Proceedings of the ASME 2014 33rd International Conferences on Ocean, Offshore and Arctic Engineering
OMAE2014
June 8-13, 2014, San Francisco, California, USA

OMAE2014-23865

COST-EFFECTIVE LOAD MONITORING METHODS FOR FATIGUE LIFE ESTIMATION OF OFFSHORE PLATFORM

Nevena Perišić
Marine Structure Department
Ramboll Oil & Gas
Willemoesgade 2, Esbjerg 6700
Denmark
Tel: +45 51 61 80 53
Email: nepe@ramboll.com

Ulf T. Tygesen
Marine Structure Department
Ramboll Oil & Gas
Willemoesgade 2, Esbjerg 6700
Denmark
Tel: +45 51 61 73 98
Email: utt@ramboll.com

ABSTRACT

The lifetime of offshore structures are ruled by accumulated fatigue damage so structural load monitoring is of special importance for re-assessment of offshore platforms. However, direct measuring of the actual loading is usually not feasible due to sensor limitations. An alternative approach to direct load measuring is load estimation from the limited number of measurements of dynamic responses of the structure. This paper presents two, conceptually different, model based, methods for load estimation in time domain: modal expansion method and Kalman filter based method. The Kalman filter based method uses the reduced FEM and provides estimations of limited number of signals, where the modal expansion method expands the mode shape vectors to estimate the displacements and stresses at all unmeasured locations. This paper is a part of ongoing development of methods for linear and nonlinear system identification, FEM updating, wave load calibration and lifetime prediction of offshore structures.

INTRODUCTION

Structural monitoring systems (SMSs) of offshore structures usually consist of a set of sensors, such as strain gauges, accelerometers, wave radars and GPSs. However direct measuring of the actual loading is usually not feasible as, if possible at all, it would require a high number of installed sensors. Consequently the loading forces need to be extracted indirectly. Knowledge of the actual loading on the structure is crucial for: prediction of the remaining lifetime and lifetime extension [1], wave load calibration, component design validation and application of the advanced control algorithms. The fatigue loads have direct influence on the lifetime of the structure, where the extreme loads can cause instantaneous failures. Sometimes, monitoring of response characteristics can also be used as part of a warning system to provide alerts even before damages are developed which is very important for improving structure performance and increasing reliability.

Methods that are solving the problem of load estimation can be divided in three main categories based on the type of the system model [2]:

1. **Deterministic methods**: These methods are based on the deterministic dependencies between data, and their results depend strongly on the accuracy of the identified model. Majority of the available load estimation algorithms belong to this group [3]. The solutions can be found in the time [4], [5] or frequency domains [6] - [11].
2. **Stochastic methods**: This group of methods is based on statistical, i.e. stochastic models between the input and the output data [12] - [14]. Thus, these methods require the measurements of the input and the output data from the real, operational systems in order to identify stochastic models of the systems. However, for some systems like wind turbines,

measuring of driving loading is not possible.

3. **Artificial intelligence methods**: This group of methods includes use of the artificial neural networks [15], [16], the evolutionary algorithms [17] and the fuzzy logics [18] for load identification. The artificial intelligence methods are used when there is not enough physical knowledge about the structure or when the model is very complex so it cannot be processed in the real time. These methods assume that the model of the system is a black-box, so they require a learning process in order to determine the relations between the inputs and the outputs.

This paper focuses on one stochastic and one deterministic load identification method, where both methods assume that the only available data are displacement measurements.

The expansion-method is typically used for load estimation in the oil & gas industry [19], [20] and it belongs to a group of deterministic techniques. The basic idea of the modal expansion process is to expand the measured mode shape vectors to estimate signals at unmeasured locations, where the finite element model (FEM) is used to fill in the missing data. As a result, displacements and stresses can be obtained at all FEM node locations. The validity of the process depends on the refinement of the FEM, the proper choice of measurement locations and the number of mode shapes. Updating of the FEM must be performed on a regular basis in order to account for any structural changes in the structure during its lifetime. The main advantage of this approach is that it allows expansion and reconstruction of signals at every FEM node.

Lately, the focus of the research has been shifted towards combined deterministic-stochastic methods. These methods are based on the Kalman filter [21] and they are spread from the completely deterministic to those where the stochastic noise is assumed to be present in all measurements and states of the system. They use reduced order FE model, thus representing an alternative to the modal expansion suitable for reducing computational complexity if only limited number of signals is required to be estimated. The basic idea is to augment the state vector of the system with the unknown loading forces / responses where their dynamic evolution is assumed known. Some of the recent works where an augmented Kamlan filter was used for direct estimation of the unknown loading force are presented in [22] - [26]. How well the distribution of the structural loads acting on the structure can be estimated depends on the complexity of the used model, and its observability. The Kalman filter approach assumes that stochastic noise is present in all measurements of the system and it accounts for model uncertainties. The main advantages of this approach are relative computational simplicity, ability to work in real time and ability to cope with noises.

