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Brief communication: Enhanced wind turbine fatigue load estimation using digital shadows with data-driven bias correction

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Abstract. Building on a previously published digital-shadow framework for wind turbine load estimation, this study augments a linearized aeroelastic model with learning-based bias correction (BC). A neural network (NN) learns operating-condition-dependent corrections while preserving the physics-based model structure. The framework is validated using field measurements under simple, complex, and mixed inflow conditions. For blade bending moments at the 25% span location, damage equivalent load (DEL) errors of 14–24% without correction are reduced to below 5%. The largest improvements occur under complex inflow. A hybrid strategy combines baseline and NN-based corrections, improving robustness across varying operating and inflow conditions.

1 Introduction

Digital twins and digital shadows are increasingly used for wind turbine monitoring, load estimation, and lifecycle management by combining physics-based models with measurement data (Hoghooghi and Bottasso, 2026b, a). In this work, we build on our previously developed digital-shadow framework, which combines an aeroservoelastic model with Kalman filtering to estimate loads (Hoghooghi et al., 2024; Hoghooghi and Bottasso, 2026b). A key challenge is the mismatch between the internal model and the physical turbine arising from model simplifications, parameter uncertainties, unmodelled dynamics, and complex inflow conditions. While bias correction (BC) can reduce these discrepancies while preserving the physical model structure (Hoghooghi and Bottasso, 2026b), fixed corrections often have limited effectiveness under changing operating conditions. Our previous work demonstrated the potential of data-driven extensions to improve the adaptability of the digital shadow (Hoghooghi and Bottasso, 2026a).

This study advances that approach by introducing a deep learning-based bias-correction strategy for wind turbine load estimation. An industrial-grade aeroelastic model serves as the internal model of the digital shadow, while an NN learns state-dependent corrections from field data and model predictions. Because the NN augments rather than replaces the physics-based model, the approach retains the physical consistency of the digital shadow while increasing its flexibility under conditions that the nominal model does not adequately represent.

The main contribution is the development and field validation of an adaptive bias-correction framework for fatigue-relevant load estimation. The proposed method combines conventional BC, which remains effective when the baseline model is reliable, with NN-based correction under complex inflow conditions. The framework is evaluated using field measurements under simple, complex, and mixed inflow conditions, with a focus on blade-bending-moment DELs. The paper is organized as

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follows: Sect. 2 describes the methodology, Sect. 3 presents the evaluation, and Sect. 4 summarizes the findings and future work.

2 Methods

The proposed digital shadow builds on the framework presented in Hoghooghi and Bottasso (2026a), combining a linearized aeroelastic model, a Kalman filter, and a learning-based BC module. In contrast to the previous architecture, the optimizer block is replaced by the proposed BC module, which uses measured turbine signals and estimated inflow conditions to improve real-time load estimation.

The digital-shadow formulation, including model scheduling and inflow observers, follows Hoghooghi and Bottasso (2026b). A reduced-order representation of a nonlinear aeroelastic model is obtained by linearization about multiple operating points, with system matrices stored in lookup tables. Rotor-equivalent wind speed and inflow shear are estimated online as described in Hoghooghi et al. (2024); Hoghooghi and Bottasso (2026b, a).

Model–plant mismatch is represented by an additive dynamic correction $\boldsymbol{f}_0$ and an output bias $\boldsymbol{b}$. The filter model is

$$\delta\dot{\boldsymbol{q}} = \delta\boldsymbol{v}, \tag{1a}$$

$$\delta\dot{\boldsymbol{v}} = -\mathbf{M}^{-1}\left(\mathbf{C}\delta\boldsymbol{v} + \mathbf{K}\delta\boldsymbol{q} + \mathbf{U}\delta\boldsymbol{u} + \boldsymbol{f}_0 + \boldsymbol{\omega}\right), \tag{1b}$$

$$\dot{\boldsymbol{b}} = \boldsymbol{\omega}_b, \tag{1c}$$

$$\delta\boldsymbol{y} = \mathbf{D}_v\delta\boldsymbol{v} + \mathbf{D}_q\delta\boldsymbol{q} + \mathbf{E}\delta\boldsymbol{u} + \boldsymbol{b} + \boldsymbol{\nu}, \tag{1d}$$

$$\delta\boldsymbol{z} = \mathbf{F}_v\delta\boldsymbol{v} + \mathbf{F}_q\delta\boldsymbol{q} + \mathbf{G}\delta\boldsymbol{u}. \tag{1e}$$

Here, $\boldsymbol{q}$ and $\boldsymbol{v}$ denote generalized displacements and velocities, $\boldsymbol{u}$ the inputs, $\boldsymbol{y}$ the measured outputs, and $\boldsymbol{z}$ additional estimated outputs. The matrices $\mathbf{M}$, $\mathbf{C}$, $\mathbf{K}$, and $\mathbf{U}$ represent the mass, damping, stiffness, and control matrices, respectively.

