DAMAGE DETECTION IN AN OFFSHORE STRUCTURE

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ABSTRACT

The structural integrity of a multi-pile offshore platform is investigated by using a vibration based damage detection scheme. Changes in structural integrity are assumed to be reflected in the modal parameters estimated from only output data using an Auto-Regressive Moving Average (ARMA) model. By use of the estimates of the modal parameters and their corresponding variances a probability based damage indicator is formulated. This approach indicates, that since the construction of the platform, minor structural changes have taken place.

NOMENCLATURE

y_t : Dynamic displacement
Φ_i : Auto Regressive parameters
$\mathcal{O}_1$: Moving Average parameters
e_t : White noise sequence
N : Number of sample points
V_N : Loss function
y_t^M : Measured response
$\hat{y}_t$: Estimated response
λ_i : Root of characteristic polynomial
ζ_n : Damping ratio of n'th mode
ω_n : Natural cyclic frequency of n'th mode
f_n : Frequency of n'th mode
Δt : Sampling interval
FPE : Final Prediction Error
AIC : Information Theoretic Criterion
$\overline{\overline{J}}$: Fisher information matrix
λ_ε : Variance of noise process
$E[\cdot]$: Expectation operator
$\overline{\Phi}$: Vector including AR-parameters
$\overline{\Psi}(t,\overline{\Phi})$: Stochastic process
$\overline{\psi}(t,\overline{\Phi})$: Realization of $\overline{\Psi}(t,\overline{\Phi})$
$\overline{\overline{A}}$: Transformation matrix
θ : Modal parameter vector
$\hat{\overline{\theta}}_N$: Estimate of $\overline{\theta}$
$\overline{\overline{C}}_{\hat{\overline{\theta}}_N}$: Covariance matrix

1. INTRODUCTION

Offshore structures continuously accumulate damage during their service life due to environmental forces such as waves, winds, current and seismic actions. A damage may alter the stiffness and change the modal properties of the structural system, such as natural frequencies, damping ratios and mode shapes. Therefore, much research has been done with respect to structural diagnosis (health monitoring) by measuring vibrational signals of civil engineering structures. The main impetus for doing vibrational based inspection (VBI) is caused by a wish to establish an alternative damage assessment method to the more traditional ones. The most common of the traditional methods is visual inspection. However, damage assessment by visual inspection can be costly, risky and difficult when civil engineering structures such as offshore structures are considered. Besides, a reduction of inspection cost a capable VBI technique can lead to lesser risky and quicker means of assessing structural damage. Many research projects have concluded that it is possible to detect damages in civil engineering structures by VBI, and some techniques to locate damages in civil engineering structures have also been proposed. However, much of the performed research has been based on numerical simulations and/or laboratory models. A throughout review of VBI techniques can be found in Rytter [1]. The idea of using VBI on offshore structures has been developed since the early seventies, see e.g. Loland et al. [2], Campbell et al. [3], Coppolino et al. [4], Haugland et al. [5], Jensen [6], Roitman [7], Hamamonto et al. [8] and Li [9].

In order to use VBI techniques it is necessary to be able to obtain reliable estimates of the dynamic characteristics, e.g. natural frequencies. The estimation may be carried out in the frequency domain or in the time domain. Historically, parameter estimation based on frequency domain models seemed to dominate the theory and practice of the system identification up to the sixties. Since the end of the sixties the interest in the system identification based on time domain models has increased, and now literature on system identification is very much dominated by time domain methods. Often the intended use of the model as well as accuracy requirements on parameter estimates motivates the use of a time domain model and corresponding system identification procedure. In Ljung [10] and Söderström et al. [11] the basic features of system identification based on time and frequency domain approaches are highlighted. For many years the identification techniques based on ARMA models in the time domain have attracted limited interest concerning structural engineering applications. A factor contributing to this situation is that ARMA models have been developed primarily by control engineers and applied mathematicians. Further, ARMA models have been primarily developed concerning systems for which limited a priori knowledge is available, whereas the identification of structural systems relies heavily on understanding of physical concepts. However, in recent years the application of ARMA models to the description of structural systems has become more common, see e.g. Gersch et al. [12] Pandit et al. [13], Hac et al. [14], Kozin et al. [15], Jensen [6], Safak [16], Hamamonton et al. [8] and Li et al. [9]. The structural time domain identification techniques using ARMA representation have been compared with frequency domain techniques in e.g. Davies et al. [17]. In this and other papers it has been documented that these ARMA time domain modelling approaches are superior to Fourier approaches for the identification of structural systems. These foundings make identification techniques utilizing ARMA algorithms interesting for modal parameter estimation. Especially, with respect to damage detection where modal parameters are used as damage indicators. If modal parameters are used as damage indicators it is important to be able to obtain unbiased estimates. Further, one also want to be able to quantify the uncertainty of the parameters, so conclusions about changes in parameters caused of possible structural changes can be done. This problem can be partially solved by using ARMA models in the time domain.

