Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 59-21 (2025) 23–27

# Control-Oriented Data-Driven Modelling of Wind Turbine Blade Dynamics Using ERA-OKID ⋆

**Satyam Panda** * **Shubham Baisthakur** * **Breiffni Fitzgerald** *

* *Department of Civil, Structural and Environmental Engineering, School of Engineering, Trinity College Dublin, Ireland.*

**Abstract:** This study presents a reduced-order modeling framework for offshore wind turbine blade dynamics using the Eigensystem Realization Algorithm with Observer Kalman Filter Identification (ERA-OKID) approach. A compact state-space model is constructed from a single input-output dataset, enabling efficient linear system identification without repeated calibration across wind conditions. The blade dynamics are represented using three dominant modes, two flapwise and one edgewise, capturing key structural responses under aerodynamic loading. Subspace methods and modal reduction are employed to approximate distributed forces through a weighted modal summation, resulting in a control-oriented model suitable for real-time estimation, fatigue analysis, and model predictive control. Validation on a 15 MW offshore turbine demonstrates accurate reproduction of blade tip dynamics across various wind speeds, including turbulence intensities, with good agreement in time and frequency domains. By combining data-driven identification with physics-informed modeling, the framework offers a scalable, low-data-demand solution that bridges high-fidelity simulation and control-oriented implementation, making it valuable for wind turbine monitoring, control, and performance optimization.



*Keywords:* Model reduction; Linear system identification; Modal analysis; Subspace methods; ERA-OKID modeling; Offshore wind turbine dynamics

## 1. INTRODUCTION

With global climate change rapidly increasing, the urgency to transition from fossil fuels to sustainable energy sources has never been more critical. Wind energy, especially offshore wind power, is at the forefront of this transformation, offering a powerful combination of high energy yield and minimal environmental impact Strielkowski et al. (2016); Esteban et al. (2011). The drive towards deploying larger offshore wind turbines, capable of generating substantial power, introduces significant engineering and operational complexities. Addressing these complexities requires innovative modeling, advanced engineering solutions, and sophisticated control techniques to ensure that turbines perform reliably, efficiently, and sustainably in challenging marine environments Veers et al. (2023); Sarkar et al. (2020); Das et al. (2019); Fitzgerald and Sarkar (2024).

Data-driven models have emerged as essential tools for representing turbine blade dynamics and adapting to varying wind conditions Nejadkhaki et al. (2018); Baisthakur and Fitzgerald (2024b). Unlike traditional methods focusing primarily on steady-state performance, modern data-driven approaches prioritize dynamic adaptability and real-time applications such as fatigue analysis McAuliffe et al. (2024); Kong et al. (2023); Nielsen et al. (2021), reliability assessments Baisthakur et al. (2024), and condition monitoring Fitzgerald and Basu (2017); Kong et al. (2020); Wang et al. (2020). These models effectively capture complex dynamics, supporting efficient large-scale simulations and predictive maintenance strategies.

System identification methods have evolved significantly from single-input single-output (SISO) systems to sophisticated multi-input multi-output (MIMO) frameworks, suitable for complex systems like wind turbines Zhang et al. (2018); Cezayirli and Ciliz (2008). Although machine learning (ML) methods offer flexible modeling capabilities, they often demand extensive training data and lack transparent representation of underlying physics Stetco et al. (2019). Conversely, state-space models offer a structured, mathematically rigorous alternative, directly reflecting physical dynamics and requiring minimal recalibration Palmeri (2010). Linear system identification primarily includes the prediction error approach, optimizing model fit to observed data Liu et al. (2019), and subspace-based techniques derived from Ho and Kalman's system realization methods Ho and Kálmán (1966); Oymak and Ozay (2021). While these methods are robust, they struggle with high-dimensionality and noise typically encountered in offshore wind applications.

To address these challenges, this study utilizes the Eigensystem Realization Algorithm (ERA) integrated with Observer Kalman Filter Identification (OKID). ERA alone is robust primarily for impulse-response data, whereas OKID enhances ERA by approximating impulse responses effec-

⋆ This work is supported by Science Foundation Ireland (SFI) grant no. 20/FFP-P/8702, and SFI project NexSys grant no. 21/SPP/3756.