The filter model, including its nine degrees of freedom, input/output definitions, and lookup-table scheduling, is identical to that of Hoghooghi and Bottasso (2026b) and is not repeated here. In the present implementation, the scheduling vector contains only the rotor-equivalent wind speed, $\boldsymbol{s} = \{V\}$. Vertical and horizontal shear and yaw misalignment are estimated online and included through the input vector $\boldsymbol{u}$ using the observer framework described in Hoghooghi et al. (2024); Hoghooghi and Bottasso (2026b, a). In this study, the output bias $\boldsymbol{b}$ is calibrated and subsequently fixed, while the learning-based approach described in Sect. 2.1 determines the dynamic correction $\boldsymbol{f}_0$ as a function of the operating condition.

2.1 Learning-based bias correction

The two BC terms in Eq. (1), $\boldsymbol{f}_0$ and $\boldsymbol{b}$, are calibrated sequentially to reduce coupling effects. First, $\boldsymbol{b}$ is identified while neglecting $\boldsymbol{f}_0$. The resulting $\boldsymbol{b}$ is then fixed and used to identify $\boldsymbol{f}_0$. Further details are given in Hoghooghi and Bottasso (2026a).

The main contribution of this work is a learning-based strategy for estimating $\boldsymbol{f}_0$ under varying operating and inflow conditions. Baseline BC factors are first identified as functions of wind speed and then systematically shifted to generate over-

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and under-corrected cases, providing a wider range of load-estimation errors for training. The flapwise correction is calibrated before the edgewise correction because flapwise loading dominates blade fatigue.

The digital shadow is evaluated over the resulting range of BC factors, generating a mapping between operating conditions, correction parameters, and load-estimation errors. A feedforward NN is then trained to learn the inverse relationship and predict correction parameters that minimize these errors.

The input space includes wind speed, rotor speed, generator torque, and either shear-based descriptors (vertical and horizontal shear) or blade-load harmonic components (Hoghooghi and Bottasso, 2026b). Pitch angle may additionally be included near the Region II/III transition.

The trained NN provides operating-condition-dependent estimates of $\boldsymbol{f}_0$. In the hybrid strategy, the baseline BC is retained unless the vertical- and horizontal-shear indicators exceed 0.4 and 0.05, respectively, in which case the NN-based correction is activated. These thresholds were selected empirically from the available field data and are application-specific.

3 Results

The digital shadow is evaluated using field measurements from a 3.5 MW eno126 wind turbine in northeast Germany (eno energy GmbH). The dataset, collected during two measurement campaigns in October 2020, contains generator torque, rotor speed, pitch angle, tower-top accelerations, and blade-root and tower-base bending moments sampled at 10 Hz. Details on the turbine, instrumentation, and preprocessing are provided by Hoghooghi and Bottasso (2026b).

After removing data gaps, turbine stops, faults, and non-production periods, approximately 49 h of simple inflow and 23 h of complex inflow data remained. Of these, 43 h and 20 h were used for training, leaving 6 h and 3 h for testing, respectively. In addition, 7.5 h of mixed and transitional inflow conditions, excluded from training, were reserved for evaluating generalization. The wind-speed and shear estimators employed in the analysis were previously developed and validated in Schreiber et al. (2020); Bertelè et al. (2021).

3.1 Fatigue-load evaluation

Fatigue performance is assessed using DELs derived from rainflow counting (Natarajan, 2022; Hoghooghi and Bottasso, 2026b). Wöhler exponents of $m = 10$ and $m = 4$ are used for blade and tower-base bending moments, respectively. DELs are computed following the formulation in Natarajan (2022). Prediction error is defined as the relative difference between estimated and measured DELs.

The baseline and learning-based BC approaches are compared for blade-root bending moments at 25% span and tower-base bending moments, with emphasis on the unseen mixed-inflow dataset to evaluate generalization beyond training conditions.