The aim of the research presented in this paper is to investigate the possibility of detecting changes of the structural integrity of an offshore structure. The structural integrity has been assumed to be reflected in the modal parameters estimated by using full-scale measurements based on natural excitation. The parameter estimation is solved by using a time domain identification method (ARMA). Section 2 deals with the foundation of the ARMA-model while in section 3 an example with a multi-pile offshore structure is given.

2. ARMA-Model

An Auto-Regressive-Moving-Average ARMA(n,m) model of order n,m describing the response at the discrete time points y_t is given by

$$y_t = \sum_{i=1}^{n} \Phi_i y_{t-i} - \sum_{i=1}^{m} \mathcal{O}_i e_{t-i} + e_t \qquad (1)$$

Φ_i is an Auto Regressive (AR) parameter, $\mathcal{O}_i$ is the Moving Average (MA) parameter and e_t is a time series of a white noise process. This model involves a difference equation in which the output of the system is expressed as a linear combination of past output, as well as present and past input. This kind of model is particular well suited for identification and response calculation purposes since they provide efficient system representations.

If an ARMA$(2n, 2n-1)$ model is used for a stationary Gaussian white noise excited linear n-degrees-of-freedom system it can be shown that the covariance of the response due to the ARMA-model and that of the white noise excited structure will be identical, see e.g. Kozin et al. [15]. In other words, an ARMA model will provide an unbiased estimate of the autospectrum provided the assumptions hold. It is seen that the parameter identification of civil engineering structures by using an ARMA model assumes that the response data are caused by a white noise input to the structure. However, for wave or wind excited lightly damped civil engineering structures, this assumption will normally hold, see e.g. Morgan et al. [18], Jensen [6] and Srinavasan [19].

The AR and MA parameters are obtained by minimizing an error function V_N expressing the variance of e_t

$$V_N = \frac{1}{N}\sum_{t=1}^{N} \epsilon_t^2 = \frac{1}{N}\sum_{t=1}^{N} \frac{1}{2}(y_t^M - \hat{y}_t)^2 \qquad (2)$$

where N is the number of data and ϵ_t is the prediction error. y_t^M and $\hat{y}_t$ are the measured response and the predicted response by (1), respectively. It may be noticed that the white noise assumption must be checked when the AR and MA parameters and the residuals have been estimated. If the assumption does not hold it may indicate that the order of magnitude of the model is too low and therefore should be increased.

When the AR parameters are estimated the $2n$ roots, λ_i of the characteristic polynomial of the AR parameters are found

$$\lambda^{2n} - \Phi_1 \lambda^{2n-1} - \cdots - \Phi_{2n-1}\lambda - \Phi_{2n} = 0 \qquad (3)$$

In e.g. Pandit et al. [13] it is shown that the roots are related to the modal parameters through the $2n$ relations

$$\lambda_i = \exp(\mu_i \Delta t) \qquad i = 1, 2, .., 2n \quad (4)$$

where Δt is the sampling interval. μ_i has the following relation to the modal parameters for an underdamped system

$$\mu_i = -\omega_i \zeta_i \pm i\omega_i \sqrt{1 - \zeta_i^2} \qquad \zeta_i < 1.0 \quad (5)$$

By using the ARMA model all the information in the measured time series is used to estimate the AR-parameters. This implies that a large amount of data has to be handled in the system identification process implying that it can be time consuming to estimate the parameters. Especially, when the model order increases, caused of the non-linear optimization which has to be used to get the AR-parameters and the MA-parameters. However, Pandit et al. [13] has shown that any ARMA model can be represented by an AR model if the model order is chosen sufficiently high. This implies that the AR-parameters can be estimated directly by linear regression obtaining at least squares fit between the measured time series and the AR-model.

