Sensor selection for cost-effective virtual torque measurements on a wind turbine gearbox

Cedric Cappelle¹, Michiel Cattebeke¹, Jelle Bosmans^{1,2}[0000-0002-9753-3043],
Matteo Kirchner^{1,2}[0000-0002-3060-8100], Jan Croes^{1,2}, Wim Desmet^{1,2}

¹ KU Leuven, Department of Mechanical Engineering, Celestijnenlaan 300, 3001 Leuven, Belgium

² DMMS lab, Flanders Make, Belgium
jelle.bosmans@kuleuven.be

Abstract. Measuring the operational torques during the lifetime of a wind turbine gearbox offers a valuable source of information for design, monitoring, predictive maintenance and control, and can help reduce operational expenses and downtime. In this paper we investigate indirect sensing as a valuable alternative to direct sensing, which is costly and intrusive. The resulting virtual torque sensor makes use of an Augmented Extended Kalman filter (AEKF), a physics based model, and measurements. The measurements considered are encoders on the high- and low speed shaft together with strain sensors, which are easy to install on the gearbox housing. We first discuss the theoretical background of the AEKF and methods for tuning the AEKF parameters. We then give an overview on the models used. Next, we focus on a sensor selection algorithm that can select the most performant (e.g. high signal-to-noise ratio) sensors. Finally, we validate the virtual torque sensor numerically. We show that with encoder measurements on the high speed shaft and 7 strain gauges placed on the housing we can achieve a Normalized Root Mean Squared Error (NRMSE) of 1,27 % and 0,02 % for the low- and high speed shaft torque, respectively. Without any strain gauges (i.e., only with the encoders), the estimation accuracy degrades to an NRMSE of 1,37 % and 0,12 %. A further analysis of the estimation results with different amounts of strain gauges shows that the amount of strain gauges can be reduced without a significant loss in estimation accuracy. These results show the potential of virtual torque sensing as a mean to obtain operational torque information for the design, monitoring and control of wind turbine gearboxes.

Keywords: torque estimation, virtual sensing, Kalman filter, sensor selection, system performance

1 Introduction

Wind turbine gearboxes are designed to operate under certain load conditions, including regular operation loads as well as extreme load cases. These load conditions are calculated based on numerical simulations. Because of the uncertainty in the calculations and the environment, empirical safety factors are used in the design process [1]. A more detailed understanding of the operational loads is required to validate and possibly reduce these safety factors and improve the gearbox design [2]. Hence, measuring the operational torques during the lifetime of a wind turbine gearbox offers a valuable source of information for the gearbox designer. Such measurements can also be valuable for control, monitoring and maintenance strategies. In summary, measuring the operational torques paves the way towards improvements that reduce the gearbox's contribution to operational expenses and downtime of the wind turbine, as documented in [3].

The operational torques can be measured directly using suitable heavy-duty sensors (e.g. the HBM T12HT3 [4]). However, such sensors are costly and intrusive. To avoid these drawbacks, in this paper we investigate an indirect torque sensor, which makes use of a physics based model in combination with sensors on the gearbox housing that are cheaper and non-intrusive. Model predictions and measurements are combined using an augmented extended Kalman filter (AEKF), which is a computationally efficient state estimator capable of dealing with nonlinear systems. The moniker “augmented” refers to the fact that unknown input torques can also be estimated [5].

Earlier work by the authors proposed a virtual sensor to measure the torque on the low speed shaft, based on absolute encoder measurements and strain gauges placed around the ring gear of the low speed planetary stage [6]. Similar approaches have been demonstrated in literature for applications such as vehicle state and tyre force estimation [7]; and torque estimation for mechatronic drivetrains [8].

In this paper, the approach in [6] is extended to include the estimation of the high speed shaft torque as well as strain gauge measurements on the entire gearbox housing. Furthermore, we describe and validate methods to tune the parameters of the estimator and to optimize the sensor set in terms of sensor type and location.