METHODS

Problem statement and the scope of the work: This work compares the modal expansion method with its alternative, the Kalman filter based method, on a test-case when the aim is estimation of a single signal in the presence of measurement noise. As a test-case, estimation of the total equivalent loading force (or its overturning moment) on the offshore oil & gas platform is selected. In the case of the Kalman filter based method, the minimum requirement for the estimation is displacement sensor placed at a single node, where the modal expansion requires at least three nodes with displacement sensors.

The total equivalent loading force is, in the present study, defined as the point force acting on the topside of the offshore oil and gas platform, which results in the measured displacements, i.e. the estimated loading force is equivalent to the effect from the wave loading. The total overturning moment estimated is proportional to the total equivalent loading force. It must be noted that for the Kalman filter approach, the estimated equivalent loading force contains both information of the wave loading force and some fictive load content which is due to simple model used for design of the Kalman filter. The estimated signals will be post-processed by using low-pass filter, in order to validate their accuracy in the wave loading frequency range. All data used in this work are simulated data and the measurement noise is artificially added in order to account for measurement uncertainties.

1. STOCHASTIC APPROACH: KALMAN FILTER

The proposed load identification algorithm is described in details in [26] and it consists of the following steps:

1. System modeling: Design and identification of a state-space model of the reduced order FE model of the system that includes all relevant dynamics. Start with the simplest possible, and increase complexity if necessary .

2. Design of the load observer: Design of a linear or nonlinear state estimator for recursive estimation of the state vector of the model identified in the previous step. Augment the state vector to include all unknown loading forces.

3. Parameter tuning and algorithm validation: Tuning the parameters of the estimator by using simulated or measured data. Compare the estimated signal with the referent signal if available.

The Kalman filter approach transforms a FE model of the structure into the reduced order, state-space form, where all unknown signals are collected in the state vector and further estimated recursively using the Kalman filter. How well the distribution of the structural loads acting on the structure can be estimated depends on the complexity of the used model, and its observability. The Kalman filter approach assumes that stochastic noise is present in all measurements of the system and it accounts for model uncertainties.

Usually, the responses of structures exposed to wind or wave dynamic loading are driven by the first few natural modes so reduced order, linear models can be used. For the estimation of the total equivalent loading forces acting on the offshore platform, the simplest possible model consists of the first north-south (N-S) and the first east-west (E-W) fundamental modes, thus it can be represented by a linear two degrees-of-freedom model (2DOF). In this way, only translation is considered where it is assumed that rotational motion is not present. Also, it is assumed that elevation is negligible and that motions in N-S and E-W directions are independent and uncoupled, thus they can be approached independently. These assumptions are valid for the simulated data, where in practice for other projects, potential coupling need to be checked. Derivation of the augmented, discrete, state-space model is described in [26] , where the final model is given by:

$$\mathbf{X}_k^A = \mathbf{A}\mathbf{X}_{k-1}^A + \mathbf{W}_{k-1}^A \tag{1}$$

$$\mathbf{Y}_k = \mathbf{C}\mathbf{X}_{k-1}^A + \mathbf{V}_{k-1} \tag{2}$$

where the augmented state vector $\mathbf{X}_k^A$ at time instant $t_k = kT_s$ is defined as follows:

$$\mathbf{X}_k^A = \begin{bmatrix} x_k \\ y_k \\ \dot{x}_k \\ \dot{y}_k \\ F_{x,k} \\ F_{y,k} \end{bmatrix} \tag{3}$$

$x_k, y_k, \dot{x}_k, \dot{y}_k$ are displacements and velocities in N-S and E-W directions respectively, at the node of the platform where the displacement sensor is located (top side). $F_{x,k}$ and $F_{y,k}$ are the total equivalent loading forces in N-S and E-W directions respectively. The system matrices **A** and **C** are defined by the first natural frequencies, the damping ratios and the sampling time T_s. Modal parameters are identified from the dynamic responses of the structure and the sampling ratio corresponds to the measurement sampling ratio, thus completely defining the grey-box reduced order model of the system. $\mathbf{W}_k$ and $\mathbf{V}_k$ are the stationary, stochastic system and measurement noise vectors with appropriate dimensions. For the sake of clarity, it is assumed that they are zero mean with covariance matrices **Q** and **R** respectively. It is assumed that the only available measurements $\mathbf{Y}_k$ are displacements x_k and y_k.