2.1 Model Selection and Model Validation

Model selection involves the selection of the form and the order of the ARMA model, and constitutes the most important part of the system identification. Model validation is to confirm that the model estimated is a realistic approximation of the actual system. A throughout description of the problem of model selection and validation is given in e.g. Ljung [10] and Söderström [11]. The selection of the model to a large extent should be made according to the aim of the final purpose. There is no general solution to this problem but a large number of methods to assist in the choice of an appropriate model structure exist. For such comparisons as mentioned above a discriminating criterion is needed. The comparison of the model structures can be interpreted as a test for a significant decrease in the minimal values of the loss function V_N associated with the model structures in question. As a model structure is expanded, e.g. increasing the number of adjustable parameters, the minimal value of V_N decreases since new degrees of freedom have been added to the optimization problem. The decrease of V_N is a consequence that more flexible model structures give a possibility for better fit to the data. On the other hand when a good fit can be obtained there is no reason to increase e.g. the number of adjustable parameters. An overparameterized model structure, i.e. containing several models giving a perfect description of the actual system, can lead to unnecessarily complicated computations for finding the parameter estimates. An underparameterized model, i.e. a model having too few parameters to describe the system adequately, may be inaccurate. In order to deal with this problem Akaike, see Akaike [20], suggested a Final Prediction Error (FPE) criterion and a closely related Information Theoretic Criterion (AIC) of the type

$$FPE = \frac{1 + \frac{n}{N}}{1 - \frac{n}{N}} V_N \qquad (6)$$

$$AIC = \log[(1 + \frac{2n}{N})V_N] \qquad (7)$$

where N is the length of the data record and n is the total number of estimated parameters. The model structure giving the smallest value of these criteria is selected. The AIC and FPE criteria penalize using too high model orders, i.e. their value may increase with increasing model order.
Model validation is the final stage of the system identification procedure. In fact model validation overlaps with model structure selection. Since the system identification is an iterative process various stages will not be separated: models are estimated and the validation results will lead to new models etc. One of the dilemmas in the model validation is that there are many different ways to determine and compare the quality of the estimated models. First of all, the subjective judgement in the model validation should be stressed. It is the user that makes the decision based on numerical indicators. The variance of the parameter estimates can be such an indicator. It is also important to check whether the model is a good fit for the data recording to which it was estimated. Simulation of the system with the actual input and comparing the measured output with the simulated model output can also be used for model validation. One can also compare the estimated transfer function with one estimated by FFT. Statistical tests of the prediction errors ϵ_t are also typically used numerical indicators in model validation.

2.2 Estimation of Parameter Uncertainty

From measurements of the response process it is possible to get unbiased estimates of the AR-parameters Φ_i see e.g. Pandit et al. [13], where estimates of the variances of the estimated parameters can be estimated by the Cramer-Rao lower bound. This implies that the covariance matrix of parameter estimates can be obtained by the inverse of the Fisher information matrix $\overline{\overline{J}}$ which can be written

$$\overline{\overline{J}} = \frac{N}{\lambda_{\mathcal{E}}} E[\overline{\Psi}_t(\overline{\Phi})^T \overline{\Psi}_t(\overline{\Phi})] \qquad (8)$$

A realization of the stochastic process $\{\overline{\Psi}_t(\overline{\Phi})\}$ is given by

$$\overline{\psi}_t(\overline{\Phi}) = \frac{\partial \epsilon_t(\overline{\Phi})}{\partial \overline{\Phi}} \tag{9}$$

It is assumed that the variance $\lambda_{\mathcal{E}}$ of the prediction error process $\{\mathcal{E}_t\}$ is V_N. $\overline{\Phi}$ is a vector including the AR-parameters.
When the elements of the information matrix are calculated the parameter covariance matrix $\overline{\overline{C}}_{\hat{\overline{\theta}}_N}$ of estimates of the parameter vector $\hat{\overline{\theta}}_N$ can be expressed in the following way

$$\overline{\overline{C}}_{\hat{\overline{\theta}}_N} \approx \overline{\overline{A}}\,\overline{\overline{J}}^{-1}\overline{\overline{A}}^T \tag{10}$$

