled three dimensional structures is essential for ensuring their safety in service. A robust structural damage detection method must consider the characteristics of the target structure and damage in the development stage. Many identification methods have been proposed and further verified based on experimental data. But, few papers are reported on comparative investigation of several output-only identification methods, especially based on measured signals from transmission towers. This work is an experimental investigation on a laboratory model of a transmission tower for developing the system identification methods using time series signal for long-term structural health monitoring purposes. In a comparative investigation of two different methods, we discuss the difficulties of implementing damage detection techniques for complex structures. The combined algorithm of a fuzzy logic system and a model updating method are briefly discussed, and a method based on stochastic autoregressive moving average is adopted for the structure. The efficiency of the techniques is validated by different damage scenarios foreseen on the physical model. The results show that the developed methods are suitable for damage classification, but the quality of the acquired signals must be considered an important factor influencing successful classification.

KEYWORDS
Transmission tower; Damage Identification; Experimental verification.

INTRODUCTION
Structural health monitoring (SHM) and fault detection processes are essential for warranting structural safety performance during the service life of a structure. Research on vibration-based damage identification using changes in output signals from the structure has expanded rapidly in the last decades. Doubling et al. (1998) published a detailed, state-of-the-art review on vibration-based damage identification methods. In recent years, several researchers have studied damage detection in transmission towers. Heung and Tao (2011) discussed structural monitoring in this kind of structures described a fault-detection algorithm using dynamic reduction-based methods. This work provides a detailed overview of the background research and serves as a good reference in this field. Elshafey et al. (2010) examined damage diagnosis in platforms using mode shapes and a combined method of random decrement signature and neural networks. Liu et al. (2009) investigated a method based on the Hilbert-Huang transform method for modal parameter identification. Roitman et al. (2004) presented a methodology using frequency response functions to determine the actual conditions of the structure to detect damage.

In this study, the problems of uncertainties were considered to be the main objectives in developing and evaluating a robust damage detection system. These concepts are investigated by the adaptation
of two methods based on different standpoints: experimental modal analysis and time-capture data processing. In addition, one implicit objective of this study is to discuss the inherent difficulties of implementing SHM techniques for complex structures, such as transmission towers. The development of such methodologies would be extremely useful in enabling technologies that can be applied to structures in service to provide improved damage detection with fewer false alarms. In this work, a physical platform model was constructed for this purpose. To allow for the empirical evaluation of the proposed damage assessment method, the model was designed so that several damage scenarios can be introduced by stiffness reduction in selected structural members.

First, a combined algorithm incorporating a fuzzy logic (FL) system and a model updating method is briefly described. The method uses a modal parameter in the frequency domain with a consideration of the uncertainties associated with ambiguous damage states. This technique is demonstrated to be effective for diagnosing degradation and quantifying damage. However, investigation of the experimental results revealed an unsatisfactory classification of some damage scenarios. Therefore, a method using extracted features from an output time-series signal was adopted for the structure. This approach is based on a stochastic autoregressive moving average with exogenous input (ARMAX) method. One advantage of this method is the direct handling of the time-series data, whereas the previous frequency domain method required the measured time data to be transformed from the time domain to the frequency domain before feature extraction processing. Moreover, the first method is based on a model updating technique that requires the construction of a numerical model. Although the first method offers the advantage of identifying the damage location and possibly calculating the remaining life time, it generally requires more computational time (Modak et al., 2000). The second method was validated using the same experimental data; however, despite the noted advantages, similar to the first method, it failed to correctly diagnose several cases. After a reasonable investigation, the observed error rates of the methods were attributed to neglecting some nonlinear activation.

Probabilistic damage identification approaches in this study

Method based on experimental modal features: Combined model updating and FL system

This method consists of a combined strategy of experimental and numerical modal analysis. Therefore, the FE model is updated with the aim of aligning the results of the numerical natural frequencies to the experimental values. A brief description of the method follows.