3.2 Learning-based BC evaluation

The learning-based BC is trained using the baseline-corrected factors together with systematically shifted variants derived from field data. The shifts preserve the wind-speed-dependent trend while generating over- and under-corrected cases, thereby providing a range of load-estimation errors for NN training.

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Two input formulations are investigated: a shear-based formulation using estimated vertical and horizontal shear, and a harmonic-based formulation using blade-load harmonics. Both also include estimates of wind speed, rotor speed, generator torque, and blade load. Separate NNs are trained for simple and complex inflow conditions.

The NN estimates BC parameters rather than loads directly. Blade-root bending moments are assimilated by the digital shadow and provide the training signal for the correction, whereas the blade bending moment at 25% span ($M_{B-25\%}$) and tower-base bending moment (M_{TB}) are used exclusively for validation.

3.3 Performance under simple and complex inflow

The No-BC, baseline-BC, shear-based NN, harmonic-based NN, and hybrid strategies are compared using independent test data under simple and complex inflow conditions. The learning-based and hybrid BC strategies are evaluated on independent test data under simple and complex inflow conditions. For brevity, only the mixed-inflow case is illustrated.

Table 1. Overview of RMSE and estimated output DEL errors for $M_{B-25\%}$ under simple and complex inflow conditions.

Inflow conditions	Time duration [hrs]	Estimation error $M_{B-25\%}$ [%] (RMSE / DEL)				
		No BC	Baseline BC	Shear-based inputs	Harmonic-based inputs	Hybrid
Simple inflow	6	4 / 15	3 / 6	6 / 8	5 / 3	**3 / 4**
Complex inflow	3	3 / 24	3 / 13	2 / 9	**3 / 4**	3 / 13

Table 1 summarizes the root mean squared error (RMSE) and DEL errors for the different correction strategies. Under simple inflow, the baseline BC remains effective, reducing the error from 4% (RMSE) / 15% (DEL) without correction to 3% (RMSE) / 6% (DEL). Under complex inflow conditions, the harmonic-based NN provides the best fatigue-load estimation performance, reducing the DEL error from 13% with the baseline BC to 4%.

For the independent tower-base bending moment, the corrected digital shadow achieves errors of 3% (RMSE) / 2% (DEL) under simple inflow and 2% (RMSE) / 6% (DEL) under complex inflow, demonstrating improved estimation of loads that are not used as NN training targets.

Overall, the learning-based correction is most beneficial under complex inflow, while the baseline BC remains sufficient under simple conditions. The superior performance of the harmonic-based NN under complex inflow suggests that harmonic load signatures provide a more informative representation of inflow complexity than estimated shear alone.

3.4 Mixed inflow condition

Two unseen datasets are used to evaluate generalization under mixed and transitional inflow conditions: a 4.5 h post-sunset period with intermittent mixing and a 3 h near-sunrise period with strongly varying wind speed and shear.

For the post-sunset case (Fig. 1), the $M_{B-25\%}$ error decreases from 4% (RMSE) / 15% (DEL) without BC to 3% (RMSE) / 4% (DEL) with the baseline BC. The NN trained on simple inflow achieves 3% (RMSE) / 5% (DEL), while the NN trained on

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complex inflow further reduces the DEL error to 3%. The hybrid strategy provides the best overall result, with 3% (RMSE) / 3% (DEL). For the independent tower-base bending moment, M_{TB}, the corrected estimates achieve 2% (RMSE) / 2% (DEL).