This paper is organized as follows: The first three sections describe the three basic ingredients of the proposed virtual load sensor. First, section 2 introduces the AEKF, together with the automated tuning methods to optimize the estimator parameters. Second, section 3 describes the model representing a wind turbine drivetrain, with a focus on the gearbox. The resulting model is capable of predicting the strain gauge and encoder outputs. Third, section 4 introduces the sensor selection algorithm which selects the most performant (e.g. high signal-to-noise ratio) strain gauge and encoder locations from a large pool of potential sensor locations. Finally, in section 5 we present the virtual torque sensor results, including a trade-off analysis between amount of sensors and estimation accuracy.

2 State estimator

Before introducing the AEKF in section 2.2, we first include a few notions of state space representations in section 2.1. These are necessary information that we will use not only in the formulation of the AEKF but also in the tuning methods for the AEKF parameters (section 2.3) and the sensor selection algorithm (section 4).

2.1 State space representation

The AEKF estimates the states of the system (i.e., angular position and velocity of gears and shafts) as well as the unknown input torques of the gearbox. The latter constitute additional states of the system which are referred to as “augmented states”. The gearbox is modelled by the following nonlinear, discrete-time state-space representation [5]:

$$\begin{aligned} \mathbf{x}_k &= \mathbf{f}(\mathbf{x}_{k-1}, \mathbf{u}_{k-1}) + \mathbf{w}_{k-1} \\ \mathbf{y}_k &= \mathbf{h}(\mathbf{x}_k, \mathbf{u}_k) + \mathbf{v}_k \end{aligned} \quad (1)$$

where $\mathbf{x}_k \in \mathbb{R}^{N_s}$ is the state vector, $\mathbf{u}_k \in \mathbb{R}^{N_u}$ is the vector of unknown torques, and $\mathbf{y}_k \in \mathbb{R}^{N_m}$ is the measurement vector. N_s , N_u and N_m are the number of states, unknown inputs and measurements, respectively. All variables are defined at a discrete time step k . $\mathbf{f}$ and $\mathbf{h}$ are non-linear functions which determine the state evolution and the measurements, respectively. $\mathbf{w}$ and $\mathbf{v}$ are noise vectors that represent the mismatch between the model equations and the real asset. These noise terms are assumed to be zero-mean Gaussian white noise processes, with covariance matrices Q and R for $\mathbf{w}$ and $\mathbf{v}$, respectively.

The AEKF and the sensor selection algorithm use the linearization of the system around the current operation point. For functions $\mathbf{f}$ and $\mathbf{h}$ the linearization involves the following Jacobian matrices:

$$\begin{aligned} A_k &= \left. \frac{\partial \mathbf{f}}{\partial \mathbf{x}} \right|_{\mathbf{x}_k}, & B_k &= \left. \frac{\partial \mathbf{f}}{\partial \mathbf{u}} \right|_{\mathbf{u}_k}, \\ C_k &= \left. \frac{\partial \mathbf{h}}{\partial \mathbf{x}} \right|_{\mathbf{x}_k}, & D_k &= \left. \frac{\partial \mathbf{h}}{\partial \mathbf{u}} \right|_{\mathbf{u}_k}. \end{aligned} \quad (2)$$

In order to estimate an unknown input vector $\mathbf{u}$ (such as the torques) together with the states of the system, we can add the unknown inputs to the state vector as augmented states [8]: $\mathbf{x}_{a_k} = \begin{bmatrix} \mathbf{x}_k \\ \mathbf{u}_k \end{bmatrix} \in \mathbb{R}^{N_{x_a}}$ where $N_{x_a} = N_x + N_u$. The state space model is then reformulated in terms of the augmented state vector:

