A digital twin based on OpenFAST linearizations for real-time load and fatigue estimation of land-based turbines

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Abstract. Monitoring a wind turbine requires intensive instrumentation, which would be too cost-prohibitive to deploy to an entire wind plant. This work presents a technique that uses readily available measurements to estimate signals that would otherwise require additional instrumentation. This study presents a digital twin concept with a focus on estimating wind speed, thrust, torque, tower-top position, and loads in the tower using supervisory control and data acquisition (SCADA) measurements. The model combines a linear state-space model obtained using OpenFAST linearizations, a wind speed estimator, and a Kalman filter algorithm that integrates measurements with the state model to perform state estimations. The measurements are: top acceleration, generator torque, pitch, and rotational speed. The article extends previous work that derived the linear state-space model using a different method. The new implementation, based on OpenFAST linearization capability, allows for a systematic extension of the method to more states, inputs, outputs, and to the offshore environment. Results from the two methods are compared, and the validation is made with additional measurements using the GE 1.5-MW turbine located at the National Renewable Energy Laboratory test site. Real-time damage equivalent loads of the tower bottom moment are estimated with an average accuracy of approximately 10%. Overall, the results from this proof of concept are encouraging, and further application of the model will be considered.

1 Introduction

Wind turbines are designed to withstand the set of operating conditions they are likely to experience during their lifetime. The design methodology is based on numerical simulations under various environmental conditions, weighted by the probability of occurrence, or number of events [1]. Multiplicative safety factors are applied to account for the uncertainty of the simulation tools and environmental data. The designer has limited options to assess the validity of the safety factors, unless failure occurs before the expected lifetime. The current study considers the possibility of predicting the lifetime consumption of a turbine after it has been designed and installed.

The suggested approach uses a digital twin concept, which combines measurements from the turbine and a numerical model to build a digital equivalent of the real-world turbine. The turbine states and life cycle can then be tracked via this digital twin. This article uses the Kalman filter technique [2] to perform load estimations. Inverse methods and neural network methods are examples of alternative approaches that can be used. Kalman filtering is used to estimate the
wind turbine states based on a linearized state-space model and a set of measurements. This technique has been used previously in the literature for the estimation of inflow wind speed [3, 4], wind shear [5], yaw misalignment [6], and rotor loads [7, 8]. Recently, an augmented Kalman filter approach was used to perform tower load estimations [10]. The method relied on a structural model based on shape functions and generalized joint coordinates, which was developed in previous work [11]. A linear form of the model was assumed, without explicitly performing a linearization.

The current study follows up on the work presented in [10], this time using the tool OpenFAST [12] and its linearization capabilities. The use of OpenFAST should ease the extension of the method to include additional degrees of freedom (DOF) and the offshore environment. The objective is to perform real-time estimation of loads using a limited set of commonly available measurements: tower-top acceleration, pitch angle, generator torque, and rotational speed. The work focuses on the estimation of tower loads, which requires an estimation of aerodynamic torque, wind speed, aerodynamic thrust, and tower-top position. In this work, the technique is validated using additional measurements available on a heavily instrumented wind turbine at the National Renewable Energy Laboratory (NREL) test site.

In Section 2, we present the main components of the digital twin model, and we highlight the differences in our approach to those presented in previous work. In Section 3, we use simulations to assess the errors and sensitivities of the model. In Section 4, we apply the model and validate it against measurements of a GE 1.5-MW turbine.

2 Main components of the digital twin model and its variations

The main components of the model are described in detail in [10]. Section 2.1 briefly highlights the approach used and the typical workflow. The adaptation of the model to OpenFAST is the topic of the following sections.

2.1 Overview of the digital twin concept

The Kalman filter method combines a set of measurements with a numerical model to estimate the states of a system. At each time step, the Kalman filter algorithm adjusts the uncertainty associated with the numerical model while accounting for the uncertainty of the measurements to provide an optimal estimate of the states (see, e.g., [2]). Our goal is to estimate the wind speed, aerodynamic torque and thrust, and tower-top position. From this information, the loads at different tower heights can be estimated. The main workflow of the model is illustrated in Figure 1.

