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Vibration-based identification of hydrodynamic loads and system parameters for offshore wind turbine support structures

D.J.M. Fallais[a,*], S.Voormeeren[b], E.Lourens[a]

[a]*Faculty of Civil Engineering and Geosciences, Delft University of Technology, Delft, Netherlands*
[b]*Siemens Wind Power, Offshore Engineering, The Hague, Netherlands*

Abstract

For reliable structural health monitoring and possible lifetime extension of offshore wind turbine support structures, accurate predictions of the response of these structures at all critical locations are required. Response predictions in offshore wind applications are, however, affected by large uncertainties on environmental (wind/wave/soil) as well as system parameters (eigenfrequencies/damping). As a first step towards robust health monitoring in the presence of these uncertainties, a methodology for simultaneous estimation of a response equivalent hydrodynamic loading and a system parameter from measured vibration signals is proposed. Use is made of a recently proposed coupled input-state-parameter estimation technique based on the Extended Kalman filter. The identification process is driven by a limited set of artificially generated vibration response data in combination with an approximate reduced-order model of the support structure. The results show that the proposed method is capable of tracking both the response equivalent hydrodynamic loading and a parameter that is related to the stiffness of the substructure.

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Keywords: Coupled input-state-parameter estimation; offshore wind turbine; support structure monitoring; hydrodynamic load identification; reduced-order model.

1. Introduction

The predicted response of an offshore wind turbine support structure is affected by uncertainties in the excitation as well the assumed physical parameters; both may originate from either the offshore wind turbine (OWT) or its environment. Examples of environmental parameters and loads are soil stiffness and wave/wind loads, respectively. System parameters may be natural frequencies, modal damping values, control parameters related to different operational states. Loads as well as parameters are site-specific and/or subjected to a varying degree of uncertainty. Accurate information on these uncertainties is crucial for reliable response predictions or structural health monitoring purposes. Since most uncertainties typically cannot be measured directly there is a need for the development of identification

* Corresponding author. Tel.: +31-15-278-8030.
E-mail address: d.j.m.fallais@tudelft.nl

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techniques that would allow for the estimation of uncertain parameters and loadings from available vibration response signals.

The estimation of physical system parameters from vibration response data has received a lot of attention over the past years. When on-line applicability is desired, Kalman or particle filters are often proposed. The resulting joint parameter and state estimation problem is non-linear, since parts of the physical model used in these filters depend on the unknown parameter(s) – see [1] for a recent literature review. When simultaneously tracking parameters and states using these techniques, it is often assumed that the uncertainty in the model is originating from the parameters only, and that either deterministic or statistical knowledge (e.g. Gaussian white noise) of the input forces is available. The latter assumption renders these techniques inapplicable to offshore wind turbines where the loading is typically unknown and characterized by high spatial and temporal variability.

When the aim is load identification, on the other hand, the system parameters are mostly assumed known. Restricting the discussion to model based methods with on-line applicability again, many Kalman-type filters for simultaneous input and state estimation have been proposed in recent years [2,3,4]. A state of the art review can be found in [5].

For the monitoring of offshore wind turbines, where the loading as well as certain physical parameters (e.g. damping, foundation stiffness) are characterized by uncertainty, algorithms capable of jointly estimating both the input forces and the uncertain parameters are desired. In [6], Naets and Desmet recently coupled the Extended Kalman filter (EKF) to a physical model of a cantilever beam in order to estimate the inputs, a system parameter and the states of the system. In this contribution, the same methodology will be applied to an offshore wind turbine in order to simultaneously estimate the hydrodynamic loading, states, and a stiffness-related system parameter. The identification process is driven by a limited set of vibration response data and with an approximate reduced-order model of the support structure.

Artificial acceleration and strain response data is generated by subjecting a realistic FE model of a 6 megawatt offshore wind turbine installed in 40 meter water depth to hydrodynamic loading associated with a normal sea state. To account for measurement errors, the generated data is corrupted with artificial noise. In this contribution, the E-modulus of the support structure is estimated in conjunction with an equivalent hydrodynamic load. The results show that the proposed method is capable of tracking both the hydrodynamic loading and a response governing stiffness parameter of the support structure.

