ON THE SYSTEM IDENTIFICATION MODELLING OF OFFSHORE DYNAMIC SYSTEMS

Dr. S. Mandal
Ocean Engineering Division
National Institute of Oceanography, Dona Paula,
Goa 403 004, INDIA

Dr. G. J. Lyons
Dept. of Mechanical Engineering
University College London
Torrington Place
London WC1E 7JE, UK

SYNOPSIS

This paper describes an investigation into the analysis methods arising from identification aspects of the theory of dynamic systems with application to full scale offshore monitoring and marine environmental data. Based on the input-output of the dynamic systems, the system identification techniques are used first to identify the model type and then estimate the model parameters. Here system identification techniques, namely autoregressive, moving average and autoregressive moving average algorithms are applied to time series data on sea waves and semisubmersible motions. The system identification modelling of full scale offshore dynamic systems yields additional information which could not be identified by the theory or laboratory experiment.

INTRODUCTION

In offshore engineering conventional analytical and empirical methods are extensively used in the design of offshore structures. Many complicated offshore phenomena, owing to lack of in-depth knowledge, are analyzed based on empirical methods.

Structural fatigue, structural damping and external loading on structures in marine environment are very different from the conventional land-based structural problems for which theories are well established. Even though offshore dynamic problems are solved generally based on linear assumptions and modified land-based structural theories, actually there are many unknown phenomena happening in the offshore environment for which presently used theories may not be sufficient.

Often theoretical models require validation to ensure that engineers have high confidence in their design. One common design verification procedure is to carry out model scale tests. Model scale tests are also useful for providing additional information in structural design. However, there is always an element of uncertainty associated with the predicted response of the final design owing to initial assumptions made in the structural modelling process and the natural variation of marine environmental conditions.

It is for the above reasons that many offshore platforms have been equipped with structural monitoring systems which collect long term data on the marine environment and the structure's response. Examples of typical data collected are wave elevations, fluid velocities and accelerations, wind velocity and direction, structural accelerations and structural strains. These full scale data are useful for verification of the predicted response of the structure and for future improvements in designs. The task of establishing dynamic models from these full scale data is known as *System Identification* (SI). The structural models identified from measured data using SI algorithms may be compared with the theoretical models used in the design process. This leads to the estimation of some unknown phenomena present in offshore dynamic systems.

SYSTEM IDENTIFICATION PROCEDURES

SI algorithms are becoming powerful tools for solving many complex phenomena in offshore dynamic systems. If the measured time series data can be well defined by some mathematical rules it is said to be a true system. But in practice, comparing certain aspects of the physical systems with its mathematical description will never establish an exact or true relationship. However, mathematical rules can establish as best as possible a representation to describe the physical system, from the point of view in usefulness rather than truth. Sometimes, due to lack of measured data, approximation of the dynamic system by SI methods reasonably well describe the dynamic system. For constructing a model from the data, the SI procedure generally be expressed in steps as given below.

- a) Input-Output data: The input-output data required for a specifically designed experiment. Collecting, storing, and handling vast volumes of time series data in marine environment is an expensive and complicated procedure. Accordingly, measurement programmes need to be properly planned keeping in mind that one should have prior knowledge (as much as possible) about what are the data to be measured and when to measure. The experiment design gives some choices so that the data become maximally informative. Several choices are available in experiment design. These are: which signals to measure, when to measure them, which signals to manipulate, how to manipulate them, and how to choose presampling filters and how to smooth them by removing trends.
- b) Define some SI models and choose the most suitable one which appropriately represents the dynamic system. This is the most difficult and important step of the SI procedure. If one does not know the physical background of the system as prior knowledge or information being available, standard linear models could be used (Ljung, 1987 and Marple, 1987). If the prior information which leads to the dynamic system is known, this may be a good starting step for choosing a suitable SI model. Some knowledge about the nature of relationships between the measured signals can lead to appropriate selection of model structures. Fast Fourier Transform (FFT) analysis of the data (Newland, 1984) also can lead to a meaningful selection of SI model order, based on the spectral shapes.
- c) The performance of the SI model is dependent on assessment

of the model quality. One must identify the best model which yields the best representation or reproduction of measured data.

Once a particular model is chosen based on certain criteria it is to be confirmed that the estimated model is a realistic approximation of the system. This is called as validation of the model. Therefore, one should test whether the estimated model is good enough for its purpose. Model validation involves various procedures to assess how the model relates to measured data and to its intended use. The simplest test is to compare the estimated power spectrum with that obtained from FFT analysis. The second test may be to compare the output time series of the model with the measured time series. Another way of validating the SI model is to estimate the residuals of the The residuals estimation is based on the condition that the difference between the model output and measured one should be a white noise process. If the estimated residuals of the SI model is closer to white noise, the better the model is. checks can be made by using various statistical tests.