$$\begin{aligned} \mathbf{x}_{a_k} &= \overbrace{\begin{bmatrix} \mathbf{f}(\mathbf{x}_{a_{k-1}}) \\ \mathbf{f}_u(\mathbf{x}_{a_{k-1}}) \end{bmatrix}}^{\mathbf{f}_a(\mathbf{x}_a)} + \begin{bmatrix} \mathbf{w}_{k-1} \\ \mathbf{w}_{u_{k-1}} \end{bmatrix} \\ \mathbf{y}_k &= \mathbf{h}(\mathbf{x}_{a_k}) + \mathbf{v}_k \end{aligned} \quad (3)$$

where $\mathbf{f}_u$ is the model equation for the unknown torques. In this paper, a random walk model [9] is used to model the uncertainty of the estimated torques: $\mathbf{f}_u(\mathbf{x}_{a_{k-1}}) = \mathbf{u}_{k-1}$. This equation assumes that, on average, the unknown torques remain constant. A noise vector $\mathbf{w}_u$ with a covariance matrix Q_u is added to allow for torque variation. $\mathbf{f}$ and $\mathbf{h}$ are the same functions as in (1), only the notation of the arguments is different. Finally, we also define the Jacobian matrices for the augmented system, and the augmented covariance matrix as:

$$\begin{aligned} A_{a_k} &= \left. \frac{\partial \mathbf{f}_a}{\partial \mathbf{x}_a} \right|_{\mathbf{x}_{a_k}} = \begin{bmatrix} A_k & B_k \\ 0 & I \end{bmatrix} , \\ C_{a_k} &= \left. \frac{\partial \mathbf{h}}{\partial \mathbf{x}_a} \right|_{\mathbf{x}_{a_k}} = \begin{bmatrix} C_k & D_k \end{bmatrix} , \\ Q_a &= \begin{bmatrix} Q & 0 \\ 0 & Q_u \end{bmatrix} . \end{aligned} \quad (4)$$

2.2 The Augmented Extended Kalman Filter

As mentioned in the introduction, we choose to use the AEKF in this paper since it is a computationally efficient estimator capable of handling non-linear systems with unknown inputs [5]. An overview of alternative estimators can be found in [10].

The AEKF is a stochastic estimator which, along with the mean value of the estimates, also tracks their related uncertainty, represented by the covariance matrices $P_{x_{a_k}}$ and P_{y_k} , for the states and the measurements, respectively. These covariance matrices are used to determine optimized weighting factors between the information coming from the model and the measurements.

The AEKF starts with a *prediction* phase, where the current estimates are propagated in time by the model (3) to predict the state and measurements at the next time step.

$$\begin{aligned} \hat{\mathbf{x}}_{a_k}^- &= \mathbf{f}_a(\hat{\mathbf{x}}_{a_{k-1}}^+) \\ \hat{\mathbf{y}}_k^- &= \mathbf{h}(\hat{\mathbf{x}}_{a_k}^-) \end{aligned} \quad (5)$$

Variables indicated as $\hat{\bullet}$ are estimated quantities, and the superscript $\bullet^-$ indicates the results of the prediction phase. The state and measurement covariance matrices $P_{x_{a_k}}$ and P_{y_k} are also updated during the prediction phase, making use of the linearized state space model (4):

$$\begin{aligned} P_{x_{a_k}}^- &= A_{a_{k-1}} P_{a_{k-1}}^+ A_{a_{k-1}}^\top + Q_{a_{k-1}} \\ P_{y_k}^- &= C_{a_k} P_{x_{a_k}}^- C_{a_k}^\top + R_k \end{aligned} \quad (6)$$

As soon as a new measurement $\mathbf{y}_k$ becomes available, the *correction* phase of the AEKF updates the estimates based on the difference between the actual measurement $\mathbf{y}_k$ and the predicted measurement $\hat{\mathbf{y}}_k^-$, which is also referred to as the *innovation*:

$$\hat{\mathbf{x}}_k^+ = \hat{\mathbf{x}}_k^- + K_k \underbrace{(\mathbf{y}_k - \hat{\mathbf{y}}_k^-)}_{\text{innovation}}. \quad (7)$$