Experimental modal analysis

Experimental modal analysis is identified simply as a process for describing a structure in terms of its dynamic properties, such as frequencies, damping and mode shapes. Modal analysis is basically the study of the natural characteristics of a structure. In the mechanical and signal processing laboratories, the measured responses can be obtained from the shaker or hammer impact tests. From a theoretical standpoint, there is no difference between these methods, but there are many different practical considerations when performing the shaker or impact tests (P. Avitable, 2001). FE software packages can be used to analyse the initial FE model according to the specifications of the structure. Here, the term “initial” implies that the FE model is considered to be the basis for model updating. The material properties and the boundary conditions are very important aspects of the modelling process. The equation of motion for a multi degree damped structural system under support excitation can be expressed as follows:

$$M\ddot{X}(t) + C\dot{X}(t) + KX(t) = F(t)$$

(1)

where $M$, $C$ and $K$ are the mass, damping and stiffness matrices and $X(t)$, $\dot{X}(t)$ and $\ddot{X}(t)$ denote the nodal displacement, velocity and acceleration vectors of the structure, respectively. In most damage detection problems, the method is not affected by damping, so the undamped natural frequencies are
considered to be the desired extracted features. Thus, the following standard Eigenvalue problem must be solved:
\[ \text{det}([K] - [M]\omega^2) = 0 \] (2)

The updating of the initial FE model is necessary to minimize the numerical model error according to the experimental signatures. The concepts of the “Modal Assurance Criterion (MAC)” method can be applied for this purpose. A more detailed explanation of this method and a design sensitivity analysis can be found elsewhere (Ting et al. 1993).

**Fuzzification and the highest degree of membership for fault isolation**

Here, the input variables into the FL system are defined by the Gaussian membership functions of the MDs:
\[ \mu_{k_j}^{(l)}(\alpha) = e^{-0.5\frac{(\alpha-m_j)^2}{\sigma_j}} \] (3)

In this function, parameter \( m_j \) is the midpoint of each column of the \( z_k^{(l)} \) database in the fuzzy set. The parameter \( \sigma_j \) is the standard deviation obtained by an algorithm that maximizes the success rate (\( S_R \)):
\[ S_{R_k}^{(l)} = \left( \frac{N_C}{N_N} \right) \times 100 \] (4)

Where \( N_C \) is the number of times the system classifies damage correctly and \( N_N \) is the number of noisy samples MD tested; here, \( N_N \) is considered to be equal to 1,000. In equation 10, the \( x \) values with the highest degree of membership for slight damage, moderate damage and severe damage are obtained by considering \( \Delta E = 25\% \), \( \Delta E = 50\% \) and \( \Delta E = 75\% \), respectively.

The fuzzy system rules are obtained for each damage class by relating the number \( d \) of the membership functions of the MDs:
\[ M_k^{(l)} = \prod_{j=1}^{d} \mu_{k_j}^{(l)} \] (5)

During the damage detection process, the class with the highest degree of membership is selected as the most likely fault.

**Method based on extracted features using recorded time-series data: Black-box polynomial parametric model**

This methodology is based on a strategy that can reduce the number of steps necessary for the extraction of features from the recorded data. Thus, in this case, the features have a higher heritability of the physical nature of the structure than in the previous method. Therefore, the warning changes in the physical characteristics become more traceable. Although the updating process of the first method offers some advantages, the conclusions about the roots of the error are more reasonable for the method based on the above-mentioned strategy. The general form of the black-box polynomial models is based on subsets of the following equation (Ljung, 1987):
\[ A(q)y(t) = \sum_{a=1}^{n_u} B_a(q)u_a(t-n_k_a) + \sum_{m(q)} C(q)e(t) \] (6)

The parameters \( A, B_a, C, H \) and \( F_a \) are polynomials containing the time-shift operator \((q)\); \( u_a \) is the \( a^{th} \) input, \( n_u \) is the total number of inputs and \( nK_a \) is the \( a^{th} \) input delay. The model structures differ in the number of polynomials included in this structure. In the case of the ARMAX model, the autoregressive, moving average and the innovation variance parameters of the model are all expanded in proper form as follows:
\[ A(q).y(t) = B(q).u(t-n_k) + C(q).e(t) \] (7)