In our application, the measurements, noted \( y \), are: tower-top acceleration, pitch angle, generator torque, and rotational speed of the high-speed shaft. These signals are readily available from the supervisory control and data acquisition (SCADA) data of commercial turbines. The states used in this study, noted \( z \), consist of DOF (such as the tower-top motion and the shaft rotation) and loads (such as the aerodynamic torque and thrust). The fact that loads are included in the state vector is referred to as “state augmentation” [13]. The framework also uses external inputs, noted \( u \), such as controller inputs (generator torque and pitch angle). Yet the distinction between states and inputs becomes subjective in the augmented state approach. This is discussed in Section 3.3. The numerical model required by the Kalman filter needs to be a linear state-space model. Obtaining such a model is the topic of the following sections. Extended Kalman filters, unscented Kalman filters, and particle filters are examples of techniques that can be used for nonlinear systems, but these approaches are left for future work. The linear state

1 If the generator torque is not available, it can be readily obtained from the power, the high-speed shaft speed, and the generator losses.
Figure 1. Main components of the model: wind turbine measurements and a turbine model are combined to estimate tower loads. A wind speed estimator and a Kalman filter algorithm are used in the estimation. Turbine model dependencies are framed in blue. Figure modified from [10].

The model and measurements are of the following form:

\[
\dot{z} = Az + Bu + w_z \quad \text{(state equation)} \tag{1}
\]
\[
y = Cz + Du + w_y \quad \text{(output/measurement equation)} \tag{2}
\]

where \(A, B, C,\) and \(D\) are matrices describing the expected relationships among measurements, states, and inputs; \(w_z\) and \(w_y\) are Gaussian, uncorrelated noise sources, which correspond to the uncertainty on the model and measurements, respectively; and the dot notation corresponds to the time derivative. The determination of the matrices is described in Section 2.2. Once the model is established, the digital twin can be implemented, and we perform the following actions at each time step:

- Receive new measurements from the SCADA system.
- Estimate the system states using the linear state-space model, the measurements and inputs at the current time, and the states at the previous time step. In particular, the aerodynamic torque and the tower-top position are estimated by the Kalman filter.
- Estimate an effective wind speed from the aerodynamic torque based on the tabulated performance power coefficient \((C_P)\) data, the pitch angle, and the estimated rotor speed (see, e.g., [14]).
- Estimate the thrust force based on the effective wind speed and tabulated thrust coefficient \((C_T)\) data.
- Estimate the tower loads from the tower-top position, the tower bending stiffness, and the tower shape function curvature.

The wind speed, thrust, and tower load estimations are described in detail in [10]. We continue by focusing on the linear model used for the system.

2.2 Assumed and linearized state-space models

In previous work [10], the structural model was provided using the library YAMS [15], which relies on generalized coordinates based on Rayleigh-Ritz shape functions and joint coordinates.
This type of formulation is similar to the one used by the tool Flex [16] and to the ElastoDyn module of OpenFAST [12]. The advantage of YAMS is that it can represent the tower and blades with as many shape functions as desired. The YAMS framework is monolithic instead of modular, which facilitates the extraction of the mass, stiffness, and damping matrices. The code has a simple Python interface, and it reads in the same input files as OpenFAST. Yet the YAMS structural code does not contain the shaft torsion DOF, is currently not coupled with an aerodynamic or hydrodynamic model, does not support linearization, and is not undergoing active development. OpenFAST offers an advantage on these four points.

\[ \dot{q} + M^{-1}K \dot{q} + M^{-1}C \dot{q} + f = A_a x + B_a u_a \] (3)

where \( M \), \( C \), and \( K \) are the mass, damping, and stiffness matrices; \( x = [q \ \dot{q}]^t \) is the vector of all the DOF with their first time derivatives; and \( f \) is the vector of the generalized loads acting on the DOFs. The matrices are gathered into \( A_a \) and \( B_a \) to highlight the similarity with Equation 1 where the subscript \( a \) stands for “assumed.” The main issue is that the matrices are nonlinear functions of \( q \), and the forces are nonlinear functions of \( q \) and \( \dot{q} \). In our previous work, we discarded the nonlinearities as a first approximation, and we assumed that Equation 3 could be derived for a standstill condition and then applied for various operating conditions without changing the matrices. This assumption is evaluated in Section 3.3. A linear output equation was also obtained by leveraging the fact that the tower-top acceleration is available from the measurements (see [13]).