where the transformation matrix $\overline{\overline{A}}$ is given by

$$\overline{\overline{A}} = \begin{bmatrix} \frac{\partial f_1}{\partial \Phi_1} & \frac{\partial f_1}{\partial \Phi_2} & \cdot\ \cdot\ \cdot\ \cdot & \frac{\partial f_1}{\partial \Phi_{2n}} \\ \frac{\partial \zeta_1}{\partial \Phi_1} & \frac{\partial \zeta_1}{\partial \Phi_2} & \cdot\ \cdot\ \cdot\ \cdot & \frac{\partial \zeta_1}{\partial \Phi_{2n}} \\ \cdot & \cdot & \cdot\ \cdot\ \cdot & \cdot \\ \cdot & \cdot & \cdot\ \cdot\ \cdot\ \cdot & \frac{\partial f_n}{\partial \Phi_{2n}} \\ \cdot & & \cdot\ \cdot\ \cdot & \frac{\partial \zeta_n}{\partial \Phi_{2n}} \end{bmatrix} \tag{11}$$

$\hat{\overline{\theta}}_N$ is an estimator of the parameter vector $\overline{\theta} = [f_1, \zeta_1, f_2, \zeta_2, ..., f_n, \zeta_n]^T$. The above estimation of $\overline{\overline{A}}$ will only be accurate if the function is sufficiently smooth since it corresponds to a linear approximation of the function describing the inverse transformation from AR- parameters to the parameters $\overline{\theta}$, see e.g. Kirkegaard [21].

3. MULTI-PILE PLATFORM

The structural integrity of a multi-pile offshore platform is investigated by using a vibration based damage detection scheme. Changes in structural integrity is assumed to be reflected in the modal parameters estimated from only output data by use of an ARMA model. The modal parameters are estimated by using the MATLAB, see PC-MATLAB [22].

3.1 Description of Platform

The considered offshore platform built in 1993 is a 58 m long by 20 m wide multi-pile structure of reinforced concrete holding a steel superstructure which supports the power generation equipment for a large oil production complex. Water depth at the location of the offshore platform is about 30 m. Wave heights in this zone have been reported between 1.2 m and 2.5 m in the longitudinal direction of the platform with recurrence periods of 3.8 and 4.9 s, respectively. The information reported for current action near the platform shows values in the order of 1.4 m/s in the direction of the waves. This particular new platform is very flexible and it experiences continuous vibrations caused by wave and current actions. The platform has been constructed with less number of piles and a different distribution from other offshore platforms built up to 1992. The reinforced concrete base structure is supported by 42 pre-stressed circular piles, 0.9 m in diameter.
The platform was instrumented with three accelerometers measuring the acceleration response in the longitudinal, transversal and vertical direction, respectively. In the period from May 1993 to July 1994 160 acceleration signals were recorded. The signals were sampled at 200 Hz. The length of the records varies between 20 s and 76 s.
Since the vertical accelerations were neglected, it was decided to limite the identification to the first two modes. one in the longitudinal and one in the transversal direction.
Since the number of points of the records were too short for identification using an ARMA-model, records from the same day were combined into one time series. This reduces the number of time series to 29. The discontinuities between the individual data segments were smoothed by use of a tapering function (a half Hanning Window). In order to improve the precision of the identification the signals were detrended and outliers were removed. Since the expected highest frequency in the structure is much smaller than the Nyquist frequency. the sampling rate was decreased by decimating the records in order to reduce the noise effects. The new sampling rate after decimation was 10 Hz. Before the decimation the record was low-pass filtered beyond the new Nyquist frequency.
In Kirkegaard et al. [23] a more throughout description is given of the experimental setup, the signal processing and the investigation of the measurements with respect to stationarity, linearity and normality of the response.

3.2 Selection and Validation of ARMA-model

In the following it is explained how the ARMA-model was selected and validated. The results are given for a recorded signal in the longitudinal direction.
By incorporating the FPE and AIC criteria it was determined that a 5 degrees of freedom model was appropriate. I.e. a 6th-order model giving an ARMA(6,5).
Figure 3.1 shows a plot of the poles (x) and zeros (o) and it is seen that all the poles and zeros are inside the unit circle in the complex plane. The poles and zeros are given with confidence regions corresponding to three standard deviations. If these regions overlap, a lower model order should have been tried, since this is a result of a near pole-zero cancellation in the dynamic model indicating that the model order is too high. The most dominant mode of the system is the one corresponding to the pole closest to the unit circle.