The Kalman Gain matrix K_k is defined in (8), and determines the magnitude of the correction. K_k can be interpreted as a relative comparison between the estimation error covariance matrices $P_{x_{a_k}}^-$ and $P_{y_k}^-$. If the values in $P_{x_{a_k}}^-$ are large compared to $P_{y_k}^-$, K_k will increase, resulting in a significant update of $\hat{\mathbf{x}}_k^-$. This reflects the fact that in such a situation more trust should be given to the measurements, since the uncertainty on the measurements is lower. The reverse also holds.

$$K_k = P_{x_{a_k}}^- C_{a_k}^\top (P_{y_k}^-)^{-1} \quad (8)$$

Through the setting of the Kalman Gain, the AEKF minimizes the covariance of the estimation error. The correction phase concludes with a second update of the state estimation covariance matrix:

$$P_{x_k}^+ = (I - K_k C_k) P_{x_k}^-. \quad (9)$$

The results of the correction phase (indicated with superscript $\bullet^+$) form the input to the next estimation step ($k + 1$).

2.3 Covariance matrix tuning

As shown in (6), the noise covariance matrices R , Q and Q_u influence the estimation error covariance matrices $P_{x_{a_k}}$ and P_{y_k} , which are used to define the Kalman Gain (8). As such, their tuning is crucial since it affects the accuracy of the AEKF.

Assuming the measurement function $\mathbf{h}$ has negligible error, the measurement noise stems only from sensor or acquisition system imperfections such as electromagnetic interference or temperature variation. The tuning of R is then relatively straightforward, since the noise properties of a sensor are often given by the manufacturer or can be identified by measuring a known reference signal. On the other hand, setting Q and Q_u is more challenging since it is generally not possible to measure the statistical properties of $\mathbf{w}$ and $\mathbf{w}_u$, and hence Q and Q_u are often set in a trial-and-error fashion, resulting in a time-consuming process that relies on significant expertise. To overcome this, in the next paragraphs we introduce automated, systematic tuning methods for Q and Q_u .

Tuning Q . Q originates from structural modelling errors and parametric errors. In this paper we use an approach to calculate Q based on parametric uncertainties which was first presented in [11] and further refined in [12]. The approach starts from a set of model parameters such as torsional inertia and stiffness and a related probability distribution. A series of simulations is then performed, where the parameters are varied according to their distribution. For an individual simulation, the deviation of the results with respect to the results using the nominal parameters can be regarded as an observation of the random process error $\mathbf{w}$. When collected, these observations can be used to determine Q .

This way, the problem of tuning the full covariance matrix Q (including off-diagonal elements) is transformed into tuning the probability distribution for the parameters. We assume a Gaussian distribution around on the nominal parameter, and assume that the parameters are uncorrelated. This limits the tuning problem to the standard deviations of all parameters, simplifying it since there are fewer variables to tune (in our case, 14 parameter standard deviations instead of 171 elements in Q ¹). Furthermore, the physical meaning of the standard deviation of the parameters is easier to interpret than that of the elements of Q .

For every parameter, we assumed a standard deviation equal to 10% of the nominal value. Although the tuning method likely underestimates the uncertainty because only parametric errors are taken into account, the resulting estimation accuracy when employing this tuning is comparable to the accuracy that we can reach through manual tuning [12]. Consequently, the tedious manual tuning procedure is avoided while achieving the same estimation accuracy.

Tuning Q_u . Tuning Q_u involves a trade-off between response speed and noise rejection. Assuming a diagonal Q_u matrix, the value of diagonal element Q_{u_i} describes the variance of the i -th unknown torque. A high variance for a certain torque will make the AEKF very responsive to changes but a value that is “too high” causes the estimates to become noisy, as process and measurement noise leak into the torque estimate.

Methods to automatically tune Q_u can be formulated based on the innovation of the AEKF, as defined in (7). The innovation contains new information used to update the estimate of the state and delivers a prediction for the estimation error given the measurements. One method uses the L-curve, a standard regularization technique [13]. However, the L-curve becomes difficult to interpret when more than one input is estimated, so it is not considered further.