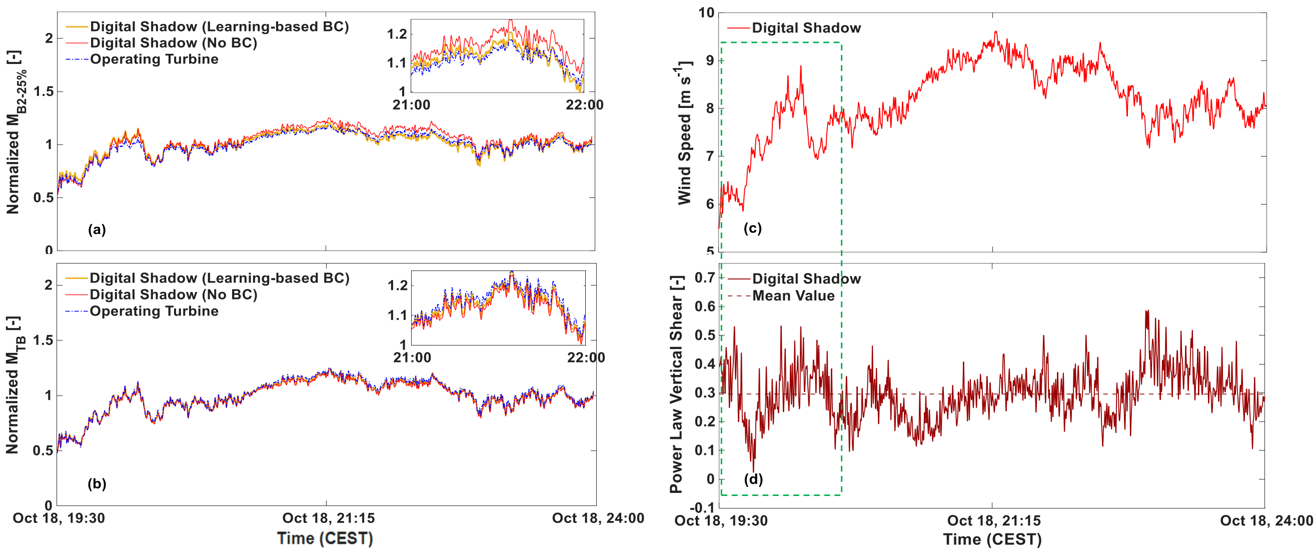

Figure 1. Time histories of normalized $M_{B-25\%}$ **(a)**, M_{TB} **(b)**, wind speed V **(c)**, and vertical shear α **(d)** for 18 Oct 2020 under post-sunset mixed inflow conditions. Measurements are shown as dashed blue lines, baseline digital-shadow estimates as solid red lines, and learning-based BC-corrected estimates as solid yellow lines.

For the near-sunrise case (Fig. 2), the uncorrected digital shadow yields 7% (RMSE) / 6% (DEL) for $M_{B-25\%}$. The baseline BC reduces these errors to 2% (RMSE) / 4% (DEL), whereas the simple-inflow NN gives 5% (RMSE) / 5% (DEL). The hybrid strategy retains the baseline performance at 2% (RMSE) / 4% (DEL), avoiding unnecessary NN corrections when the baseline BC is already effective. The corrected M_{TB} estimates achieve 3% (RMSE) / 8% (DEL).

These unseen cases show that the baseline BC remains highly effective under some mixed-inflow conditions, while the learning-based correction can provide additional improvements when the baseline correction becomes insufficient. The hybrid strategy combines both advantages by retaining the baseline correction when it performs well and activating NN-based correction when beneficial.

4 Conclusions

A digital-shadow framework for wind turbine load estimation was extended with a learning-based BC approach that augments an industrial aeroelastic model while preserving its physics-based structure.

Validation using field measurements under simple, complex, and mixed inflow conditions showed that the proposed approach reduced blade bending-moment DEL errors at the 25% span from 14–24% without correction to below 5% in the investigated cases. The largest improvements were obtained under complex inflow, where the harmonic-based NN reduced the DEL error

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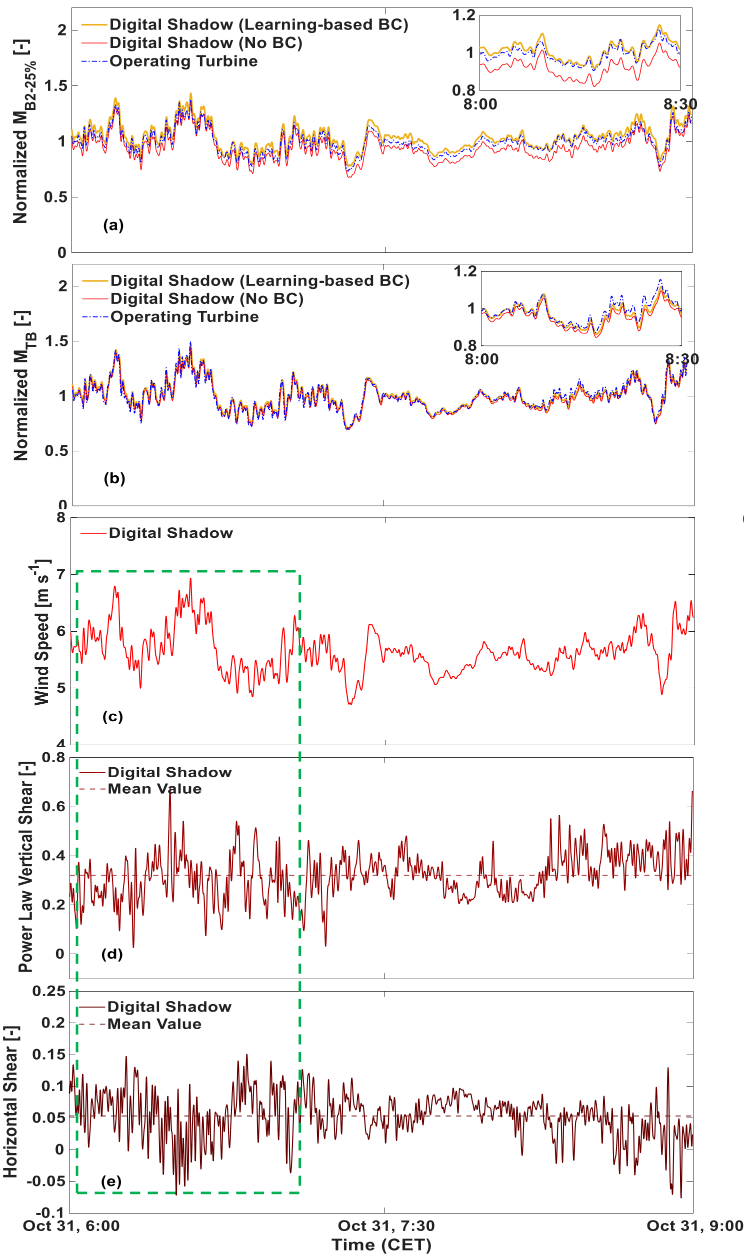