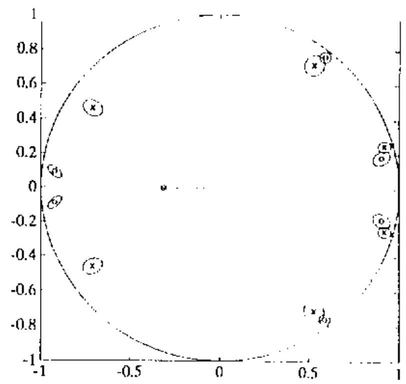

Figure 3.1: Pole-Zero plot.

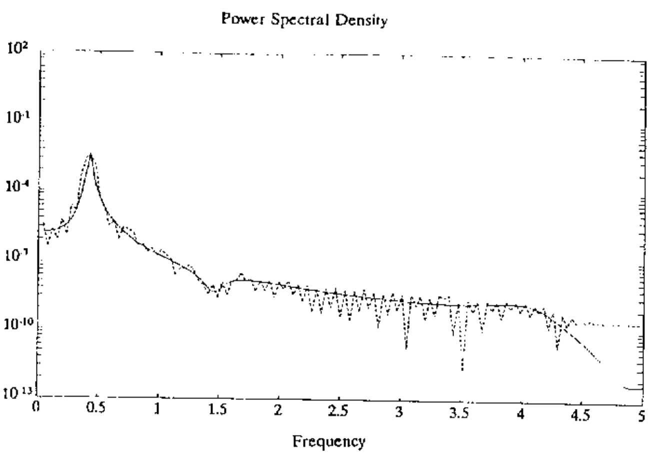

Figure 3.2: Comparison of direct estimated spectrum and spectrum obtained from the ARMA-model (full-line).

As discussed in section 2.1, after the model is selected and the parameters are determined, the next step is to check the validity of the model. The match of the power spectrum obtained by a Fast Fourier Transformation and the spectrum obtained from the ARMA-model are shown in figure 3.2. The figure shows a good match. Next the residuals of the identification are checked. Residuals are defined as the difference between the model output and the recorded output signal. In order to have a valid identification, the residuals should be a white-noise sequence. The plot of the spectrum and autocorrelation of the residual time series are given in figure 3.3.

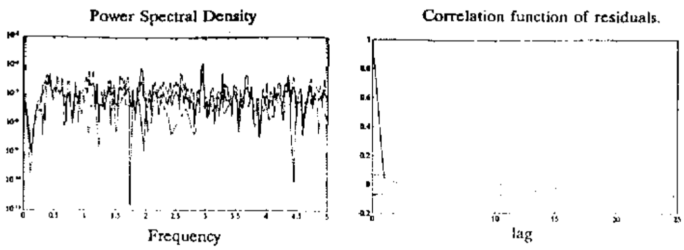

Figure 3.3: Spectrum and Autocorrelation of the residual time series.

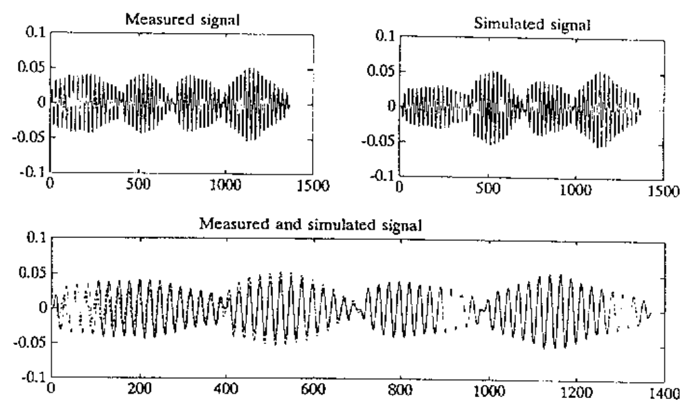

Figure 3.4: Comparison of calculated accelerations with recorded accelerations, plotted separately and together.