Mathematical system model

Consider the dynamic model of a structure in Eq. (1), where the mass, damping and stiffness matrices, denoted by $(\mathbf{M}, \mathbf{C}, \mathbf{K}) \in \mathbb{R}^{n\times n}$, respectively, could depend on a time varying-parameter p. $(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}) \in \mathbb{R}^{n}$ denote the displacement, velocity and acceleration of the degree of freedom, respectively. $\mathbf{B} \in \mathbb{R}^{n\times n_f}$ is the force allocation matrix and $\mathbf{f} \in \mathbb{R}^{n_f}$ the external force vector. The variables n and n_f denote the number of degrees of freedom and the number of applied forces respectively.

$$\mathbf{M}(p)\ddot{\mathbf{q}} + \mathbf{C}(p)\dot{\mathbf{q}} + \mathbf{K}(p)\mathbf{q} = \mathbf{B}\mathbf{f} \tag{1}$$

In order to use the above model in the EKF it has to be transformed into state-space form, which is the standard first order form for a dynamic system model in most control and estimation applications. The state-space model consists of a set of state equations (Eq. (2)) and a set of output equations (Eq. (3)).

$$\begin{bmatrix} \dot{\mathbf{q}} \\ \ddot{\mathbf{q}} \end{bmatrix} = \begin{bmatrix} 0 & \mathbf{I} \\ -\mathbf{M}_p^{-1}\mathbf{K}_p & -\mathbf{M}_p^{-1}\mathbf{C}_p \end{bmatrix} \begin{bmatrix} \mathbf{q} \\ \dot{\mathbf{q}} \end{bmatrix} + \begin{bmatrix} 0 \\ \mathbf{M}_p^{-1}\mathbf{B} \end{bmatrix} \mathbf{f} \tag{2}$$

$$\mathbf{y} = \mathbf{S}_d\mathbf{q} + \mathbf{S}_v\dot{\mathbf{q}} + \mathbf{S}_a\ddot{\mathbf{q}} = \begin{bmatrix} (\mathbf{S}_d - \mathbf{S}_a\mathbf{M}_p^{-1}\mathbf{K}_p) & (\mathbf{S}_v - \mathbf{S}_a\mathbf{M}_p^{-1}\mathbf{C}_p) \end{bmatrix} \begin{bmatrix} \mathbf{q} \\ \dot{\mathbf{q}} \end{bmatrix} + (\mathbf{S}_a\mathbf{M}_p^{-1}\mathbf{B})\mathbf{f} \tag{3}$$

The state equations describe the response of the system in terms of the state variables and a known load, whereas the output equations translate the state of a system to a desired quantity e.g. a measured output. The state vector $\mathbf{x}$ and its derivative $\dot{\mathbf{x}}$ are defined as $\mathbf{x} = [\ \mathbf{q}\ \ \dot{\mathbf{q}}\ ]^T$ and $\dot{\mathbf{x}} = [\ \dot{\mathbf{q}}\ \ \ddot{\mathbf{q}}\ ]^T$ respectively. The subscript p indicates a dependence on the time-varying parameter p. In Eq. (3), $\mathbf{y} \in \mathbb{R}^{n_y}$ is the output vector containing n_y measured outputs. The matrices

$\mathbf{S}_d, \mathbf{S}_v, \mathbf{S}_a \in \mathbb{R}^{n_y \times n}$ represent the output selection matrices for displacement, velocity and acceleration, respectively. These matrices can be generalized to construct linear combinations of the state vector, e.g. to compute strains.

Until now the state-space model was assumed to be free of any errors with respect to the real structure and the measured outputs. In order to include uncertainties on the state and output equation, each equation is appended with a stochastic variable. The output given in Eq. (3) is set equal to the measured data by adding a stochastic process representing an assumed measurement error. In order to account for uncertainties in the state equations, a stochastic process is added to Eq. (2) as well. The modifications result in Eq. (4) and (5), respectively:

$$\dot{\mathbf{x}} = \mathbf{A}(\mathrm{p})\mathbf{x} + \mathbf{E}(\mathrm{p})\mathbf{f} + \mathbf{w} \tag{4}$$

$$\mathbf{y} = \mathbf{H}(\mathrm{p})\mathbf{x} + \mathbf{D}(\mathrm{p})\mathbf{f} + \mathbf{v} \tag{5}$$

in which the so-called process and measurement noise, $\mathbf{w}$ and $\mathbf{v}$, are assumed to be uncorrelated, zero-mean, white noise terms coming from Gaussian distributions $\mathbf{w} \sim N(0, \mathbf{Q})$ and $\mathbf{v} \sim N(O, \mathbf{R})$, with known covariances $\mathbb{E}[\mathbf{w}(t)\mathbf{w}(\tau)^{\mathrm{T}}] = \mathbf{Q}\delta(t-\tau)$ and $\mathbb{E}[\mathbf{v}(t)\mathbf{v}(\tau)^{\mathrm{T}}] = \mathbf{R}\delta(t-\tau)$, respectively.