10.1016/j.ifacol.2025.11.581

tively from various data types. The combined ERA-OKID framework thus offers systematic, adaptive identification of turbine blade dynamics from limited input-output data, ensuring stability under varying operational conditions. The developed ERA-OKID model captures three critical degrees of freedom per turbine blade—two flapwise and one edgewise—to represent essential vibration modes and aerodynamic interactions influenced by pitch adjustments. This state-space approach provides a concise yet comprehensive representation of turbine dynamics, facilitating real-time adaptability, predictive maintenance, and robust control applications without frequent recalibration.

This paper's main contributions are the tailored application of the ERA-OKID method to offshore wind turbine blades, providing an efficient, accurate, and computationally economical framework for dynamic modeling and control under varying wind conditions. Although ERA-OKID is an established technique, this work uniquely applies it to reliably capture complex blade dynamics based on minimal data, highlighting its suitability for practical offshore wind applications.

## 2. REDUCED-ORDER STATE-SPACE MODELING OF THE IEA-15MW TURBINE

This work employs the IEA-15MW reference wind turbine Gaertner et al. (2020), a direct-drive IEC Class 1B system with a 240 m rotor diameter and 150 m hub height. The governing equilibrium equation for a holonomic system is:

$$\mathcal{Q}_{\text{act}} + \mathcal{Q}_{\text{inert}} = 0 \tag{1}$$

where $\mathcal{Q}_{\text{act}}$ and $\mathcal{Q}_{\text{inert}}$ are the generalized active and inertial forces, respectively. These are constructed using partial velocities and accelerations of system components. Each blade is modeled with three dominant vibration modes—two flapwise and one edgewise—using modal reduction. The modal characteristics are derived using `BModes` Bir (2005), and the dynamics are captured by:

$$\mathbf{M}(\mathbf{q}, t)\ddot{\mathbf{q}} + \mathbf{f}(\mathbf{q}, \dot{\mathbf{q}}, t) = 0 \tag{2}$$

Here, $\mathbf{q}$ represents the modal coordinates, $\mathbf{M}$ the mass matrix, and $\mathbf{f}$ includes both external and restoring forces. To formulate the dynamics, Kane's method Kane and Levinson (1985) is used due to its computational efficiency and suitability for multi-body systems. The detailed derivation of the governing equations of motion for this numerical model can be found in Sarkar and Fitzgerald (2021) and its application in the surrogate modeling domain are detailed in previous works Baisthakur and Fitzgerald (2024b,a, 2025). In this work, these nonlinear dynamics are linearized into a state-space model to facilitate control design.

We employ the ERA-OKID algorithm to identify a reduced-order state-space representation directly from input-output data. By integrating prior physical knowledge such as structural flexibility and aerodynamic interactions, the approach yields a compact model suitable for applications like Model Predictive Control (MPC). In addition to control, the model is computationally efficient, enabling use in fatigue analysis, reliability assessment, and real-time simulation tasks.

### 2.1 Observer/Kalman Filter Identification (OKID)

To estimate a reduced-order model from input-output data, we adopt the Observer/Kalman Filter Identification (OKID) approach, a well-established method for dynamic system identification Alenany et al. (2019). OKID first estimates the Markov parameters of an associated observer using linear regression, and subsequently reconstructs the underlying system's impulse response. The Eigensystem Realization Algorithm (ERA) is then used to derive a minimal-order discrete-time state-space representation.

Consider a discrete linear time-invariant (LTI) system in the form:

$$\begin{aligned} \mathbf{x}_{k+1} &= \mathbf{A}\mathbf{x}_k + \mathbf{B}\mathbf{u}_k, \\ \mathbf{y}_k &= \mathbf{C}\mathbf{x}_k + \mathbf{D}\mathbf{u}_k, \end{aligned} \tag{3}$$

where $\mathbf{x}_k \in \mathbb{R}^n$ is the state vector, $\mathbf{u}_k \in \mathbb{R}^m$ the input, and $\mathbf{y}_k \in \mathbb{R}^p$ the output.