SYSTEM IDENTIFICATION MODELLING

A SI model can be expressed by any mathematical representation which approximates the relation between the input and output of a dynamic system. The SI models are principally categorized into parametric and nonparametric types.

a) Parametric models: These are a particular type of SI model where the essential features of the input-output relations are described in the form of parametric polynomials. These parameters must be assigned values before the model is completely specified. Various parametric model structures are available (LJUNG, 1987 and SAFAK, 1989). As an example, time series of an offshore dynamic system is expressed by the difference equation

$$y_r = -\sum_{k=1}^{r} a_k y_{r-k} + \sum_{i=1}^{r} b_i w_{r-i}$$
 (1)

where a and b are unknown parameters of the model to be

estimated, w_i is the white noise as input and y_i is the t^{i*} sample of the dynamic system as output.

Assuming that the model is linear and time-invariant, equation (1) can be expressed in polynomial form in terms of z-transform notation as

$$Y(z) = H(z) W(z)$$
where
$$H(z) = B(z^{-1})/A(z^{-1})$$

$$A(z^{-1}) = 1 + a_1 z^{-1} + a_2 z^{-1} + \dots + a_n z^{-n}$$

$$B(z^{-1}) = b_1 + b_1 z^{-1} + b_2 z^{-1} + \dots + b_n z^{-n}$$
(2)

Coefficients a, and b, are determined based on procedures stated in MANDAL (1992). The power spectrum of dynamic system can be expressed as

$$S(y) = |H(e^{(y)})|^{2}$$
 (3)

For autoregressive (AR) process, $B(z^{(1)}) = \text{square root of noise}$ variance. For moving average (MA) process, $A(z^{(1)}) = 1$. For autoregressive moving average (ARMA) process, equation (1) is used.

b) Nonparametric models: These types of SI models have unknown parts in the form of functions rather than parameters. For non-parametric modelling, the system can be treated as black box, since its aim is to determine a function which relates the input to the output without recourse to any prior information about the internal structure of the system. As an example, a time-invariant linear model with a single input and single output can be defined by the impulse function, h(t), and it is expressed as

$$y(t) \cdot \int_{1}^{\infty} h(\tau) x(t-\tau) d\tau$$
 (4)

where x(t) is the input and y(t) is the output. Equation (4) can be written in z-transform as

$$Y(z) = H(z) X(z)$$
 (5)

Here h(t) and H(z) are arbitrary transfer functions to be estimated from the input and output of the dynamic system. Whereas the transfer functions in equations (1) and (2) are in the form of unknown parameters. Therefore, different identification

procedures are required for each of the above cases.

The parametric SI models of offshore dynamic systems could achieve higher spectral resolution as compared with that by classical approaches (MARPLE, 1987). The parametric approach gives users choices in ability to fit an assumed model with few parameters. The optimal model order selection can be obtained using the least squares error, Akaike information criterion (Akaike, 1976) and minimum description length methods (Rissanen 1983). The SI methods, namely Autoregressive (AR), Moving Average (MA) and Autoregressive Moving Average (ARMA) models are extensively applied to offshore dynamic systems (MANDAL, 1992). Some examples are described here in the next section.

APPLICATIONS

Various SI techniques are available for modelling of time series offshore dynamic systems. Here AR, MA and ARMA algorithms are used for ocean wave spectral estimation and offshore structural motion responses.

The time series wave data set (K15) collected off Karwar, west coast of India (Figure 1) at 16m water depth is used here for wave power estimation using AR, MA and ARMA algorithms. formulations of the AR, MA and ARMA modelling applied to various offshore dynamic processes are described by MANDAL (1992). This study considered waves (K15) of 2048 data points collected at asampling frequency of 2 Hz. The initial order of the SI model is determined based on an autocorrelation (Figure 2) and the least squares error (Figure 3) method. The selected model orders are AR(40), MA(30) and ARMA(20,20). It is observed from Figures 2 &3 that it is a pure convergent process. Therefore, by increasing the model orders, it gives improved results. The FFT spectrum of above data set is compared with SI models' spectra (Fig. 4). For further reduction of the model orders, the techniques developed by MANDAL et al (1992) is used here for above data set. Considering initial AR estimates, the roots of the AR polynomial are determined and then complex roots are multiplied to form second ord-