Where \( A(q), B(q) \) and \( C(q) \) are the model parameters defined below:
\[ A(q) = \sum_{k=1}^{n_a} a(k) \cdot q^{-k}, B(q) = \sum_{k=1}^{n_b} b(k) \cdot q^{-k}, C(q) = \sum_{k=1}^{n_c} c(k) \cdot q^{-k}; \quad q^{-k} \ast \ast \ast (t - k) \]  

Here, \( n_a, n_b \) and \( n_c \) are model orders representing the number of coefficients for each polynomial, \( n_k \) is the parameter corresponding to the input delay, and \( e(t) \) is the variance of the white noise. In addition, \( y(t) \) is the output signal of the dynamic system responses recorded as time-series data. Another important step is selecting the order of the parameters and the dimension of the AR, MA and innovation variance. Various order selection criteria are available, such as the Akaike/Bayesian Information Criterion (AIC/BIC). The prediction error method is an extended form of the least squares method, which is used here to estimate the model parameters. Note that the extracted features can be weighted by certain membership functions:

\[ M^{(t)} = \left( \frac{1}{2\pi} \right)^{(n_a+n_b+n_c)} \cdot \prod_{i=1}^{n_a} \frac{1}{a_i^{(t)}} \cdot e^{-0.5 \left( \frac{x-n_a^{(t)} \Delta a_i}{a_i^{(t)}} \right)^2} \cdot \prod_{j=1}^{n_b} \frac{1}{b_j^{(t)}} e^{-0.5 \left( \frac{x-n_b^{(t)} \Delta b_j}{b_j^{(t)}} \right)^2} \cdot \prod_{k=1}^{n_c} \frac{1}{c_k^{(t)}} e^{-0.5 \left( \frac{x-n_c^{(t)} \Delta c_k}{c_k^{(t)}} \right)^2} \]  

Here, \( \sigma^{(t)} \) and \( m^{(t)} \) in equation (16) are obtained by calculating the standard deviation and midpoint of the number of measurement deltas for the \( t \)th test scenario. For this purpose, the recorded signals are divided into \( s \) equal parts, and the ARMAX parameters are obtained based on the input and output signals for the first \( s - 1 \) parts (in this study, \( s = 7 \)). The measurement deltas are defined by equation (10):

\[
\begin{align*}
\Delta a_q^{(t)}(g) &= 100 \frac{a_q^{(t)}(g)_{\text{undamaged}} - a_q^{(t)}(g)_{\text{damaged}}}{a_q^{(t)}(g)_{\text{undamaged}}}; \quad g = 1, 2, ..., n_a \\
\Delta b_q^{(t)}(g) &= 100 \frac{b_q^{(t)}(g)_{\text{undamaged}} - b_q^{(t)}(g)_{\text{damaged}}}{b_q^{(t)}(g)_{\text{undamaged}}}; \quad g = 1, 2, ..., n_b \\
\Delta c_q^{(t)}(g) &= 100 \frac{c_q^{(t)}(g)_{\text{undamaged}} - c_q^{(t)}(g)_{\text{damaged}}}{c_q^{(t)}(g)_{\text{undamaged}}}; \quad g = 1, 2, ..., n_c 
\end{align*}
\]  

The flowcharts in Fig. 1 illustrate the processes of the two methods schematically.

\[ \text{Time series domain} \quad \text{Frequency domain} \]

\[ \begin{align*}
\text{Recording time series} & \quad \text{OMAX} \\
\text{Dividing signals into } s \text{ parts} & \quad \text{FEMU (MAC)} \\
\text{Obtaining ARMAX parameters} & \quad \text{MCS} \\
\text{Obtaining MDs} & \quad \text{Experimental Validation (test scenarios)} \\
\text{Membership Functions} & \quad \text{No} \\
\end{align*} \]

\[ \begin{align*}
\text{Decision making} & \quad \text{Yes} \\
\end{align*} \]

**Figure 1.** Flowcharts of proposed classification methods.

**Description of the physical model and test setup**
For the implementation and validation of the identification methods described above, experimental modal tests were performed on a physical model. The general shape of the model represents a space frame with four main legs that are connected to the top deck, as shown in Fig. 2.
A physical model was constructed of stainless steel pipes that were welded together using argon arc welding to ensure proper load transfer. Metal spacers were attached separately at the middle parts of the four diagonal braces. The removal of a spacer was used to simulate the complete collapse of the brace due to damage ($D = 100\%$). Furthermore, two replaceable diagonal bracing members were designed to be replaced with members made of different materials, i.e., aluminium, copper, and brass, with different Young’s module to simulate stiffness reductions due to a degradation-like process. The aforementioned bracing members are illustrated in Fig. 3.