**Linearized model from OpenFAST** Because OpenFAST uses a modular framework [17], with loose coupling between modules, it is not straightforward to obtain a monolithic system of equations, such as the one given in Equation 1. Yet the linearization capabilities of OpenFAST provide a system of equations in a form similar to Equation 1 and Equation 2. The link to the augmented state model is discussed in Section 2.3. The linearized equations are obtained for \( x = x_0 + \delta x \) and \( u = u_0 + \delta u \), where \((x_0, u_0)\) is the operating point, and \((\delta x, \delta u)\) are small perturbations about that point, as:

\[
\dot{\delta x} = A_0 \delta x + B_0 \delta u \\
\delta y = C_0 \delta x + D_0 \delta u
\] (4, 5)

where the subscript 0 is used on the matrices to indicate that they are bound to the operating point \((x_0, u_0)\).

**Link between the two approaches** The states used by ElastoDyn and YAMS are mostly identical. A strong advantage of OpenFAST is that it can perform the linearization for a large suite of states, inputs, and outputs. For instance, the inputs could be mean wind speed, tower-top load, generator torque, or pitch. Similarly, linearized output equations can be directly obtained for the acceleration or loads at a given point of the structure. In our previous implementation, such input and output linearizations were computed from hand calculations, making the extension of the method more difficult.

\( \dot{x} \) and \( y \) also have operating point values, but these are not independent from \( x \) and \( u \) because they can be derived from the nonlinear state and output equations.
If the mechanical model of the turbine were linear (i.e., $A_a$ and $B_a$ constant), then for the same choice of inputs and states, the matrices involved in Equation 3 and Equation 4 would be identical, i.e., $A_0 = A_a$ and $B_0 = B_a$. This assumption is evaluated in Section 3.3. If the operating point is taken as $(x_0, u_0) = (0, 0)$, then the model from Equation 4 applies to $x$, $u$, and $y$ directly. Outside of this region, accounting for the operating point offset (i.e., $(x_0, u_0)$) is needed.

### 2.3 Formulation of the Kalman filter state-space model

As mentioned in Section 2.1, the augmented state approach allows for some freedom in the choice of the states and inputs, where part of the inputs can be inserted in the state vector. If the Kalman filter states are taken as the states of the linearized models presented in Section 2.2, then Equation 1 is directly given by:

$$\dot{z} = \dot{x} = A_a x + B_a u + w_z$$

where the symbol $\bullet$ stands for the subscript 0 or $a$. An augmented state-space equation is obtained by introducing the partitioning $u_\bullet = [p, u]^t$ and $B_\bullet = [B_p, B_a]$. The extended state vector is taken as $z = [x, p]^t$, and Equation 1 is then given by:

$$\dot{z} = \begin{bmatrix} \dot{x} \\ \dot{p} \end{bmatrix} = \begin{bmatrix} A_a & B_p \\ 0 & A_p \end{bmatrix} \begin{bmatrix} x \\ p \end{bmatrix} + B_a u + w_z$$

where $A_p$ is a matrix introduced to potentially model the time evolution of the extended state variables $p$ based on engineering or linearized models. Similar manipulations are introduced for the output equation. In our application, the aerodynamic torque is included in the vector $p$, and the matrix $A_p$ is set to zero.

### 3 Evaluation of the model

#### 3.1 Validity of the linear model

The comparison of the assumed linear model (from YAMS) and the linearized model (from OpenFAST) is performed using a two DOF model of a turbine [10]: $q_t$, representing the tower fore-aft shape function; and $\psi$, symbolizing the azimuthal position of the shaft. The state vector is $x = [q_t, \dot{q}_t, \psi, \dot{\psi}]^t$, and the input vector is $u = [T_a, Q_a, Q_g]^t$, with $Q_g$ the generator torque. The assumed linear state model is given by:

$$A_a = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -M^{-1}K & -M^{-1}C & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, \quad B_a = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ M^{-1} & 0 & 0 \\ 0 & J^{-1} & -J^{-1} \end{bmatrix}$$

where $M$, $K$, and $C$ are the generalized mass, stiffness, and damping values associated with $q_t$; and $J$ is the rotor inertia. In this section, the model is investigated using the NREL 5-MW turbine [18]. The elements of $A_a$ and $B_a$ are set up using the YAMS library. The matrices $A_a$ and $B_a$ are obtained for the turbine at a standstill and a fixed azimuthal position.

3 The azimuthal position $\psi$ may be removed from the state vector of this model. Yet the knowledge of the azimuthal position might be beneficial to other Kalman filter models, where additional measurements—such as blade root moment—could allow for an estimate of the azimuthal position and thereby improve the estimation of additional turbine loads.