Parametric model order reduction

To reduce computational costs, a grid-based parametric model order reduction technique is used. This approach allows for simulation of a modally reduced parameter dependent system without solving the eigenvalue problem for each change in the parameter. The method consists of building a database of modally reduced-order models and derivative information on a predefined parameter grid [6,7]. Subsequently the database is used to relate the time varying-parameter to a modally reduced model. The numerical derivative information is used for interpolating reduced order models between available grid points and to compute local system linearizations in the EKF of section 2 for every estimate. In order to prevent errors in numerical derivatives due to sign switching of mode shapes, the signs of the mode shapes are corrected w.r.t. an arbitrarily chosen reference configuration. In the future this approach could be extended to include parameters which relate to operational states of the turbine.

Changing the physical coordinates in Eq. (1) to a set of reduced modal coordinates $\mathbf{q} = \mathbf{\Phi}_p\mathbf{z},\ \dot{\mathbf{q}} = \mathbf{\Phi}_p\dot{\mathbf{z}},\ \ddot{\mathbf{q}} = \mathbf{\Phi}_p\ddot{\mathbf{z}}$, and premultiplying by the transposed reduction basis, results in the truncated modally reduced system representation given in Eq. (7):

$$\mathbf{\Phi}_p^{\mathrm{T}}\mathbf{M}_p\mathbf{\Phi}_p\ddot{\mathbf{z}} + \mathbf{\Phi}_p^{\mathrm{T}}\mathbf{C}_p\mathbf{\Phi}_p\dot{\mathbf{z}} + \mathbf{\Phi}_p^{\mathrm{T}}\mathbf{K}_p\mathbf{\Phi}_p\mathbf{z} = \mathbf{\Phi}_p^{\mathrm{T}}\mathbf{B}\mathbf{f} \tag{6}$$

$$\mathbf{I}\ddot{\mathbf{z}} + \mathbf{\Gamma}_p\dot{\mathbf{z}} + \mathbf{\Omega}_p\mathbf{z} = \mathcal{B}\mathbf{f} \tag{7}$$

in which $\mathbf{\Phi}_p \in \mathbb{R}^{n \times n_r}$ is a matrix containing the $1 \le n_r \le n$ mass normalized eigenvectors belonging to the undamped eigenvalue problem at parameter p. The modal displacement, velocity and acceleration vectors are represented by $(\mathbf{z}, \dot{\mathbf{z}}, \ddot{\mathbf{z}}) \in \mathbb{R}^{n_r}$, respectively, where n_r is the number of retained modes. $(\mathbf{I}, \mathbf{\Gamma}_p, \mathbf{\Omega}_p) \in \mathbb{R}^{n_r \times n_r}$ are the identity matrix, the modal damping matrix, and the modal stiffness matrix, respectively. Note that due to mass normalisation of the modes, the modal mass matrix does not depend on p anymore. $\mathcal{B} \in \mathbb{R}^{n_r \times n_f}$ is the modal force allocation matrix.

The state-space transformation is invariant under a coordinate transformation, which allows for rewriting Eq. (7) and the corresponding output equation in the form of Eq. (8) and (9), respectively.

$$\dot{\mathbf{x}} = \begin{bmatrix} 0 & \mathbf{I} \\ -\mathbf{\Omega}_p & -\mathbf{\Gamma}_p \end{bmatrix}\mathbf{x} + \begin{bmatrix} 0 \\ \mathcal{B} \end{bmatrix}\mathbf{f} + \mathbf{w} \tag{8}$$

$$\mathbf{y} \approx \begin{bmatrix} (\mathbf{S}_d\mathbf{\Phi}_p - \mathbf{S}_a\mathbf{\Phi}_p\mathbf{\Omega}) & (\mathbf{S}_v\mathbf{\Phi}_p - \mathbf{S}_a\mathbf{\Phi}_p\mathbf{\Gamma}) \end{bmatrix}\begin{bmatrix} \mathbf{z} \\ \dot{\mathbf{z}} \end{bmatrix} + \mathbf{S}_a\mathbf{\Phi}_p\mathcal{B}\mathbf{f} + \mathbf{v} \tag{9}$$

The modal state vector is now defined as $\mathbf{x} = [\ \mathbf{z}\ \ \dot{\mathbf{z}}\ ]^{\mathrm{T}}$. The output equation is adapted for use with modal coordinates by substitution of the (reduced) set of modal coordinates, which results in Eq. (9). Note that these output equations are formulated using the information that is present in the modally reduced system matrices only.