In order to estimate unknown values of the augmented vector, Equations 1 and 2, the Kalman filter is used as an optimal, linear state estimator. The idea is to estimate states of the system

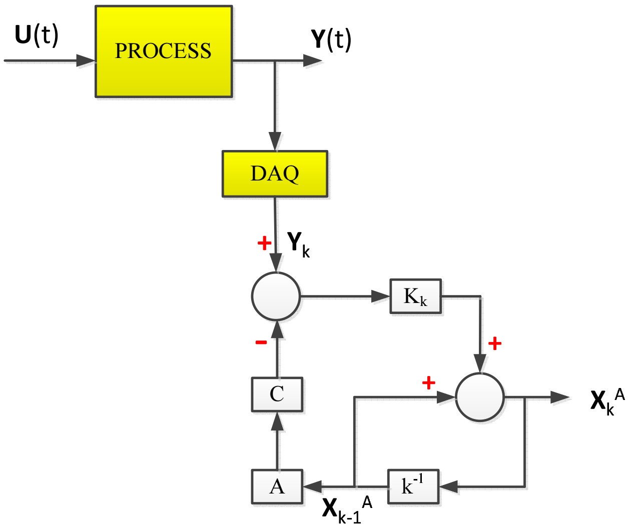

FIGURE 1. Structure of the Kalman filter in parallel with the real process.

by using recursive algorithm. The structure of the Kalman filter is given in Figure 1, [27], where K_k represents the Kalman gain calculated at time instant k. One way to describe the Kalman filter is as a filter that whitens the measurements and extract the maximal information from them. The Kalman filter is the optimal filtering solution for the discrete-time filtering model, when the dynamic and measurements models are linear Gaussian, uncorrelated, unbiased and independent white noises. If they are uncorrelated, unbiased and independent white noises but not Gaussian, the Kalman filter represents the best linear filter. The filter is optimal in a sense that the Kalman gain K_k is calculated so that it minimizes a weighted 2-norm of the expected value of the estimation error $\mathbf{e} = \mathbf{Y} - \hat{\mathbf{Y}} = \mathbf{Y} - \mathbf{C}\mathbf{X}$.

The complete procedure for deriving the Kalman filter equations can be found in [28]. The tuning parameters of the Kalman filter are covariance matrices of the measurement and process noises. By increasing the covariance of the process noise, more emphasis is given to the measurements where by increasing the covariance of the measurement noise, more confidence is placed on the model than on the measurements.

2. DETERMINISTIC APPROACH: EXPANSION-METHOD

The proposed load identification method based on modal expansion consists of the following steps:

1. Modal expansion: Based on analytical mode shapes matrix and measured data, application of modal expansion method and calculation of modal coordinate vector.

2. Signals extraction: Extraction of the FE model responses by scaling the natural mode shapes with the calculated modal coordinate vectors.

The basic idea of the modal expansion is to expand the measured data and to fill in the missing data using the FE model. There are different approaches how to do this. Expansion in this paper is performed by using modal transformation method where the modal data from the FE model are used to estimate data at unmeasured DOF. This method is also known as SEREP [29]. The measured data are assumed to be a linear combination of the analytical modes, so that linear transformation $\mathbf{T}$ is defined by:

$$\phi_m = [\phi_a]\,\mathbf{T} \tag{4}$$

where $[\phi_a]$ is the full analytical mode shape matrix, with dimensions *(N x M)*, N is the number of measured DOFs of the FE model and M is the number of the modes used for expansion. ϕ_m are the measured data with dimensions *(N x n)*, n is the number of measurements/ samples. In the case that N is higher than M, the system is overdetermined and it is possible to invert $[\phi_a]$. By applying pseudo inverse transformation to Equation 5, it is possible to estimate the $\mathbf{T}$, i.e. modal coordinates:

$$\mathbf{T} = [\phi_a]^{+}\,\phi_m \tag{5}$$

The full FE model of the offshore oil & gas platform considered in this work consists of 381 nodes, with displacements in three directions, where the number of nodes with displacement sensors is three. The chosen FE model modes could be static deflection shapes or dynamic mode shapes or a combination. Number of modes used for the expansion is two dynamic and/ or two static mode shapes.

The dynamics modes shapes are determined from a natural frequency analysis. The static deflection shapes are found by applying only static load on finite element model of the structure. The static load is selected to act at the water level and the results are not sensitive to the load level as the obtained deflection shapes are normalized.