4 The matrices would vary with wind speed (in particular because of tower and blade deflections) and with azimuthal positions, but this variation was discarded in previous work, and it is thus kept constant for this example study.
These constant matrices are then compared to the linearized matrices $A_0$ and $B_0$ obtained with OpenFAST for different operating points, obtained at 16 wind speeds and six azimuthal positions per the wind speeds. The dominant (nonzero) terms of the matrices are compared in Figure 2, taking the constant matrices from the YAMS model as a reference. Apart from the

$A(3, 3)$, the dominant terms obtained by the linearization remain within 0.2% of the value obtained using the assumed model derived with YAMS. This confirms that both YAMS and OpenFAST use a similar representation of the structure. These terms do not show significant variation with the wind speed nor with the azimuth (slight variations with the azimuth are observed for the term $A(3, 1)$). The term $A(3, 3)$, which is related to the fore-aft damping, shows a strong correlation with the wind speed because of the presence of aerodynamic damping in the OpenFAST linearization. In previous work, the term $-M^{-1}C$ was scaled to account for an average aerodynamic damping over the range of aerodynamic conditions, which explains why the term $A_0(3, 3)$ is on average close to the value of $A_a(3, 3)$. The comparison of the assumed “zero” terms of $A_a$ and $B_a$ (not shown in the figure) is difficult because of the small amplitude of the terms and the need to scale the matrix terms. The predominant term is $A_0(4, 4)$, which includes aerodynamic damping of the shaft speed, and it takes a higher value than the pitch-regulation region. This term is kept at zero for now because part of the damping is included by providing the nonlinear aerodynamic torque directly into the system. From this analysis, the assumed linear model appears to be a fair assumption because limited variations were observed for the terms constituting the model.

### 3.2 Example simulation

The Kalman filter model was tested with the NREL 5-MW reference wind turbine [18] and a set of numerical results obtained with OpenFAST. A full 3D synthetic turbulent field was generated using the Kaimal spectrum and exponential coherence model within the TurbSim tool [12] to cover the different operating regions of the turbines during a 10-min period, with the wind speed starting at 3 m/s and ramping up to 14 m/s. A sudden drop in wind speed is also added at 500 s to test the robustness of the estimator.

A digital twin model of the NREL 5-MW turbine was set up by first determining the tabulated $C_P$ and $C_T$ values of the turbine as a function of pitch angle and tip-speed ratio. Then a linear state-space model $(A_*, B_*, C_*, D_*)$ was computed by averaging the matrices obtained with the OpenFAST linearizations presented in Section 3.1 over all operating points. This approach was found to have little impact compared to using the linearized matrices at the operating point.
The averaging approach is likely to be problematic for matrix terms that change signs for different operating points. The linear state-space model is used to form the Kalman filter matrices \( (A, B, C, D) \) using \( z = [q_t, \dot{q}_t, \dot{\psi}, Q_a]^T \) as the augmented state; \( u = [T_a, \theta_p] \) as the input; and \( y = [\ddot{q}_t, \dot{\psi}, Q_g, \theta_p]^T \) as the measurement, with \( Q_g \) the generator torque, and \( \theta_p \) the pitch angle. The covariance matrices required by the Kalman filter were obtained based on the standard deviation expected for each signal [10]. The bending stiffness and shape function of the tower are stored in the model to estimate tower loads.

The wind turbine was simulated with OpenFAST using the synthetic turbulent field and with all DOF activated. Signals were extracted from the simulation and then used as “measurements” to feed the digital twin model. Results from the OpenFAST simulations and the digital twin are shown in Figure 3. The digital twin can reconstruct all the signals shown with a mean relative error, \( \epsilon \), less than 10%. The errors reported for this simulation are of the same order of magnitude as those reported in previous work that used the YAMS approach. Errors in the estimation of the tower-top position translate directly to errors in the estimated tower bottom moment because of the method used to estimate the tower loads [10]. Future work will consider using an integration of the shear forces based on the tower-top position and thrust force. Frequencies well represented in the acceleration and rotor speed measurements are directly found in the estimated signals. Filtering the acceleration can improve the issue of higher frequency content present in the tower-top signal. Further discussion on this topic are given in previous work [10].