Augmented modally reduced system model

Rewriting the state space model such that the loads and parameter are included in the state vector allows for the use of optimal state estimation techniques (e.g. the EKF) to estimate the new state vector based on response measurements and a parametric reduced-order model. In this work, one response-equivalent dynamic load and one physical parameter are augmented to the state space model. As in [6,8], the random walk models presented in Eq. (10) are used for this purpose, where $\mathbf{w}^{\mathrm{f}} \in \mathbb{R}^{\mathrm{n_{fe}}}$ and $\mathrm{w}^{\mathrm{p}} \in \mathbb{R}^{\mathrm{n_p}}$ are called the force and parameter process noise, respectively. The variable $\mathrm{n_{fe}}$ denotes the number of response-equivalent forces to be estimated, which may differ from the number of applied forces $\mathrm{n_f}$. They are assumed to be zero-mean, uncorrelated Gaussian white noise processes with known (co)variance $\mathbf{Q}^{\mathrm{f}}$ and Q^{p}, respectively.

$$\begin{aligned} \dot{\mathbf{f}} &= 0\mathbf{x}' + \mathbf{w}^{\mathrm{f}} \\ \dot{\mathrm{p}} &= 0\mathbf{x}' + \mathrm{w}^{\mathrm{p}} \end{aligned} \tag{10}$$

Introducing of the augmented state vector, $\mathbf{x}' = [\,\mathbf{z}\ \ \dot{\mathbf{z}}\ \ \mathbf{f}\ \ \mathrm{p}]^{\mathrm{T}}$, and rewriting Eq. (8) and (9), results in the augmented modal state and output equations presented in Eq. (11) and (12), respectively.

$$\dot{\mathbf{x}}' = \begin{bmatrix} 0 & \mathbf{I} & 0 & 0 \\ -\mathbf{\Omega}_{\mathrm{p}} & -\mathbf{\Gamma}_{\mathrm{p}} & \mathcal{B} & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \mathbf{z} \\ \dot{\mathbf{z}} \\ \mathbf{f} \\ \mathrm{p} \end{bmatrix} + \begin{bmatrix} \mathbf{w} \\ \mathbf{w}^{\mathbf{f}} \\ \mathrm{w}^{\mathrm{p}} \end{bmatrix} = \mathbf{A}(\mathrm{p})\mathbf{x}' + \mathbf{w}' \tag{11}$$

As a consequence of augmenting the state vector by a system parameter the system will inherently become non-linear, since the system model at a certain time level will depend on the state at the same time level. In Eq.(11), $\mathbf{A} \in \mathbb{R}^{(2\mathrm{n_r}+\mathrm{n_{fe}}+\mathrm{n_p})\times(2\mathrm{n_r}+\mathrm{n_{fe}}+\mathrm{n_p})}$ is the augmented state transition matrix and $\mathbf{w}'$ denotes the augmented process noise vector. The augmented output equation is presented in Eq.(12), where the augmented augmented output matrix is denoted by $\mathbf{G} \in \mathbb{R}^{\mathrm{n_y}\times(2\mathrm{n_r}+\mathrm{n_{fe}}+\mathrm{n_p})}$.

$$\begin{aligned} \mathbf{y} &= [\,(\mathbf{S}_d\mathbf{\Phi}_{\mathrm{p}} - \mathbf{S}_a\mathbf{\Phi}_{\mathrm{p}}\mathbf{\Omega}) \quad (\mathbf{S}_v\mathbf{\Phi}_{\mathrm{p}} - \mathbf{S}_a\mathbf{\Phi}_{\mathrm{p}}\mathbf{\Gamma}) \qquad \mathbf{S}_a\mathbf{\Phi}_{\mathrm{p}}\mathcal{B} \quad 0\,]\begin{bmatrix}\mathbf{z} & \dot{\mathbf{z}} & \mathbf{f} & \mathrm{p}\end{bmatrix}^{\mathrm{T}} + \mathbf{v} \\ &= \mathbf{G}(\mathrm{p})\mathbf{x}' + \mathbf{v} \end{aligned} \tag{12}$$