RESULTS AND DISCUSSION
SIMULATION SETUP

In order to generate simulated data for testing of the load estimation algorithm, the RAMBOLL Offshore Structure Analysis Program package, ROSAP is used. The ROSAP package is a finite element program for static, dynamic and non-linear analysis of frame and truss structures for wind and wave load conditions. The Valdemar BA offshore platform is a tripod platform, installed in 2006 in the Danish North Sea 250 km west of Denmark. The platform is designed as a Not-Normally-Manned Platform (NNMP). The operator of the platform is Maersk Oil. Ramboll

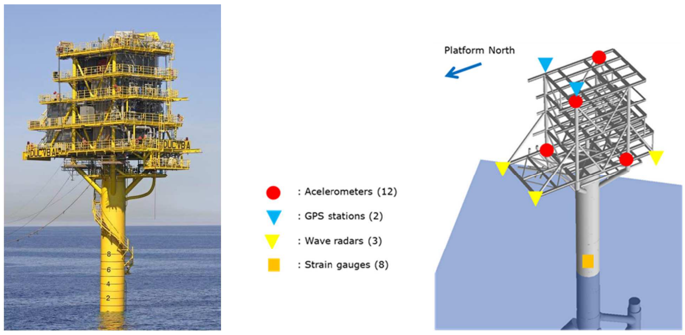

FIGURE 2. Valdemar BA offshore platform (left) and FE model (right). In the FE model, the installed sensors for the SMS are also shown.

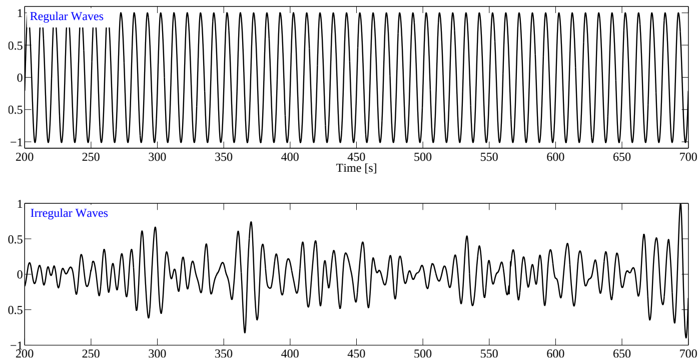

FIGURE 3. Total normalized loading forces [-] of the regular and irregular waves acting on the structure, time domain.

Oil & Gas (ROG) is the engineering consultant preparing technical specification for the SMS, sensor layout pre-testing, data post-processing, operational modal analysis (OMA), FE model updating, wave load calibration and fatigue re-assessment analysis. The FE model of the Valdemar BA platform installed with the sensor set-up is shown in Figure 2.

Simulations are performed for irregular wave loading. Irregular waves are characterized by a sum of harmonic sinus with different wave heights, frequencies, phases and directions. Figure 3 shows simulated time series of the normalized total wave loading forces acting on the structure for the case of regular and irregular waves. The total loading force is calculated as a sum of all the forces acting on each of the elements in the FE model of the structure.

In order to compare the quality of the estimations, the normalized mean square error (NMSE) function is calculated for the estimated equivalent loading force time-series, see Figure 6. The

NMSE compares the simulated total loading force time series **F** with the estimated $\hat{\mathbf{F}}$ signal, where σ_F^2 is the variance of the simulated force.

$$NMSE[\%] = \frac{100}{N\sigma_{\mathbf{F}}^2} \sum_{i=1}^{N} \left(\mathbf{F} - \hat{\mathbf{F}}\right)^2 \tag{6}$$

The locations on the platform, where the displacements are assumed to be measured, correspond to the locations of the two GPS and one accelerometer sensors installed on the Valdemar BA offshore platform.

METHOD 1: KALMAN FILTER

The NMSEs of the total equivalent loading force estimations for different measurement noise levels, for the case of irregular waves are presented in Table 1, NMSE1 values. The NMSE values are around 30% for the E-W case, and around 42% for the N-S case. It should be noted that the values for the NMSE are calculated in the frequency range from 0Hz to 25Hz only for presentation purposes, as the actual wave loading is in the frequency range of 0.03Hz to 0.5Hz. For the present simple formulation of the adopted Kalman filter method, the unknown loading contains information both of the wave loading and some fictive structural modes. The reason for the calculated high NMSE values is mainly due to the fact that a simple 2DOF system is used to represent the response at all frequencies in the wide frequency range from 0Hz to 25Hz.

It is observed that the NMSE is higher in the N-S direction than in the E-W direction. This is due to the fact that the wave loading in the N-S direction is very small (the wave loading direction is in the E-W direction), hence the uncertainties are higher. Another observation is that the torsion mode is present in one of the fictive structural modes, but it is not present in the reference horizontal reaction force, i.e. a measured displacement response due to torsion cannot be detected in a horizontal reaction force. As the torsion part is most visible in the low activated N-S direction this also contributes to higher NMSE values in the N-S direction of the estimated total reaction force. In order to see how well the estimations perform in the lower frequency range that corresponds to the quasi-static wave loading force of interest, the estimated and the reference signals are post-processed using low-pass filter. The NMSE values are calculated again, see NMSE2 in Table 1, and top plots in Figures 4 and 5. It can be seen that much better NMSE values are achieved when the contribution of the fictive structural frequencies to the response is filtered out. In the main wave direction, E-W, the NMSE of the filtered estimations are around 5% which is very good, especially taking in consideration the simplicity of the used model and the assumptions that were made in the work. The higher NMSE values of around 10% for the N-S direction is due to almost no wave loading in this direction, i.e. small values and hence higher uncertainties.