Assuming $\mathbf{x}_0 = \mathbf{0}$, the output sequence can be compactly written as:

$$\mathbf{y} = \mathcal{H}\mathbf{u}, \tag{4}$$

where $\mathcal{H}$ contains the Markov parameters $\mathbf{C}\mathbf{A}^i\mathbf{B}$ and $\mathbf{u}$ is a Toeplitz matrix constructed from past inputs. Due to ill-conditioning in practice, this relation is truncated to a finite window $T$ such that $\mathbf{C}\mathbf{A}^i\mathbf{B} \approx 0$ for $i \geq T$:

$$\mathbf{y} \approx \widehat{\mathcal{H}}\hat{\mathbf{u}}. \tag{5}$$

However, this truncation can be numerically unstable for lightly damped systems. To improve robustness, an observer is introduced:

$$\begin{aligned} \mathbf{x}_{k+1} &= (\mathbf{A} + \mathbf{L}\mathbf{C})\mathbf{x}_k + (\mathbf{B} + \mathbf{L}\mathbf{D})\mathbf{u}_k - \mathbf{L}\mathbf{y}_k \\ &= \widetilde{\mathbf{A}}\mathbf{x}_k + \widetilde{\mathbf{B}}\mathbf{z}_k, \end{aligned} \tag{6}$$

where $\mathbf{z}_k = [\mathbf{u}_k^\top, \mathbf{y}_k^\top]^\top$ combines input and output, and $\mathbf{L}$ is the observer gain. The dynamics of this auxiliary system are then used to estimate a sequence of observer Markov parameters.

The corresponding input-output relationship becomes:

$$\mathbf{y} \approx \widetilde{\mathcal{H}}\mathbf{Z}, \tag{7}$$

where $\mathbf{Z}$ is constructed from sequences of $\mathbf{z}_k$ and $\widetilde{\mathcal{H}}$ comprises observer-based Markov terms. These are obtained via least-squares estimation.

*Recovering System-Level Markov Parameters* Let the observer Markov sequence be denoted by:

$$\widetilde{\mathcal{H}} = \begin{bmatrix} \widetilde{\mathbf{H}}_{-1} \\ \widetilde{\mathbf{H}}_0 \\ \widetilde{\mathbf{H}}_1 \\ \vdots \\ \widetilde{\mathbf{H}}_{T-1} \end{bmatrix}, \tag{8}$$

where each block $\widetilde{\mathbf{H}}_k$ is split as:

$$\widetilde{\mathbf{H}}_k = \begin{bmatrix} \mathbf{H}_k^{(u)} \\ \mathbf{H}_k^{(y)} \end{bmatrix},$$

with superscripts indicating contributions from input and output, respectively.

The actual system Markov parameters $\mathbf{G}_k$ are recursively reconstructed as:

$$\mathbf{G}_k = \mathbf{H}_k^{(u)} + \sum_{j=0}^{k-1} \mathbf{H}_j^{(y)} \mathbf{G}_{k-j-1} + \mathbf{H}_k^{(y)} \mathbf{D}. \quad (9)$$

Likewise, the observer gain dynamics can be retrieved via:

$$\mathbf{G}_k^{(L)} = -\mathbf{H}_k^{(y)} + \sum_{j=0}^{k-1} \mathbf{H}_j^{(y)} \mathbf{G}_{k-j-1}^{(L)}, \quad (10)$$

where $\mathbf{G}_k^{(L)} = \mathbf{C}\mathbf{A}^k\mathbf{L}$. Once the sequence $\{\mathbf{G}_k^{(L)}\}$ is known, $\mathbf{L}$ is estimated by solving:

$$\mathbf{L} = \left(\mathcal{O}^\top \mathcal{O}\right)^{-1} \mathcal{O}^\top \mathbf{G}^{(L)}, \quad (11)$$

where $\mathcal{O} = [\mathbf{C}^\top, (\mathbf{C}\mathbf{A})^\top, \ldots]^\top$ is the system observability matrix.