Temporal discretization

In order to use discrete-time algorithms, the continuous-time augmented modal state-space model presented in Eq.(11) and Eq.(12) has to be discretized as presented in [9]. The discrete random walk models are presented in Eq. (13). Throughout the discretization it is assumed that the force and parameter are constant over the time interval.

$$\begin{aligned} \mathbf{f}_{k+1} &= \mathbf{f}_k + \mathbf{w}_k^{\mathrm{f}} \\ \mathrm{p}_{k+1} &= \mathrm{p}_k + \mathrm{w}_k^{\mathrm{p}} \end{aligned} \tag{13}$$

The augmented state equation is similarly discretized using a time step of $t_k = k\Delta t$, in which Δt is the discretization time step:

$$\begin{aligned} \dot{\mathbf{x}}'_{k+1} &= \mathbf{A}'_k(\mathrm{p})\mathbf{x}'_k + \mathbf{w}'_k, &\qquad \text{with: } \mathbf{A}'_k(\mathrm{p}) = \exp^{\mathbf{A}(\mathrm{p})\Delta t} \\ \mathbf{y}_k &= \mathbf{G}'_k(\mathrm{p})\mathbf{x}'_k + \mathbf{v}_k, &\qquad \text{with: } \mathbf{G}'_k(\mathrm{p}) = \mathbf{G}(\mathrm{p}) \end{aligned} \tag{14}$$

In Eq. (14), the augmented process noise is denoted by $\mathbf{w}'_k = [\mathbf{w}_k\ \mathbf{w}_k^{\mathrm{f}}\ \mathrm{w}_k^{\mathrm{p}}]^{\mathrm{T}}$, with covariance $E[\mathbf{w}'_k\mathbf{w}'^{\mathrm{T}}_j] = \mathbf{Q}_k\delta_{k-j}$. The above discrete augmented modally-reduced state-space model is coupled to the discrete EKF in te next section.

2. Extended Kalman filter

In this section the equations for the discrete EKF will be briefly present. A derivation can be found in [9]. The extended Kalman filter is an extension of the linear Kalman filter (KF) for use with non-linear system and output equations. The extension is based on a linearization of the state-space model around the current best estimate. This allows for the use of the linear Kalman filter equations, provided the system is linear on the time scale of the measurement intervals. The linear Kalman filter is a recursive least squares estimator coupled to a time update mechanism which propagates the state estimate and its error covariance between two consecutive measurement instants using a deterministic linear state-space model. The two stages are called the measurement update and the time update (or prediction phase), respectively. Both, the KF and EKF allow for inclusion of modeling errors in the state prediction phase by adding the process noise covariance matrix to the state estimate error covariance, while measurement errors are accounted for in the sequential least square process.

In this section, an estimate of state vector $\mathbf{x'}_k$ is denoted by $\hat{\mathbf{x}}'^{+/-}_k$. The term apriori estimate (superscript $^-$) refers to the predictions done for time level k without including the measurement data at time level k, whereas the term aposteriori estimate (superscript $^+$) refers to the estimates at time level k including the measurements at time level k.

The time update mechanism is presented in Eq. (15). The aposteriori state estimate $\hat{\mathbf{x}}'^{+}_{k-1}$ and its error covariance $\mathbf{P}^{+}_{k-1}$ are propagated in time using a deterministic model, resulting in the corresponding apriori estimates $\hat{\mathbf{x}}'^{-}_k$ and $\mathbf{P}^{-}_k$, respectively. In order to use the linear covariance propagation, the state equations have to be linearized w.r.t. the augmented state vector around the current best estimate. The information to compute the jacobian matrix in Eq. (16) is available in the parametric reduced order model database – for more details it is referred to [6]. The filter is initialized by an aposteriori estimate of the augmented state vector at $t = 0$, denoted by $\hat{\mathbf{x}}'^{+}_0$, and an initial state estimate error covariance matrix denoted by $\mathbf{P}^{+}_0$.