### 3.3 Choices of formulation

As mentioned in Section 2.3, different partitioning could be used in the augmented state approach. The simulation from Section 3.2 was run with four different choices of partitioning:
\( p = [Q_a] \) (same as Section 3.2), \( p = [T_a, Q_a]^t \), \( p = [T_a, Q_a, Q_g]^t \), and \( p = [T_a, Q_a, Q_g, WS]^t \).

The rationale behind the state augmentation is that additional information is provided to the Kalman filter, which could potentially increase the observability of some of the state. Also, this gives the option to input an uncertainty on some of the estimated values, something that is possible only if the variables are part of the state vector. The set of simulations (not shown) revealed that the choice of partitioning had no impact on the estimation of the wind speed, aerodynamic load, and rotational speed. Yet the error on \( q_t \) and \( M_y \) was observed to deteriorate with an additional error of 0.5% as the number of states was increased. The increase in the number of states also had a negative impact on the numerical performance, though moderate: the 10-min simulation with eight states ran in 47 s, whereas the case with five states ran in 45 s. Additional tests would be required to conclude, but from these results, we chose to continue with using the five-states model (as presented in Section 3.2).

### 3.4 Comparisons over a range of simulations

The estimator used in Section 3.2 is applied in this section for a range of operating conditions. The linearized OpenFAST estimator is labeled “OFLin,” and it is compared to the one used in a previous study [10], labeled “YAMS.” Simulations for 11 wind speeds ranging from 4 m/s to 24 m/s, with six turbulence seeds per wind speed, were run with OpenFAST. Relevant sensors were extracted from these simulations. Gaussian noise was added to these sensors before feeding them as “measurements” to the estimators. The noise level was such that the standard deviation of the noise was 10% that of the original signal. No bias was added. The estimations of the tower bottom moment from both estimators were compared to those obtained with the OpenFAST simulation in Figure 4. In a first set of runs, the “measured” acceleration signal was unfiltered, delivered at 20 Hz to the estimators. In the second set of runs, labeled “Filter Acc.,” the acceleration signal was filtered using a moving average window of 15 time steps prior to being fed to the estimators. Both estimators performed similarly. As observed in previous work, the filtering of the acceleration signals improved the accuracy of the modeling.

### 4 Validation against measurements

Measurements from a GE 1.5-MW turbine are used as inputs to the Kalman filter model. A description of the measurement setup is given in [19]. The turbine is instrumented with the four measurements sensors considered in the previous sections, i.e., \([\ddot{q}_t, \dot{\psi}, Q_g, \theta_p]\), but also with additional sensors that are now used for validation: low-speed shaft torque (\(\approx Q_a\)) and tower bottom bending moment (\(M_y\)). A meteorological mast is also located two diameters from the
turbine, measuring at the turbine hub height, allowing for a comparison between the estimated and actual free-stream wind speed values. For the wind direction considered, the mast and the turbine form a line orthogonal to the main flow. A 10-min time period of measurements at 50 Hz is selected (starting on 2019/11/19-13:50) based on the availability of the sensors. Because the model currently does not support yaw misalignments, the 10-min period is further reduced to approximately 300 s, where the yaw angle and the wind direction were aligned. The four measurements are provided at 50 Hz to a digital twin of the GE 1.5-MW turbine.

The estimated values are compared to the three additional measurement data ($Q_a$, $M_y$ and WS) in Figure 5. The comparison of wind speed is not obvious because the met mast represents a

![Figure 5](image)

Figure 5. Comparison of the digital twin estimation performance when fed with measurements from the GE 1.5-MW turbine as inputs. Extra measurements (labeled “Extra. Meas.”) of wind speed, low-speed shaft torque, and tower bottom moment are used to validate the estimator.

“point” measurement instead of the estimated wind speed, which is representative of the average rotor wind speed (in Figure 3, rotor average wind speed was used as a reference). The mean wind speed value is in good agreement, validating the basic functionality of the wind speed estimator, which relies on the estimated torque. The error in $Q_a$ is observed to be larger in this real situation than what was observed using simulated results. This is likely because the measured signal is the low-speed shaft torque and not the aerodynamic torque. Yet the overall level and time evolution of the torque is well captured by the estimator. Similar conclusions are drawn for the tower bottom moment values. Analyses of the power spectra show that the first fore-aft frequency is captured in the tower bottom moment (it is expected to be captured by the tower top acceleration measurement). The generator torque measurement used was based on the power signal. The power signal is unfortunately largely filtered and does not provide frequency content other than the 3-p harmonics. Analyses of other frequencies would require longer time series as well as adding more measurements and states to the model.