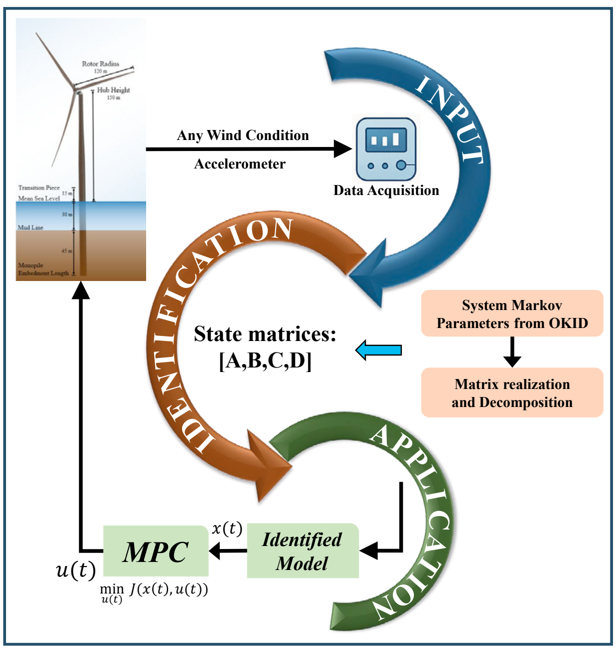


Fig. 1. Identification of State-Space Models for Wind Turbine Blades Using ERA-OKID Algorithm

## 2.2 Reduced-Order Model Identification via ERA

The Eigensystem Realization Algorithm (ERA), proposed by Juang and Pappa Juang and Pappa (1985), extends the classical realization framework of Ho and Kalman Ho and Kálmán (1966) to derive discrete-time state-space models from impulse responses. For a discrete LTI system with impulse input $\mathbf{u}_0 = 1$, $\mathbf{u}_k = 0$ $(k \geq 1)$, the output sequence forms the Markov parameters:

$$\mathbf{H}_0 = \mathbf{D}, \quad \mathbf{H}_k = \mathbf{C}\mathbf{A}^{k-1}\mathbf{B}, \quad k \geq 1 \quad (12)$$

A Hankel matrix is constructed using these parameters:

$$\mathbb{H}_0 = \begin{bmatrix} \mathbf{H}_1 & \mathbf{H}_2 & \cdots & \mathbf{H}_r \\ \mathbf{H}_2 & \mathbf{H}_3 & \cdots & \mathbf{H}_{r+1} \\ \vdots & \vdots & & \vdots \\ \mathbf{H}_r & \mathbf{H}_{r+1} & \cdots & \mathbf{H}_{2r-1} \end{bmatrix} \quad (13)$$

Applying singular value decomposition (SVD) to $\mathbb{H}_0$:

$$\mathbb{H}_0 = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^\top \quad (14)$$

The system order $n$ is determined by retaining the top $n$ singular values. Define:

$$\mathbf{O}_r = \mathbf{U}_n \mathbf{\Sigma}_n^{1/2}, \quad \mathbf{C}_r = \mathbf{\Sigma}_n^{1/2} \mathbf{V}_n^\top$$

To compute the discrete-time state matrix, we use the shifted Hankel matrix $\mathbb{H}_1$:

$$\mathbf{A}_d = \mathbf{\Sigma}_n^{-1/2} \mathbf{U}_n^\top \mathbb{H}_1 \mathbf{V}_n \mathbf{\Sigma}_n^{-1/2} \quad (15)$$

The input and output matrices are taken as the first block columns/rows of $\mathbf{C}_r$ and $\mathbf{O}_r$:

$$\mathbf{B}_d = \mathbf{C}_r(:, 1:m), \quad \mathbf{C} = \mathbf{O}_r(1:p, :) \quad (16)$$

The direct transmission matrix is simply:

$$\mathbf{D} = \mathbf{H}_0 \quad (17)$$

Although ERA performs well for low-damping systems, its reliance on impulse data limits its applicability in civil structures, especially under ambient excitations or operational constraints Peeters and Roeck (1999). This motivates combining ERA with input-output techniques like OKID to extend its usability in practical scenarios Oymak and Ozay (2021); Sengar et al. (2021). The complete workflow—from data acquisition to model identification and control deployment—is outlined in Fig. 1, showing the transformation from measured system responses to an identified state-space model, which can be used towards model predictive control implementation.