$$\begin{aligned} \hat{\mathbf{x}}'^{-}_k &= \mathbf{F}_{k-1}\hat{\mathbf{x}}'^{+}_{k-1} \\ \mathbf{P}^{-}_k &= \mathbf{F}_{k-1}\mathbf{P}^{+}_{k-1}\mathbf{F}^{\mathrm{T}}_{k-1} + \mathbf{Q}' \end{aligned} \tag{15}$$

$$\mathbf{F}_{k-1} = \frac{\partial \mathbf{A}'_{k-1}(\mathrm{p})}{\partial \mathbf{x}'}\Big|_{\hat{\mathbf{x}}'^{+}_{k-1}} \tag{16}$$

The measurement update is presented in Eq. (17). During this stage the apriori estimate of the state and its error covariance are updated using new measurement data to obtain the aposteriori estimates. The Kalman Gain matrix, $\mathbf{K}_k$, provides the weights used to combine the information in the predicted state and the measurement data, such that the trace of $\mathbf{P}^{+}_k$ is minimal after combination. In order to use the presented equations, the augmented output matrix has to be linearized around the apriori state estimate (Eq. (18)).

$$\begin{aligned} \mathbf{K_k} &= \mathbf{P}^{-}_k\mathbf{H}^{\mathrm{T}}_k(\mathbf{H}_k\mathbf{P}^{-}_k\mathbf{H}^{\mathrm{T}}_k + \mathbf{R})^{-1} \\ \hat{\mathbf{x}}'^{+}_k &= \hat{\mathbf{x}}'^{-}_k + \mathbf{K_k}[\mathbf{y}_k - \mathbf{H}_k\hat{\mathbf{x}}'_k] \\ \mathbf{P}^{+}_k &= (\mathbf{I} - \mathbf{K_k}\mathbf{H_k})\mathbf{P}^{-}_k \end{aligned} \tag{17}$$

$$\mathbf{H}_k = \frac{\partial \mathbf{G}'_k(\mathrm{p})}{\partial \mathbf{x}'}\Big|_{\hat{\mathbf{x}}'^{-}_k} \tag{18}$$

In Eq. (17), $\mathbf{y}_k \in \mathbb{R}^{\mathrm{n_y}}$ contains the actual measurement and $\mathbf{H}\hat{\mathbf{x}}'_k$ is the corresponding linearized projection of the state on the measurement space obtained using Eq. (12, 14, 18) . From this point on the computations are repeated.

The Kalman gain can be tuned using the assumed measurement noise covariance $\mathbf{R}$ as well as the augmented process noise covariance $\mathbf{Q}'$, and thereby control how much information is used from either the measurement data or the deterministic predictions. These matrices should be chosen such that they resemble the noise statistics of the measurement data, and the process noise, as closely as possible.

3. Coupled estimation: wave force and foundation stiffness

The objective of this initial investigation is to estimate the states, the hydrodynamic loading and a parameter related to the stiffness of the substructure. However, limited information in the vibration data make it difficult to identify the spatial distribution of the load; therefore the aim is to identify the time history of a response-equivalent hydrodynamic load which compensates for all hydrodynamic loads and potential interactions with the structure. The equivalent load is applied close to mean sea level, whereas the parameter is chosen to be a scale factor on the E-modulus of the substructure of the FE-model.The location of the equivalent hydrodynamic load is presented in figure (1).

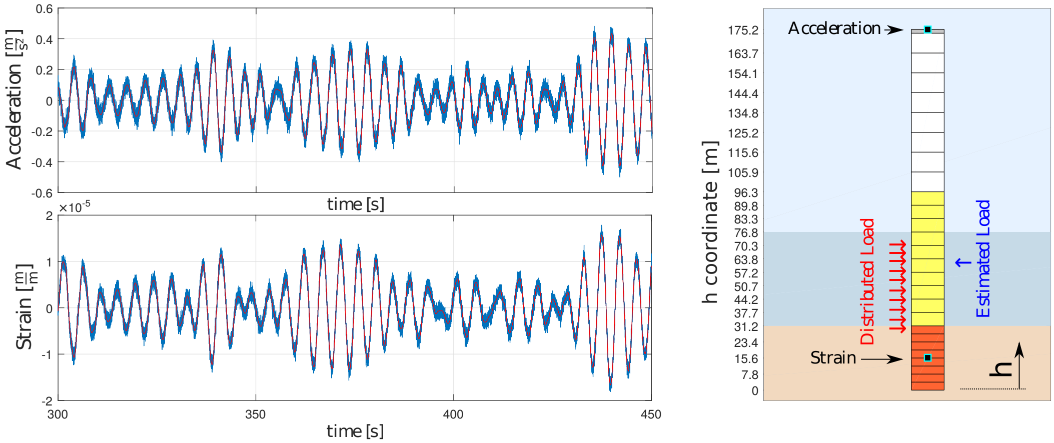

Fig. 1: Left: Measurement data. Right: measurement and equivalent load location.