TABLE 1. NMSE VALUES OF THE TOTAL EQUIVALENT LOADING FORCE ESTIMATIONS (NMSE1) AND TOTAL WAVE FORCE ESTIMATIONS (NMSE2) FOR DIFFERENT SIGNAL TO NOISE RATIOS, OBTAINED USING KALMAN FILTER APPROACH.

SNR	Direction	$NMSE1[\%]$	$NMSE2[\%]$
Inf	E-W	28.50	5.50
1000	E-W	28.58	5.51
500	E-W	28.37	5.48
200	E-W	28.59	5.55
100	E-W	29.23	5.65
20	E-W	31.64	5.83
10	E-W	35.31	6.92
Inf	N-S	41.56	10.59
1000	N-S	42.27	10.80
500	N-S	41.45	10.48
200	N-S	43.57	10.65
100	N-S	41.58	10.79
20	N-S	42.55	15.31
10	N-S	46.15	21.15

METHOD 2: MODAL EXPANSION

The NMSEs of the total equivalent overturning moment estimations for the case of irregular waves, for different measurement noise levels and different combinations of modes used for the expansion method are presented in Table 2, NMSE2 values. The NMSE values are around 38% for the E-W case, and around 32% for the N-S case. It should be noted that the values for the NMSE are calculated in the frequency range from 0Hz to 25Hz. The reason for very high NMSE values (NMSE1, Table 2) in both E-W and N-S directions is the fact that the only the first two natural frequency modes (dynamic modes) are used in the expansion even for the representation of the response from higher modes. Another reason is the very wide frequency range, which is chosen here only for illustration purposes, where the interesting quasi-static wave loading frequency is in the range of 0.03Hz to 0.5Hz.

The results from estimation of the total reaction moments based on different mode combination used in the modal expan-

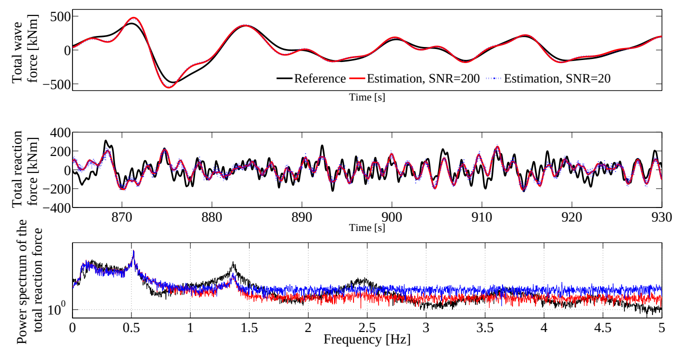

FIGURE 4. Kalman filter method: Estimated vs. simulated wave loading force and total equivalent loading force in time and frequency domains, for the case of low (SNR=200) and high measurement noise (SNR=20) and E-W motion of the platform.

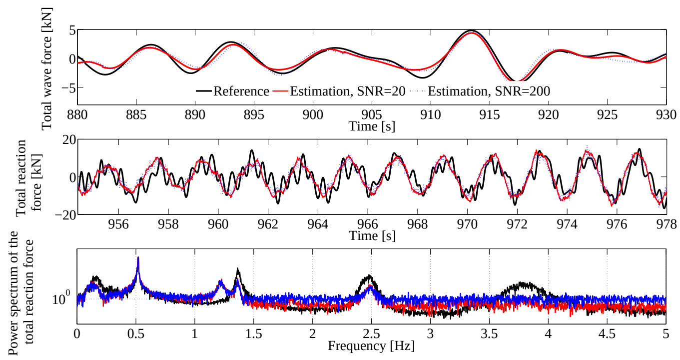

FIGURE 5. Kalman filter method: Estimated vs. simulated wave loading force and total equivalent loading force in time and frequency domains, for the case of low (SNR=200) and high measurement noise (SNR=20) and N-S motion of the platform.

sion are presented in Figures 6 and 7. It is observed that estimations based on modal expansion including only the first two dynamic modes have perfect fit around the first two natural frequencies, i.e. around 0.5Hz. However, it is observer that the fit in the quasi-static range is poor. It is also observed that estimations based on modal expansion including only the two static deformation mode shapes have perfect fit in the quasi-static range, but the fit at the first two natural frequencies is very poor. The last expansion using combination of the two static and the two dynamic modes give a good fit, both in the quasi-static wave load range and at the natural frequencies. The NMSE values for the expansion using both static and dynamic modes in the frequency range of 0.03Hz to 0.5Hz is around 5% for the E-W direction and 14% in the N-S direction, see Table 2, NMSE2 values. As in the