5 Conclusions
A recently developed digital twin concept was improved in this study to extend its applicability. The model uses OpenFAST linearization features to establish the linear state-space model. The performance of the new estimator was observed to be similar to what was reported previously,
estimating real-time damage equivalent loads with an average accuracy of approximately 10%. Comparisons with measurements were presented in this study. Overall, the results from this proof of concept were encouraging, and further application of the model will be considered. The new implementation, based on OpenFAST linearization capability, allows for a systematic extension of the method to more states, inputs, and outputs. This work could be continued by studying longer data sets and different turbines, and it could be extended further by considering the inclusion of more DOF and the estimation of additional load signals, adjustments of the state-space model based on wind speed, improvements of the wind speed estimator for non operating conditions, and applications to offshore wind turbines.

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References
[1] International Standard IEC, Workgroup 1. *IEC 61400-1 Wind turbines : Design requirements* (IEC, 2005).
[2] Grewal, M. & Andrews, A. *Kalman Filtering: Theory and Practice Using Matlab* (John Wiley & Sons, Ltd, 2014).
[3] Østergaard, K., Brath, P. & Stoustrup, J. Estimation of effective wind speed. *Journal of Physics: Conference Series* 75, 012082 (2007).
[4] Soltani, M. *et al.* Estimation of rotor effective wind speed: A comparison. *IEEE Transactions on Control Systems Technology* 21, 1155–1167 (2013).
[5] Bottasso, C., Croce, A. & Riboldi, C. Spatial estimation of wind states from the aeroelastic response of a wind turbine. In *The science of making torque from wind, Heraklion (Crete, Greece)* (2010).
[6] Simley, E. & Pao, L. Evaluation of a wind speed estimator for effective hub-height and shear components. *Wind Energy* 19, 167–184 (2016).
[7] Bossanyi, E. *et al.* Advanced controller research for multi-mw wind turbines in the upwind project. *Wind Energy* 15, 119–145 (2012).
[8] Boukhezzar, B. & Signeridjane, H. Nonlinear control of a variable-speed wind turbine using a two-mass model. *IEEE Transactions on Energy Conversion* 26, 149–162 (2011).
[9] Branlard, E., Giardina, D. & Brown, C. S. Augmented Kalman filter with a reduced mechanical model to estimate tower loads on an onshore wind turbine: a digital twin concept. *Wind Energy Science* 1, 1–20 (2020).
[10] Branlard, E. Flexible multibody dynamics using joint coordinates and the Rayleigh-Ritz approximation: The general framework behind and beyond Flex. *Wind Energy* 22, 877–893 (2019).
[11] OpenFAST. Open-source wind turbine simulation tool, available at [http://github.com/OpenFAST/](http://github.com/OpenFAST/) (2020).
[12] Lourens, E., Reyners, E., Roeck, G. D., Degrande, G. & Lombaert, G. An augmented Kalman filter for force identification in structural dynamics. *Mechanical Systems and Signal Processing* 27, 446–460 (2012).
[13] Bozkurt, T. G., Giebel, G., Poulsen, N. & Mirzaei, M. Wind Speed Estimation and Parametrization of Wake Models for Downregulated Offshore Wind Farms within the scope of PossPOW Project. *Journal of Physics: Conference Series* 524, 1–8 (2014).
[14] Branlard, E. Yams github repository [http://github.com/ebranlard/YAMS/](http://github.com/ebranlard/YAMS/) (2019).
[15] Oye, S. *Fix Dynamisk, aeroelastisk beregning af vindmøllevejers* (Report AFMS9-08, Fluid Mechanics, DTU, 1983).
[16] Jonkman, J. *The New Modularization Framework for the FAST Wind Turbine CAE Tool* . Tech. Rep. NREL/CP-5000-57228, National Renewable Energy Laboratory (2013).
[17] Jonkman, J., Butterfield, S., Musial, W. & Scott, G. Definition of a 5mw reference wind turbine for offshore system development. Tech. Rep. NREL/TP-500-38060, National Renewable Energy Laboratory (2009).

[18] Santos, R. & van Dam, J. Mechanical Loads Test Report for the U.S. Department of Energy 1.5-Megawatt Wind Turbine. Tech. Rep. Technical Report NREL/TP-5000-63679, National Renewable Energy Laboratory (2015).