It should be noted here that when the aim is to estimate an uncertain system parameter only, it suffices to identify a response-equivalent load: this load does not have to correspond to the real environmental forces in terms of temporal or spatial distribution, but should merely drive the model such that its states correspond to the measurement data.

In order to be able to verify the results, artificial response data is generated using a realistic full order FE model of a 6 megawatt offshore wind turbine in 40 meter water depth. The structure is subjected to hydrodynamic loading associated with a normal sea state ($H_s = 0.97$ $[m]$, $T_p = 5$ $[s]$). For the identification, one acceleration at the tower top and one strain close to the mudline are used. Both are corrupted with a white noise signal having a variance equal to 5% of the maximum corresponding measurement amplitude. The parametric model order reduction scheme is used with a linearly spaced parameter grid which covers a sufficiently large parameter range. The measurement data and an illustration of the FE-model is given in figure (1).

The measurement noise covariance is set to the variance values which are used for generating the measurement data. The process noise on the state equations is set to zero, which reflects full trust in the underlying state equations and implies that all potential modeling errors would be accounted for by the response equivalent load and/or the parameter. Tuning of the augmented force and parameter process variances is an active field of research and out of

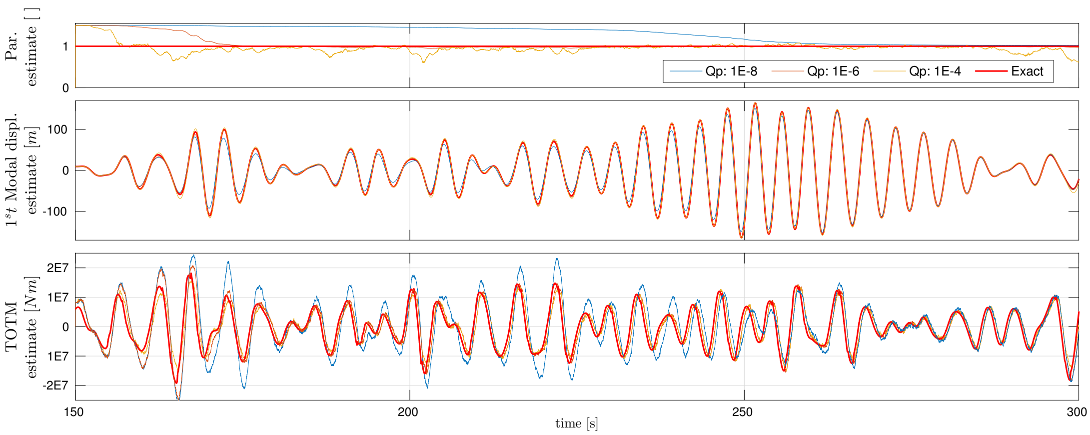

Fig. 2: Stiffness parameter, modal state and equivalent force estimate - parameter process noise variation at constant $Q_f = 1E9$.

scope of this work. Instead focus will be put more on the sensitivity of the estimate with respect to changes from a well tuned case. The latter, in this initial investigation, is determined by manual tuning which is based on insight in the gain computation.

4. Results

This section presents the results for the case introduced in section 3. As mentioned, good tuning of the augmented process noise covariance terms corresponding to the equivalent force and parameter are of significant importance for the quality of the estimate. In order to assess the quality and sensitivity of the estimate with respect to the augmented process noise, the following cases are considered: first the parameter process noise is varied at a constant force process noise, subsequently the force process noise is varied at a constant parameter process noise. For both cases the results of the force estimates are compared to the known distributed loading in terms of total overturning moment at mudline (TOTM), whereas the parameter and states are compared directly against their exact counterparts.