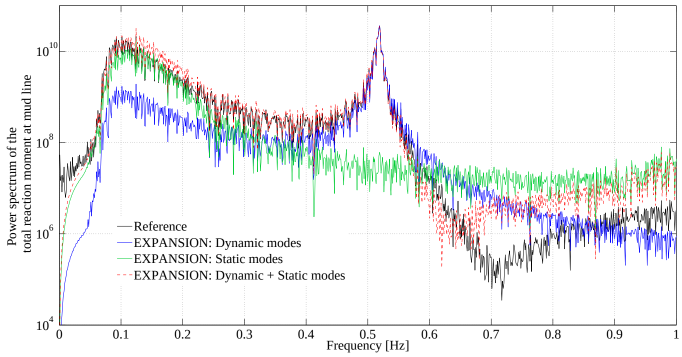

FIGURE 6. Modal expansion method: Reference and estimated total reaction moments at the mud line in the frequency domain, obtained using modal expansion approach and different assumptions for the number of modes used for expansion. For the case of E-W motion of the platform.

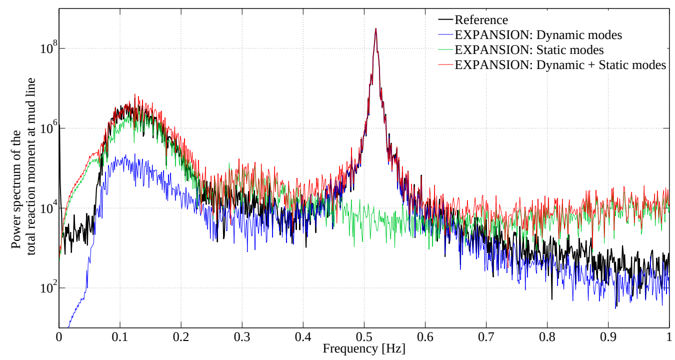

FIGURE 7. Modal expansion method: Reference and estimated total reaction moments at the mud line in the frequency domain, obtained using modal expansion approach and different assumptions for the number of modes used for expansion. For the case of N-S motion of the platform.

case of the Kalman filter approach, higher NMSE values in the N-S direction are a consequence of almost no wave loading in this direction and hence higher uncertainties.

The estimated quasi-static wave loading (low pass filtered at 0.4Hz) and the estimated total reaction moments (low pass filtered at 0.7Hz) are plotted and compared to the reference signal in the time and in the frequency domain in Figures 8 and 9 . The figures illustrate the effect of NMSEs of 5% and 10% respectively for E-W direction and N-S direction.

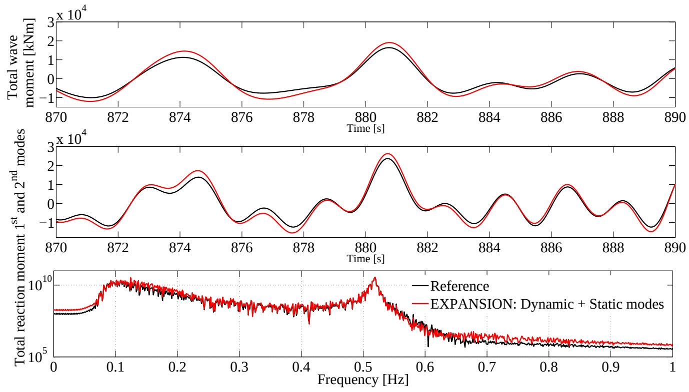

FIGURE 8. Modal expansion method: Reference (black) and estimated (red) signals using modal expansion including both dynamic and static modes. The first plot corresponds to total wave moment in time domain (frequency range [0-0.4] Hz), the second and third plot correspond to filtered total reaction moment in time and frequency domains, frequency range [0-0.7] Hz. For the case of E-W motion of the platform.

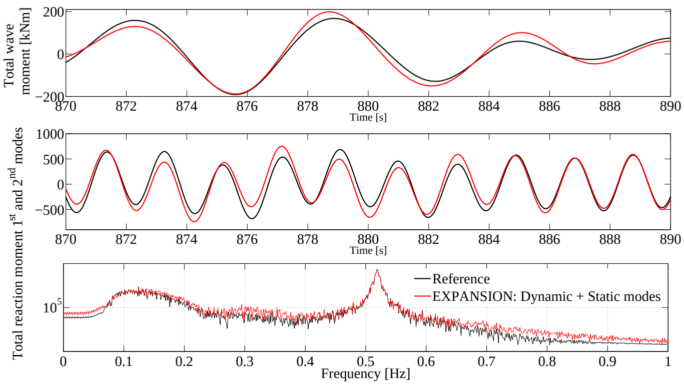

FIGURE 9. Modal expansion method: Reference (black) and estimated (red) signals using modal expansion including both dynamic and static modes. The first plot corresponds to total wave moment in time domain (frequency range [0-0.4] Hz), the second and third plot correspond to filtered total reaction moment in time and frequency domains, frequency range [0-0.7]Hz. For the case of N-S motion of the platform.