Visual inspection of the spectrum in figure 3.3 suggests that the residuals are close to a white-noise sequence, since the peaks are distributed in all frequencies. A more accurate check is to test the autocorrelation of the residuals Two straight lines in the figure show the 99% confidence level. For model validity, i.e. whiteness of residuals, the autocorrelation should not exceed these levels, except at zero lag. Figure 3.3 shows that the autocorrelation remains, for the most part, within the limits, and therefore validate the model. The autocorrelation test shows if there is any correlation in the residuals. In an ideal identification the residuals would be identical to a white-noise sequence.
As a final test for model validity, a comparison of model output with recorded output. This is a more strict test than the previous ones. However, figure 3.4 shows that the match is fairly good. Based on all the above checks, it can be concluded that the estimated ARMA-model for the offshore structure is satisfactory.

3.3 System Identification Results

In this section the estimated natural frequencies for the first and second mode, respectively, are presented and discussed. The first and second natural frequencies were estimated as approximately 0.42 s and 0.62 s, respectively, which correspond to the values obtained from FEM calculations, see Tallavó et al. [24]. In figure 3.5 the estimates of the first and second natural frequencies, respectively, are shown as a function of time. The uncertainty given as plus minus three times the standard deviation is shown with the dotted lines. As it should be expected from the spectrum f_2 seems to be more uncertain than f_1. Further, it is seen that f_2 has a small decrease. However, figure 3.5 does not show wether these changes are significant. In order to evaluate this question a probability based damage indicator is formulated based on the results in figure 3.5. Assuming f_i to be independent Gaussian distributed variables standard theory gives that the probability of negative changes $P_{\Delta f_i}$ in f_i is given by

$$P_{\Delta f_i} = 1 - \Phi\left(\frac{f_i - f_{i0}}{\sqrt{\sigma_i^2 + \sigma_{i0}^2}}\right) \qquad (12)$$

where Φ is the unit normal distribution function and σ_i^2 is the variance of f_i. σ_{i0}^2 is the variance of the frequency f_{i0} of the assumed undamaged structure, i.e. the first estimated frequency. A negative change in f_i is assumed to indicate that the structure has suffered structural changes.
Figure 3.6 shows the probability of negative change in f_1 and f_2, respectively as a function of time. It is seen that the two curves have many fluctuations perhaps due to the fact that the estimates of the two frequencies and their variances are only based on short time series. This implies that the estimates are uncertain. However, it is seen in figure 3.6 that a change has occurred in the first and second frequency with 70 and more than 90 % probability, respectively. This means that with a probability close to one the structural properties have changed during the first 12 months of the operation. If the structure has changed however, the changes are small and might be due to cracking of the concrete base structure or changes in the foundation that do not affect structural safety. The analysis of the dynamical responses indicates the usefullness of further investigations.

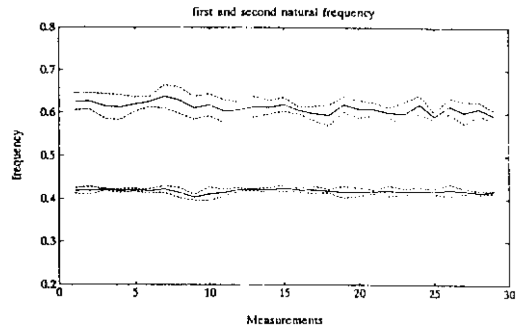

Figure 3.5: First and second natural frequencies as function of time.

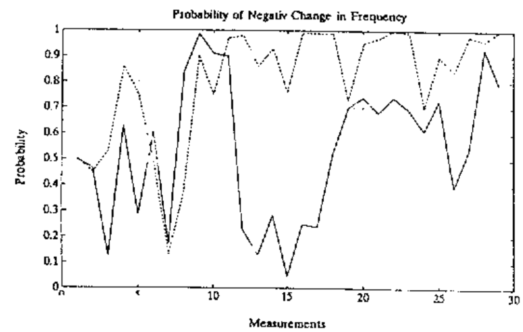

Figure 3.6: Damage indicator $P_{\Delta f_i}$ as function of time.

4 CONCLUSIONS

The structural integrity of a multi-pile offshore platform is investigated by using a vibration based damage detection scheme. The damage indicator given as the probability of negative changes in the first two natural frequencies is used to investigate the integrity of the structure. Based on this damage indicator it is concluded that with a probability close to one the considered offshore structure has suffered structural changes in the first year of operation. The changes are small however, and their influence on structural safety must be clarified by further investigations.

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5 REFERENCES

[1] Rytter, A.: *Vibration Based Inspection of Civil Engineering Structures.* Ph.D thesis, Aalborg University, 1993.