In figure (2), three estimates are presented. For each parameter process noise value the parameter, the first modal coordinate, and the equivalent force estimates are presented. The results are generated using an augmented force process noise variance equal to $Q_\mathrm{f} = 1E9$, and 3 different parameter process noise variance settings. During the generation of the measurement data the parameter was kept constant at p = 1. The simulated modal response as well as the TOTM of the applied input load are plotted as well, and denoted as 'exact'. The results show that choosing the parameter covariance smaller results in a slower but smooth convergence of the estimated quantities to their exact values. Increasing the parameter process noise covariance results in a more noisy parameter estimate. The influence of the parameter estimate on the modal state and force estimate is clearly visible as well in terms of convergence.

The next set of results take a variation of the force process variance into account while keeping the parameter process noise variance fixed at $Q_\mathrm{p} = 1E - 6$. Estimates of the parameter, first modal displacement and response equivalent force in terms of the TOTM is presented in figure (3). It can clearly be seen that a good equivalent force estimate is crucial for a good parameter estimate, which both result in an accurate state estimate.

For a practical application the measurement noise covariance can be set according to product specifications or be identified in e.g. a test setup up; therefore, in this contribution, it is assumed that the measurement noise covariance is known, leaving the process noise covariance terms to tune the filter performance. Choosing the different process noise covariance values appropriately is shown to be crucial for maintaining the quality of the estimates. The magnitude of the individual covariances is largely determined by the variability of the property to be estimated. A time-invariant parameter as used in this case will require a small process noise variance, whereas a highly variable response-equivalent wave load requires a large covariance. If the process noise value for the force or parameter is set too low, the measurement update will hardly adapt the state estimate according to the information contained in the measurement data;

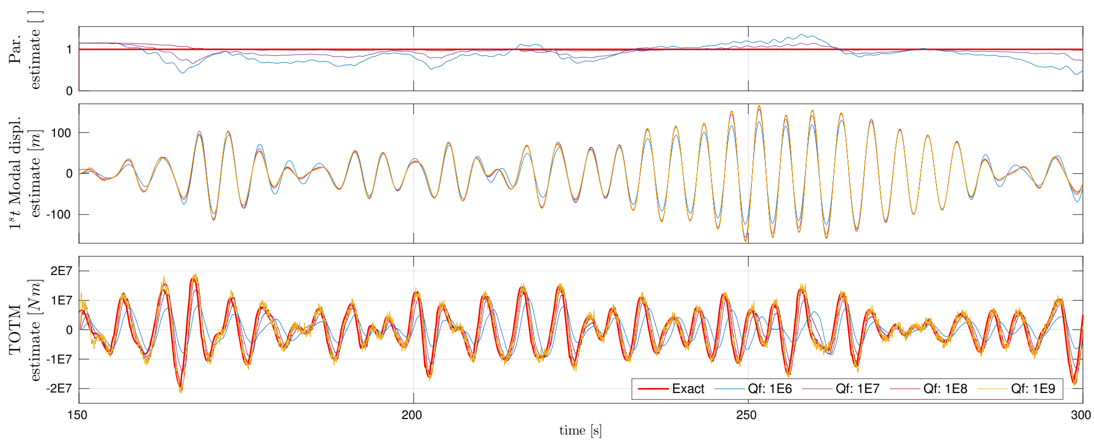

Fig. 3: Stiffness parameter, modal state and equivalent force estimate - force process noise variation at constant $Q_p = 1E - 6$.

instead the state predicted with the model will be used primarily. Choosing the value too high will result in neglecting the deterministic prediction and retrieving information mainly from the noisy measurement data - the latter will lead to an increase of the noise level of the estimate. An indirect method to tune the force process noise variance before operation could be accomplished by using response simulations from the design stage. This approach would consist of tuning the filter for some relevant operational conditions by hand.

5. Conclusion

For the monitoring of offshore wind turbines, it is of significant importance to know the experienced loading as well as the physical parameters governing the response. Unfortunately these quantities can often not be obtained by measurements directly. Therefore, algorithms capable of jointly estimating the input forces and the uncertain parameters could provide valuable tools for generating more accurate information for monitoring purposes.

The method used in this work was shown to be capable of estimating the states, a response-equivalent input load, and a physical parameter of a bottom founded OWT support structure with high accuracy. To asses the feasibility for practical applications, future work will include the addition of realistic wind loading and the estimation of more uncertain parameters like damping values. Additionally an improved (direct) method for tuning of the filter parameters has to be developed; preferably this method uses only the physical model and the measured structural response. An alternative indirect tuning could be accomplished by using simulations as performed during the design stage of an OWT.

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