er real modes. Energy in each mode is calculated based on structures of parametric modelling. Now higher energy modes are multiplied to form reduced order AR part of the final ARMA model. MA part is determined based on partial fraction and recursive Figures 5 & 6 show the spectral comparison of FFT of measured waves with ARMA(2,2) and ARMA(4,4) models respectively. Here only 5 values which are the ARMA(2,2) coefficients can reasonably represent the time series wave data (K15). Therefore, implementation of the reduced order ARMA algorithms in offshore dynamic systems has the potential advantage of storing more representation of the wave environment than is currently practically possible because of the reduced size of the data set. The second part is described here for the heave response analysis of semisubmersible. Heave accelerations of semisubmersible were measured at the North Sea by the Dept. of Mechanical Engineering, University College London. A typical 2048 digital heave acceleration data set collected at 2.5Hz interval (Figure 7) is considered to estimate the power spectrum using SI algorithms. normalized auto correlation of the initial AR algorithm for the above data is shown in Figure 8, which indicates that the data are not purely convergent. Variation of correlation increases after the lag of 98. The AR(98) model shows good matching with the FFT spectrum (Figure 9). Comparatively a lower order MA(32) model gives better spectral representation (Figure 10) than that by the AR(98) model. This study shows that the time series offshore dynamic systems can be modelled using various SI techniques.

CONCLUSIONS

The paper presented herein has briefly investigated the analysis methods arising from identification aspects of the theory of dynamic system. Using SI methods, parametric models of dynamic systems are determined based on input and output of offshore dynamic processes. Full scale offshore monitoring data or marine environmental data can be substantially reduced to a few SI parameters. Model order reduction (MANDAL et al., 1992) applied

to time series ocean waves can eliminate spurious noise modes or disturbances. Thus eliminating noise modes, the reduced order SI model with few values which are the SI parameters describes the confused ocean waves. The parametric SI models can also be used to simulate time series data based on the target spectrum.

Collection of full scale offshore structural motions and analysis by SI techniques could describe some unknown phenomena which help to improve the structural designs.

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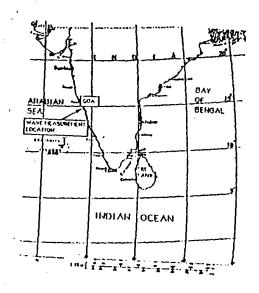


Figure 1 Wave measurement location

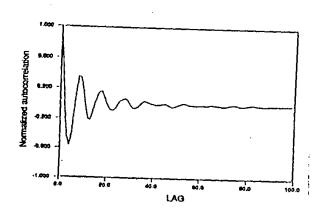


Figure 2 Normalized autocorrelation function of the measured time series sea waves: K15,

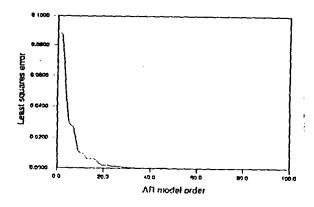


Figure 3 Least squares error variation for K15.

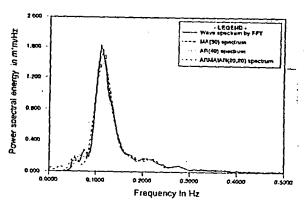


Figure 4 Comparison between FFT wave (K15) spectrum and MA(30), AR(40) and ARMAIAR(20,20) spectra.

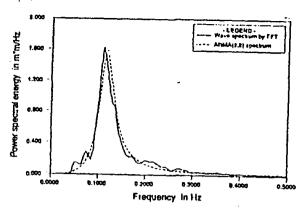


Figure 5 FFT wave (K15) spectrum and ARMA(2,2) spectrum estimated from AR(40) using MYW equations and reduction method.

Figure 6 'FFT wave (K15) spectrum and ARMA(4,4) spectrum estimated from AR(40) using MYW equations and reduction method.

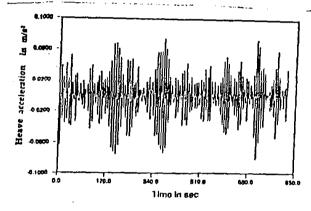
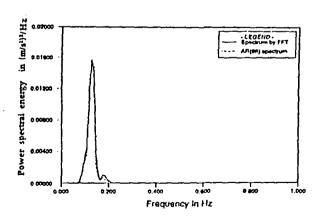


Figure 7 Time series heave acceleration (SR-2.511z) of the semisubmersible Rig135 (SF28).

Figure 8 Normalized autocorrelation function of the measured time series semisubmersible heave acceleration (SF28).



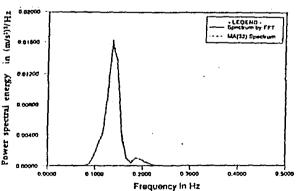


Figure 9 Semisubmersible heave acceleration (SF28) spectra calculated by FFT and AR(98) model.

Figure 10 Heave acceleration (SF28) spectra calculated by FFT and MΛ(32) model.