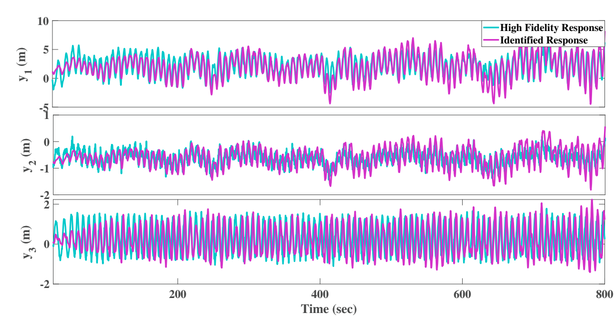


Fig. 2. Comparison of Original and identified blade tip deformation of IEA-15MW offshore wind turbine at turbulent wind condition at 20.2395 m/s

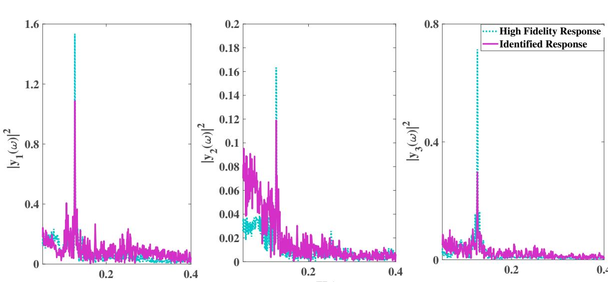


Fig. 3. Comparison of Original and identified frequency domain responses of IEA-15MW offshore wind turbine at turbulent wind condition at 20.2395 m/s

## 3. RESULTS AND DISCUSSION

To assess the effectiveness of the ERA-OKID-based state-space model, we focus on the IEA-15MW offshore wind turbine operating at a representative wind speed of 20.2395 m/s. The model is identified using input-output data consisting of (i) aerodynamic modal forces (summed over 50 blade nodes) as input, and (ii) tip deformation responses associated with two flapwise and one edgewise modes as output.

The state-space model is derived at 12.4046 m/s and evaluated directly at 20.2395 m/s by normalizing the tip response using precomputed mean and standard deviation values: $y = \mu + \sigma z$, where $z$ is the standardized response and $(\mu, \sigma)$ are wind-speed-specific statistics.

Fig. 2 shows time-domain comparison between original blade tip deformation (from high-fidelity simulations) and the identified model response. The reduced model captures the overall dynamics well, especially the third mode ($y_3$), which retains both frequency and phase accuracy. Minor mismatches in $y_1$ and $y_2$ amplitudes during transience indicate sensitivity to unmodeled nonlinearities. In the frequency domain (Fig. 3), the model reliably reconstructs the dominant frequencies of all three modes. Small deviations in higher harmonics are observed due to turbulence-induced nonlinearities and model simplification. These results confirm that the ERA-OKID framework yields compact, control-relevant models capable of accurately capturing the key vibrational features of turbine blades, even under turbulent wind conditions.

## 4. CONCLUSION

This work presents a reduced-order modeling framework for offshore wind turbine blade dynamics using the combined ERA-OKID approach. The method enables data-driven identification of discrete-time state-space models from a single input-output dataset, offering a practical and computationally efficient alternative to high-fidelity simulations. By leveraging observer-based Markov parameter estimation and modal decomposition, the framework effectively captures the dominant dynamic characteristics of flexible blades under varying aerodynamic loads.