CONCLUSIONS AND FUTURE WORK

In the present paper, the performances of the low-cost Kalman filter based method for load identification and a method based on modal expansion have been compared. For applications requiring simple means of estimating the unknown wave loading in the time domain from measurement of a single displacement sensor, the analysis performed with the Kalman filter approach for a low order DOF system shows that good estimations can be achieved. NMSE values of around 5% have been

TABLE 2. NMSE VALUES OF THE TOTAL OVERTURNING MOMENT ESTIMATIONS OBTAINED USING EXPANSION IN TWO DYNAMIC MODES (NMSE1) AND BAND PASS FILTERED TOTAL OVERTURNING MOMENT ESTIMATIONS ([0.03-0.5]Hz) OBTAINED USING EXPANSION IN TWO DYNAMIC AND TWO STATIC MODES (NMSE2) FOR DIFFERENT SIGNAL TO NOISE RATIOS.

SNR	Direction	$NMSE1[\%]$	$NMSE2[\%]$
Inf	E-W	38.07	5.16
1000	E-W	38.09	5.16
500	E-W	38.09	5.16
200	E-W	38.11	5.16
100	E-W	38.19	5.16
20	E-W	38.59	5.23
10	E-W	39.09	5.21
Inf	N-S	31.62	14.46
1000	N-S	31.68	14.45
500	N-S	31.69	14.45
200	N-S	31.73	14.45
100	N-S	31.93	14.48
20	N-S	32.93	14.42
10	N-S	34.20	14.55

calculated for both methods for the primary wave load direction, which is very good especially considering the simple model approaches adopted. The sensitivity towards noise contents representing measurement noise, process/model uncertainties or other uncertainties is also in the same range for both methods.

The estimation of the wave loading based on the expansion method, indicates that it is important to use both the static and dynamic modes in the expansion process in order to get a good estimations of the wave loading.

In Table 3, the advantages and disadvantages are compared for the two methods. In addition to tabulated values it must be highlighted that the Kalman filter method only allows data to be estimated for the limited number of the represented DOFs, whereas for the expansion method the full information for all nodes and elements in the FE model of the platform is available. Both methods will allow for wave load calibration.

The present work is part of an ongoing development project developing and introducing tools for both linear and nonlinear system identification, FE model updating, wave load calibration

TABLE 3. PROPERTIES OF THE LOAD ESTIMATION METHODS

Property	Kalman filter based method	Modal expansion
Computational complexity	Low	High
Stochastic model	Yes	No
Number of estimations	Optional	All
Operation in real time	Yes	Near-real time
Structural model complexity	Low	High

and accumulated fatigue monitoring in connection with installation of SMSs on offshore platforms.

ACKNOWLEDGMENT

Cooperation of Maersk Oil in preparing this paper and providing data is gratefully acknowledged.

REFERENCES

[1] Johannesson P., 1999, "Rainflow Analysis of Switching Markov Loads," PhD thesis, Lund Inst. of Technology, Lund University, Sweden.

[2] Uhl T., 2007, "The Inverse Identification Problem and its Technical Application, " Journal: Archive of Applied Mechanics,Springer-Verlag,**77**, pp. 325-337.

[3] Gladwell G. M. L., 1986, "Inverse Problems in Vibration," Kluwer Academic Publishers, Dordrecht, Netherlands.

[4] Klinkov M., Fritzen C.P., 2007, "An Updated Comparison of the Force Reconstruction Methods," Key Eng. Mater, **347**, pp. 461-466.

[5] Nordstroem L. J. L., Nordberg T P, 2002, "A Critical Comparison of Time Domain Load Identification Methods," Proceedings of the Sixth International Conference on Motion and Vibration Control, Saitama, Japan, pp. 1151-1156.

[6] Fabunmi J.A., 1986, "Effects of Structural Modes on Vibratory Force Determination by the Pseudoinverse Technique", AIAA J., **24** (3), pp. 504-509.

[7] Hillary B., Ewins D.J., 1984, "The Use of Strain Gauges in Force Determination and Frequency Response Function Measurements", Proceedings of IMAC II International Modal Analysis Conference, Orlando, pp. 627-634.