[2] Loland, O. & C.J. Dodds: *Experiences in Development and Operating Integrity Monitoring Systems in the North Sea.* Offshore Technology Conference, Paper 2551, Houston, 1975.

[3] Campbell, R.B. & J.K. Vandiver: *The Estimation of Natural Frequencies and Damping Ratios of Offshore Structures.* Offshore Technology Conference, Paper 3861, 1980.

[4] Copolino, R.N. & S. Rubin: *Detectability of Structural Failures in Offshore Platforms by Ambient Vibration Monitoring.* Offshore Technology Conference, Paper 3865, 1980.

[5] Haugland, H. & S.L. Yaas: *Underwater Detection and Monitoring of Fatigue Cracks on a Dynamic Loaded K-node with Internal Stiffeners.* Offshore Technology Conference, Paper 5869, 1988.

[6] Jensen, J. L.: *System Identification of Offshore Platforms.* Ph.D thesis, Aalborg University, 1990.

[7] Roitman, N, P.F. Viero, C. Magluta, R.C. Batista & L.F. Rosa: *Identification of Offshore Structural Damage using Modal Analysis Techniques.* Mechanical Systems and Signal Processing, Vol. 6, No. 3, 1992.

[8] Hamamonto, T. & I. Kondo: *Preliminary Experiment for Damage Detection of Offshore Structures.* Proc. of the Third Int. Offshore and Polar Engineering Conference, Singapore, 1993.

[9] Li, C.-S., R.-J. Shyu, W.-J. Ko & H.-T. Lin: *Multichannel Vibration Time Series Analysis of an Offshore Structural Model.* J. CSME, Vol. 14, No. 1, 1993.

[10] Ljung, L.: *System Identification: Theory for the User.* Prentice Hall, Englewood Cliffs, 1987.

[11] Söderström, T. & P. Stoica: *System Identification.* Prentice Hall, 1987.

[12] Gersch, W. & R. Liu: *Time Series Methods for the Synthesis of Random Vibration Systems.* ASME Transactions, Journal of Applied Mechanics, Vol. 98, No. 2, 1976.

[13] Pandit, S. W. & N. P. Metha: *Data Dependent Systems Approach to Modal Analysis Via State Space.* ASME paper No. 85-WA/DSC-1, 1985.

[14] Hac, A. & P. Spanos: *Time Domain Structural Parameters Identification.* Proc. of the Session of Structural Congress 87 (J. M. Roesset, ed.), 1987.

[15] F. Kozin & H. G. Natke: *System Identification Techniques.* Structural Safety, Vol. 3, 1986.

[16] Safak, E. : *Identification of Linear Structures using Discrete-Time Filters.* Journal of Structural Engineering, Vol. 117, No. 10, 1991.

[17] Davies, P., & J. K. Hammond: *A Comparison of Fourier and Parametric Methods for Structural System Identification.* Journal of Vibration, Acoustics, Stress and Reliability in Design. Vol. 106, pp.40-48, 1984.

[18] Morgan, B. J., S. C. Larson & R. G. Oesterle: *Field Measured Dynamic Characteristics of Buildings.* Proc. of the Sessions of Structures Congress 87,(D. R. Sherman, ed.), 1987.

[19] Srinavasan, M. G., C. A. Kot & B. J. Hsieh: *Dynamic Testing of As-Built Structures - A Review and Evaluation.* NUREG/CR-3649, ANL-83-20, U.S. Nuclear Regulatory Commission, Washington, D. C., 1984.

[20] Akaike, H.: *Fitting Autoregressive Models for Prediction.* Am. Inst. Stat. Math., Vol. 21, pp. 243-347, 1969.

[21] Kirkegaard, P.H.: *Optimal Design of Experiments for Parametric Identification of Civil Engineering Structures.* Ph.D-Thesis, Aalborg University 1991.

[22] PC-MATLAB for MS-DOS Personal Computers, The Math Works, Inc., 1989.

[23] Kirkegaard, P.H., J.C. Asmussen, P. Andersen & R. Brincker : *An Experimental Study of an Offshore Structure*, University of Aalborg, 1994.

[24] Tallavó F., M.E. Martĩnez & D.J. Ewins: *Experimental Evaluation of Vibrations in an Operating Offshore Platform.* Proc. of the 13th International Conference on Modal Analysis. Nashville, 1995.