The developed model was validated using time-domain and frequency-domain analyses at a representative wind speed of 20.2395 m/s. Results show that the identified state-space model accurately reproduces the primary vibrational modes—two flapwise and one edgewise—particularly in steady-state and oscillatory regimes. While small deviations in transient response and higher harmonic amplitudes were observed, the model demonstrates robust performance across realistic turbulent wind conditions at the validation wind speed. However, given that the model is derived from linearized dynamics and validated at a single operating point, further investigation is necessary to confirm its robustness across the full operational range and under highly nonlinear scenarios.

## ACKNOWLEDGEMENTS

This work is supported by Science Foundation Ireland (SFI) grant no. 20/FFP-P/8702, and SFI project NexSys grant no. 21/SPP/3756.

## REFERENCES

Alenany, A., Westwick, D., and Shang, H. (2019). A modified observer/kalman filter identification (okid) algorithm employing output residuals. *International Journal of Dynamics and Control*, 7, 636–643. doi: 10.1007/S40435-018-00502-9.

Baisthakur, S. and Fitzgerald, B. (2024a). Multi-task learning long short-term memory model to emulate wind turbine blade dynamics. *Wind Energy Science Discussions*, 2024, 1–35.

Baisthakur, S. and Fitzgerald, B. (2024b). Physics-informed neural network surrogate model for bypassing blade element momentum theory in wind turbine aerodynamic load estimation. *Renewable Energy*, 224, 120122.

Baisthakur, S. and Fitzgerald, B. (2025). Predicting wind turbine blade tip deformation with long short-term memory (lstm) models. *Wind Energy*, 28(6), e70027.

Baisthakur, S., Pakrashi, V., Bhattacharya, S., and Fitzgerald, B. (2024). Impact of sources of damping on the fragility estimates of wind turbine towers. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering*, 10(4), 041202.

Bir, G. (2005). User's guide to bmodes (software for computing rotating beam-coupled modes). Technical report, National Renewable Energy Lab.(NREL), Golden, CO (United States).

Cezayirli, A. and Ciliz, M.K. (2008). Indirect adaptive control of non-linear systems using multiple identification models and switching. *International Journal of Control*, 81, 1434 – 1450. doi:10.1080/00207170701837371.

Das, S., Sajeer, M.M., and Chakraborty, A. (2019). Vibration control of horizontal axis offshore wind turbine blade using sma stiffener. *Smart Materials and Structures*, 28(9), 095025.

Esteban, M.D., Diez, J.J., López, J.S., and Negro, V. (2011). Why offshore wind energy? *Renewable energy*, 36(2), 444–450.

Fitzgerald, B. and Basu, B. (2017). A monitoring system for wind turbines subjected to combined seismic and turbulent aerodynamic loads. *Structural Monitoring and Maintenance*, 4(2), 175–194.

Fitzgerald, B. and Sarkar, S. (2024). Observer based pitch control for load mitigation and power regulation of floating offshore wind turbines. In *Journal of Physics: Conference Series*, volume 2647, 032003. IOP Publishing.

Gaertner, E., Rinker, J., Sethuraman, L., Zahle, F., Anderson, B., Barter, G.E., Abbas, N.J., Meng, F., Bortolotti, P., Skrzypinski, W., et al. (2020). Iea wind tcp task 37: definition of the iea 15-megawatt offshore reference wind turbine. Technical report, National Renewable Energy Lab.(NREL), Golden, CO (United States).

Ho, B. and Kálmán, R.E. (1966). Effective construction of linear state-variable models from input/output functions: Die konstruktion von linearen modeilen in der darstellung durch zustandsvariable aus den beziehungen für ein-und ausgangsgrößen. *at-Automatisierungstechnik*, 14(1-12), 545–548.

Juang, J.N. and Pappa, R.S. (1985). An eigensystem realization algorithm for modal parameter identification and model reduction. *Journal of guidance, control, and* *dynamics*, 8(5), 620–627.

Kane, T.R. and Levinson, D.A. (1985). *Dynamics, theory and applications*. McGraw Hill.

Kong, K., Dyer, K., Payne, C., Hamerton, I., and Weaver, P.M. (2023). Progress and trends in damage detection methods, maintenance, and data-driven monitoring of wind turbine blades–a review. *Renewable Energy Focus*, 44, 390–412.