The external excitation (based on white noise signals) was enforced by means of an electro dynamic exciter (type 4809) with a force sensor (AC20, APTech) driven by a power amplifier (model 2706), all made by Bruel&Kjaer. The frequency range was 0 to 200 Hz.

**Results and discussion**

Five experimental tests were performed based on the reported scenarios in Table 2. The application of the mounted accelerometer sensors for damage detection purposes has been evaluated when the number of available sensors is small. Two different methods have been proposed; the first method uses the modal parameter in the frequency domain, and the second one uses the extracted features from output time series signals. The advantages and disadvantages of these methods are compared with each other, and the observed results are presented in this section and discussed as follows.

**FE model updating and experimental modal features**

The MEscope software was used to obtain the experimental modal parameters by polynomial curve fitting of the frequency response functions (FRFs). The data required for calculating the FRFs were recorded by sensors that were fixed on the physical model joints. Because there were more desired points for measurement (i.e., the twenty joints of the model) than the number of available channels
and accelerometers, the measurements were performed in twenty steps. The database of acquired parameters consists of the first four experimental natural frequencies of the physical model. The ANSYS FE package was employed to obtain the numerical modal parameters. The Young’s modulus, Poisson ratio and density were 207 GPa, 0.3 and 7,850 kg/m$^3$, respectively. The resulting numerical parameters were somewhat inconsistent with the experimental values. The first four natural frequencies are shown in Fig. 4, before and after the updating process.

![Figure 4. Sensitivity of the first four natural frequencies to variation of the modulus of elasticity on vertical bracing members; a) Long span, b) Short span.](image)

Using a sensitivity analysis, the stiffness of the bracing members were identified as adjustable parameters for the updating process, and the final values for the complete numerical model were determined, as listed in Table 1.

<table>
<thead>
<tr>
<th>Member</th>
<th>29</th>
<th>30</th>
<th>33</th>
<th>34</th>
<th>37</th>
<th>38</th>
<th>41</th>
<th>42</th>
</tr>
</thead>
<tbody>
<tr>
<td>E (GPa)</td>
<td>207</td>
<td>207</td>
<td>194</td>
<td>181</td>
<td>194</td>
<td>194</td>
<td>181</td>
<td>207</td>
</tr>
</tbody>
</table>

The updated FE model was used to train the algorithm for the first damage recognition method based on the FL system. The $MD$s (fuzzy variables), mean, standard deviations and membership functions were obtained from a Monte Carlo simulation to avoid the uncertainty associated with the variables.

**Black-box polynomial parametric model**

In this study, experimental tests were performed based on certain damage scenarios. The number and setup of the sensors must be considered key factors in the success of these methods, which also depends on the number of the PCs that are used for the calculation of the subspace angles. We should note that the detection process may deteriorate with the use of many PCs due to the noise that perturbs the procedure. Based on the observed results in the model updating process, the use of four PCs returned good cumulative energies, allowing for a suitable representation of the observation matrix. Therefore, four PCs were considered in the subspaces, and consequently, four accelerometers were installed on two different joints. The accelerometers were fixed in two directions at each joint. Random forces were applied to capture the random responses of the model. The samples of the compressed acceleration data along with their corresponding power spectral densities (PSDs) for the normal case are shown in Figs. 5 respectively. Various practical considerations must be made to collect high-quality data in an experimental test. For this purpose, the sampled signals must contain periodic repetitions of the measured data to yield a proper representation in the frequency domain. The test setup must be selected so that all modes of interest are considered. Additionally, the coherence function must be considered to be another important parameter, and an attempt should be made to obtain a relatively flat and well-behaved function.
The second identification methodology was developed based on the features that are extracted directly from the output time-series signals, unlike the previous method. Therefore, the steps necessary for the extraction of these features from the original recorded data are reduced, and the features more accurately model the physical nature for the physics of the model. Therefore, the changes in the physical parameters become more traceable. Furthermore, the first method, which is based on a model updating process, requires more computational time. The second approach is based on the stochastic ARMAX parametric models. Many advantages are found in parametric time-domain methods (Poulimenos, Fassois, 2006) such as specifying the physics of the problem with a limited number of parameters, improvement in tracking the time-varying dynamics, flexibility in both simulation and prediction goals, and flexibility in fault diagnosis.