[8] Stevens K.K., 1987, "Force Identification Problems: an Overview," Proceedings of SEM Spring Meeting, Houston, Texas, pp. 838-844.

[9] Parloo E., Verboven P., Guillaume P., Van Overmeire M., 2003 "Force Identification by Means of In-operational Modal Models," J. Sound Vib., **262** (1), pp. 161-173.

[10] Vanlanduit S., Guillaume P., Cauberghe B., Parloo E., De Sitter G., Verboven P., 2005, "On-line Identification of Operational Loads Using Exogenous Inputs," J. Sound Vib., **285**, pp. 267-279.

[11] Nordstrom L.J.L., 2006, "A Dynamic Programming Algorithm for Input Estimation on Linear Time-Variant Systems," Comput. Methods Appl. Mech. Eng., **195**, pp. 6407-6427.

[12] Zion L., 1994, "Predicting Fatigue Loads Using Regression Diagnostics," Proceedings of The American Helicopter Society Annual Forum, Washington, DC, pp. 1337-1358.

[13] Trujillo D.M., Busby H.R.,1997, "Practical Inverse Engineering," CRC Press, London.

[14] Stelzner D. A. and Krammer D. C., 1999, "Input Force Estimation Using an Inverse Structural Filter," Proceedings of 17th IMAC, Orlando, FL.

[15] Uhl T. and Petko M., 2006, "Load Identification With the Use of Neural Networks Design and Application," Mechanical Systems and Signal Processing.

[16] Uhl T., 2002, "Identification of Loads in Mechanical Structures-Helicopter Case Study," Computer Assisted Mechanics and Engineering Sciences, CAMES, **9**, pp. 151-160.

[17] Uhl T. and Pieczara J., 2003, "Identification of operational loading forces for mechanical structures," Arch. Transp., **16** (2), pp. 109-126.

[18] Goral G., Zbydon K. and Uhl T., 2002, "Intelligent Transducers of In-operational Loads in Construction Fatigue Monitoring," Mach. Dyn. Probl, **2-3**, pp. 73-78.

[19] Dascotte E., Strobbe J. and Tygesen U.T., 2013, "Continuous Stress Monitoring of Large Structures," Proceeding of 5th International Operational Modal Analysis Conference, Portugal.

[20] Skafte A., Tygesen U.T. and Brincker R., 2014, "Expansion of Mode Shapes and Responses on the Offshore Platform Valdemar," Proceedings of the 32nd IMAC, a Conference on Structural Dynamics, Orlando, Florida.

[21] Kalman R.E., 1960, "A New Approach to Linear Filtering and Prediction Problems," Journal of Basic Engineering **82** (1): pp 35-45.

[22] Lourens E., Reynders E., De Roeck G., Degrande G. and Lombaert G., 2012, "An Augmented Kalman filter for Force Identification in Structural Dynamics," Mechanical Systems and Signal Processing, **27**, pp. 446-460.

[23] Perisic N., Pedersen B.J. and Kirkegaard P.H., 2012, ”Gearbox Fatigue Load Estimation for Condition Monitoring of Wind Turbines,” Proceedings of International Conference on Noise and Vibration Engineering ISMA2012: International Conference on Uncertainty in Structural Dynamics. KU Leuven, Department Werktuigkunde, pp. 4381-4392.
[24] Perisic N. and Kirkegaard P.H., 2013, ”Low-Cost Tower Root Fatigue Load Estimation for Structural Health Monitoring of Grouted Connections in Offshore Wind Turbines,” In Damage Assesement of Strucure X: 10th International Conference on Damage Assessment of Structures (DAMAS 2013), Dublin, Ireland. Schweiz: Trans Tech Publications Ltd. pp. 676. (Key Engineering Materials, **569**).
[25] Perisic N, Pedersen B.J. and Kirkegaard P.H., 2013, ”Cost-Effective Shaft Torque Observer for Condition Monitoring of Wind Turbines,” Wind Energ.
[26] Perisic N., Kirkegaard P.H. and Tygesen U.T., 2014, ”Load Identification of Offshore Platform for Fatigue Life Estimation,” Proceedings of the 32nd IMAC, a Conference on Structural Dynamics, Orlando, Florida.
[27] Perisic N., 2014, ”System Identification of Wind Turbines for Structural Health Monitoring,” Ph.D. thesis, Aalborg University, Aalborg, Denmark.
[28] Simon D., 2006, ”Optimal State Estimation: Kalman, H Infinity, and Nonlinear Approaches,” John Wiley & Sons, Inc., Hoboken, New Jersey.
[29] OCallahan J. C., Avitabile P. A. and Riemer R., 1989, ”System Equivalent Reduction Expansion Process (SEREP),” Proceeding of the 7th Int. Modal Analysis Conf., pp 29-37.