Kong, Z., Tang, B., Deng, L., Liu, W., and Han, Y. (2020). Condition monitoring of wind turbines based on spatio-temporal fusion of scada data by convolutional neural networks and gated recurrent units. *Renewable Energy*, 146, 760–768.

Liu, L., Ding, F., Xu, L., Pan, J., Alsaedi, A., and Hayat, T. (2019). Maximum likelihood recursive identification for the multivariate equation-error autoregressive moving average systems using the data filtering. *IEEE Access*, 7, 41154–41163.

McAuliffe, J., Baisthakur, S., Broderick, B., and Fitzgerald, B. (2024). Improved fatigue life of floating offshore wind turbine towers with tuned mass damper inerters (tmdis). In *Journal of Physics: Conference Series*, volume 2647, 032007. IOP Publishing.

Nejadkhaki, H.K., Hall, J.F., Zheng, M., and Wu, T. (2018). Integrative modeling platform for design and control of an adaptive wind turbine blade. In *Dynamic Systems and Control Conference*, volume 51906, V002T28A005. American Society of Mechanical Engineers.

Nielsen, J.S., Tcherniak, D., and Ulriksen, M.D. (2021). A case study on risk-based maintenance of wind turbine blades with structural health monitoring. *Structure and Infrastructure Engineering*, 17(3), 302–318.

Oymak, S. and Ozay, N. (2021). Revisiting ho–kalman-based system identification: Robustness and finite-sample analysis. *IEEE Transactions on Automatic Control*, 67(4), 1914–1928.

Palmeri, A. (2010). A state-space viscoelastic model of double-beam systems toward the dynamic analysis of wind turbine blades. In *Earth and Space 2010: Engineering, Science, Construction, and Operations in Challenging Environments*, 1973–1980.

Peeters, B. and Roeck, G. (1999). Reference-based stochastic subspace identification for output-only modal analysis. *Mechanical Systems and Signal Processing*, 13, 855–878. doi:10.1006/MSSP.1999.1249.

Sarkar, S. and Fitzgerald, B. (2021). Use of kane's method for multi-body dynamic modelling and control of spar-type floating offshore wind turbines. *Energies*, 14(20), 6635.

Sarkar, S., Fitzgerald, B., and Basu, B. (2020). Individual blade pitch control of floating offshore wind turbines for load mitigation and power regulation. *IEEE Transactions on Control Systems Technology*, 29(1), 305–315.

Sengar, R.S., Chatterjee, K., and Singh, J. (2021). System approximation via restructured hankel matrix. *Circuits, Systems, and Signal Processing*, 40, 6354 – 6370. doi: 10.1007/s00034-021-01745-2.

Stetco, A., Dinmohammadi, F., Zhao, X., Robu, V., Flynn, D., Barnes, M., Keane, J., and Nenadic, G. (2019). Machine learning methods for wind turbine condition monitoring: A review. *Renewable Energy*. doi: 10.1016/J.RENENE.2018.10.047.

Strielkowski, W., Lisin, E., and Gryshova, I. (2016). Climate policy of the european union: What to expect from the paris agreement. *Romanian J. Eur. Aff.*, 16, 68.

Veers, P., Bottasso, C.L., Manuel, L., Naughton, J., Pao, L., Paquette, J., Robertson, A., Robinson, M., Ananthan, S., Barlas, T., et al. (2023). Grand challenges in the design, manufacture, and operation of future wind turbine systems. *Wind Energy Science*, 8(7), 1071–1131.

Wang, J., Liang, Y., Zheng, Y., Gao, R.X., and Zhang, F. (2020). An integrated fault diagnosis and prognosis approach for predictive maintenance of wind turbine bearing with limited samples. *Renewable energy*, 145, 642–650.

Zhang, Q., Khaitan, S., McCalley, J., and Ajjarapu, V. (2018). Mimo system identification for large power systems preserving dominant oscillatory dynamics. *2018 IEEE Power Energy Society General Meeting (PESGM)*, 1–5. doi:10.1109/PESGM.2018.8586598.