**Classification results**

Five damage scenarios were tested in the form of stiffness reductions by changing certain members of the model or removing them completely. The details of these scenarios, including member numbers, substituted materials and percentage damage parameters, are listed in Table 2. The performance of the FL system method was evaluated using the training and classification data, as described in previous sections. These results imply the efficiency of the technique for diagnosing the considered empirical damage. Nevertheless, the detection failed in case number 4 (Table 2).

To investigate the efficiency of the second method, the signals were divided into seven parts. The order of the ARMAX model was selected based on the Akaike’s Bayesian information criterion (AIC/BIC). Thus, the order was selected based on a criterion that is a measure of the goodness of fit for estimated statistics. The orders of the AR, MA, and X parts and the variance of the model were determined to be \( n_a = 2, n_b = 4 \) and \( n_c = 4 \), respectively. Finally, the membership functions were calculated using the ARMAX parameters related to the first six parts of the signal. The seventh part was used to validate the model. The performance of the second method was evaluated for the five damage scenarios, as for the first method. The results in Table 2 show that this method failed in the diagnosis of the fourth case, as with the first method.

**Table 2.** Experimental damage scenarios and the efficiencies of the two methods.

<table>
<thead>
<tr>
<th>Case</th>
<th>Substituted member</th>
<th>material</th>
<th>D (%)</th>
<th>Damage intensity</th>
<th>Freq. Domain</th>
<th>Time Domain</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>42</td>
<td>Copper</td>
<td>41</td>
<td>Moderate</td>
<td>Successful</td>
<td>Successful</td>
</tr>
<tr>
<td>2</td>
<td>42</td>
<td>Aluminium</td>
<td>65</td>
<td>Severe</td>
<td>Successful</td>
<td>Successful</td>
</tr>
<tr>
<td>3</td>
<td>38</td>
<td>Aluminium</td>
<td>65</td>
<td>Severe</td>
<td>Successful</td>
<td>Successful</td>
</tr>
<tr>
<td>4</td>
<td>32</td>
<td>Eliminating</td>
<td>100</td>
<td>Catastrophic</td>
<td>Unsuccessful</td>
<td>Unsuccessful</td>
</tr>
<tr>
<td>5</td>
<td>41</td>
<td>Eliminating</td>
<td>100</td>
<td>Catastrophic</td>
<td>Successful</td>
<td>Successful</td>
</tr>
</tbody>
</table>
The observed results imply that the efficiency of the proposed methods is related to the onset of geometric nonlinear behaviour in the measured signals. The problem of failing can be addressed by adjusting sensor positioning and improving the quality of the acquired signals. Also the two above-mentioned methods are basically linear methods and were developed based on the linear geometric characteristics of system responses. Therefore, they may neglect some nonlinear features of the system behaviour. This problem can be addressed by enhancement of the described techniques based on the non-stationary and nonlinearity concepts.

**CONCLUSIONS**

Two classification algorithms for classifying damages in a physical model of a transmission tower are presented and were inspired separately by experimental modal analysis and time-capture data processing. The efficiency of the methods was investigated and compared. The validation results show that these methods are suitable for damage classification in the considered structure. The first method, which is a combined algorithm consisting of an FL system and a model updating process, offers the advantage of allowing for damage location and intensity calculation. However, it generally requires more computational time than the second method. The advantages of using the second parametric time-domain method are that the physics of the problem can be specified by a limited number of parameters, tracking of the time-varying dynamics is improved, and it allows for flexibility in both simulation and prediction goals. However, with both methods, damage detection failed completely in one of the cases. The observed results imply that the efficiency of the proposed methods is related to the onset of geometric nonlinear behaviour in the measured signals.

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