Figure 2. Time histories of normalized $M_{B-25\%}$ **(a)**, M_{TB} **(b)**, wind speed V **(c)**, vertical shear α **(d)**, and horizontal shear k_h **(e)** on 31 Oct 2020 during near-sunrise mixed inflow conditions. Measurements are shown as dashed blue lines, baseline digital-shadow estimates as solid red lines, and learning-based BC-corrected estimates as solid yellow lines.

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from 13% with the baseline BC to 4%. Under conditions where the baseline BC already provided accurate estimates, the hybrid strategy retained the baseline performance while avoiding unnecessary NN corrections.

The corrected digital shadow also achieved tower-base bending-moment DEL errors of 2–8%, demonstrating improved prediction of structural loads that were not used in training. Overall, the results highlight the potential of adaptive learning-based BC to improve digital shadow accuracy and fatigue load estimation under variable inflow conditions.

Future work will extend the framework to waked, yawed, and offshore inflow conditions, additional turbine platforms, and highly transient operating conditions.

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Appendix A: Nomenclature

$\boldsymbol{b}$	Vector of sensor biases
$\boldsymbol{f}_0$	Static correction force
$\boldsymbol{q}$	Vector of generalized displacements
$\boldsymbol{s}$	Vector of scheduling parameters
$\boldsymbol{u}$	Input vector
$\boldsymbol{v}$	Vector of generalized velocities
$\boldsymbol{y}$	Vector of outputs for Kalman innovation
$\boldsymbol{z}$	Vector of other outputs of interest
$\boldsymbol{\nu}$	Measurement noise vector
$\boldsymbol{\omega}$	Process noise vector
k_h	Horizontal shear
M	Bending moment component
m	Wöhler exponent
V	Wind speed
α	Vertical power-law shear exponent
$(\cdot)^E$	Edgewise component
$(\cdot)^F$	Flapwise component
$(\cdot)^{FA}$	Fore-aft component
$(\cdot)^{SS}$	Side-side component
$(\cdot)_{B-s\%}$	Quantity referred to the $s\%$ spanwise location
$(\cdot)_{TB}$	Quantity referred to the tower base
BC	Bias correction
DEL	Damage-equivalent load
DOF	Degree of freedom
LUT	Look-up table
NN	Neural network
RMSE	Root mean squared error
ROM	Reduced-order model
SCADA	Supervisory control and data acquisition

Data availability. All figures and the data used to generate them can be retrieved in Pickle Python and MATLAB formats via https://doi.org/10.5281/zenodo.22207774. The field dataset is the property of eno energy systems GmbH.

Author contributions. HH developed the new BC training methodology, implemented the digital shadow, performed the numerical simulations, and processed the field dataset. CLB developed the core digital shadow concept and supervised the work. Both authors contributed equally to the interpretation of the results and to the writing of the paper.

Competing interests. At least one of the (co-)authors is a member of the editorial board of *Wind Energy Science*.

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