A second method that does not suffer from this issue tunes (the diagonal elements of) Q_u by minimizing the norm of the innovation: $\frac{1}{N_t} \sum_{k=1}^{N_t} \|\mathbf{y}_k - \hat{\mathbf{y}}_k^-\|_2^2$, where N_t is the total amount of time steps. This approach is referred to as the MINOR criterion (Minimum Innovation Norm) [14], [15]. The tuning method runs the AEKF with different values of Q_u and retains the value that minimizes the norm of the innovation. **Fig. 1** shows the resulting innovation norm in function Q_{u_1} and Q_{u_2} , where the optimal values are found at the minimum (red triangle). We note that the innovation norm shows a relatively flat behaviour in the vicinity of the minimum innovation norm. This predicts a low sensitivity of the estimation accuracy to Q_u , provided that Q_u is of the right order of magnitude. This prediction is in line with experimentally validated results in literature [12].

When we compare the relative magnitude of the elements of Q and Q_u , we observe that the Q_u is much larger. This is because the predictive value of random walk input model in (3) is much lower than the model equation (1).

¹ The Q matrix is an 18×18 matrix because there are 18 states in the model so it has 324 elements to set. However, covariance matrices are symmetrical by definition, so the amount of elements that can be set independently reduces to 181.

Fig. 1. Norm of the AEKF innovation as function of the tuning of Q_u . The optimal value tuning is found where the innovation norm is minimal (MINOR criterion). This value is indicated with a red triangle.

3 Drivetrain and gearbox models

The drivetrain and gearbox models must be able to predict the dynamics of the system and the measurements, and they should also use the state space form (3). Moreover, computational effort and amount of states should be limited to allow real-time execution (e.g., in view of control). Limiting the amount of states also ensures that the system is observable with a limited sensor set [5]. In the next subsections we introduce a model that satisfies these requirements. First, we introduce a torsional lumped parameter model of the drivetrain in 3.1. Next, section 3.2 describes how we link the torsional model to a quasi-static Finite Element (FE) model to predict the strain on the housing at the strain gauge locations.

3.1 Torsional drivetrain model

Fig. 2 shows a schematic representation of the lumped-parameter torsional drivetrain model developed in the port-based simulation package AMESim [16]. This model is based on previous work by the authors [17]. An analytical aerodynamic model (T_{aero}) generates a representative torque input including oscillations due to wind shear and tower shadow that occur at $3 \times$ the rotation frequency [18]. This aerodynamic torque is applied to the rotor and main shaft, which are represented by their respective equivalent inertia and stiffness. The main shaft transfers the torque to the gearbox low speed

shaft. The gearbox model contains equivalent inertias and stiffnesses for the planetary gear stage (including planet carrier, planet gears and sun shaft), and the two parallel gear stages. All gear contacts are modelled by an equivalent spring of constant stiffness, determined from the ISO standard [19]. Next to their contribution to the torsional dynamics, these gear models also output the resultant gear forces, which are an input to the housing model (section 3.2). The high speed shaft is connected to a rotational damper representing the resisting torque produced by the generator.

Fig. 2. Schematic representation of the torsional drivetrain model

3.2 Quasi-static gearbox housing model

In order to simulate the strain gauge output, we constructed an FE model of the gearbox housing for the Simcenter Nastran solver [20]. The model is relatively large, since it contains 1.4 million tetrahedral elements. To limit the computational burden of this model, we reduced the model by following these three steps [6]:

1. Static test loads $\mathbf{F}_{\text{test}}$ are applied at the bearing locations and at 360 points around the ring gear since these are the interface points where the gearbox is loaded. The strain is calculated at 200 pre-defined points spread around the housing, which are also the candidate locations for the strain gauges, shown in Fig. 3 as blue diamonds on the CAD geometry.
2. The outputs of the static test simulations are organized in a matrix $\boldsymbol{\epsilon}_{\text{test}}$ where each column contains the strain responses to one of the test loads. $\boldsymbol{\epsilon}_{\text{test}}$ is used to construct a strain response matrix $\mathbf{S}_0 = \boldsymbol{\epsilon}_{\text{test}} \cdot [\text{diag}(\mathbf{F}_{\text{test}})]^{-1}$, which is further reformulated in function of the planet carrier angle θ_{PC} as $\mathbf{S}(\theta_{\text{PC}})$. This is done by selecting the columns of $\mathbf{S}_0$ that correspond to the planet-ring contact location for a given θ_{PC} .

The value of $S(\theta_{PC})$ for an arbitrary θ_{PC} (i.e. not corresponding to one of the original 360 points) is obtained through linear interpolation.

3. The strain response ϵ to an arbitrary load F is calculated through linear superposition: $\epsilon = S(\theta_{PC})F$, where vector F contains the bearing forces and the forces applied in each planet-ring contact location.

The housing model is coupled to the torsional drivetrain model (section 3.1) by solving the quasi-static equilibrium of the shafts for the bearing forces.

4 Sensor selection algorithm & results

The sensor selection algorithm in this paper follows a procedure based on [21]. The first step consists of defining a large set of possible sensor locations: two absolute encoders measuring the position of the low- and high speed shaft (θ_{LSS} and θ_{HSS} , respectively) as well as the 200 strain gauge positions mentioned in section 3.2 (**Fig. 3**). Next, the optimal strain gauge orientation for each location is determined by maximizing the plane strain under operational loads. Furthermore, all strain sensors with a low response ($< 10 \mu\text{m/m}$) are removed, since they would have a poor signal-to-noise ratio. Finally, the set is reduced by iteratively deleting the worst sensors based on a performance metric. The metric is then recalculated and this step is repeated until no sensors remain. Note that this procedure only ranks sensors in order of performance but does not indicate how many sensors should be used – this question will be addressed in section 5 by comparing the performance with varying amounts of sensors.

In this paper we consider two performance metrics, the first based on the so-called Popov-Belevitch-Hautus (PBH) observability matrix [22], and the second based on the bandwidth of the virtual sensor. These metrics are discussed in sections 4.1 and 4.2. Section 4.3 shows the results of the sensor selection algorithm and compares the results of both metrics.

4.1 PBH metric

The metric based on the PBH matrix builds upon the concept of observability, and is usually applied on linear continuous systems [23]. A system is observable if its initial state can be uniquely determined by the knowledge of the input and the measurements [5]. The PBH matrix offers more information in comparison with the Kalman observability matrix [22], since it takes into account all eigenvalues of the continuous-time state-space matrix. In this paper, we use an adapted version of the PBH observability which can be applied to non-linear discrete systems and is focused on the observability of the unknown input (i.e., the observability of the torques instead of the observability of each state) [21]:

$$K = \left(\text{cond} \left(\begin{bmatrix} A_{ak} - I \\ C_{ak} \end{bmatrix} \right) \right)^{-1} \quad (10)$$

with A_{a_k} and C_{a_k} as defined in (4). If the unknown torques are observable with a certain sensor set, the condition number of the PBH matrix (the matrix enclosed in square brackets in (10)) will be low. Hence the inverse value K is a good metric for the observability of the torque with a certain sensor set.

4.2 Virtual sensor bandwidth metric

The bandwidth metric is based on the Frequency Response Function (FRF) of the estimated torque to the unknown torque [8]. This FRF can be constructed using a linearized approximation of the state space model (4) and the steady-state Kalman gain matrix K_{SS} , which is the value the Kalman Gain (8) converges to, assuming the input and noise terms are statistically stationary processes.

The FRF is constructed in three steps. Firstly, the ratio between the z-transform of the estimated torque $\hat{U}(z)$ and the measurements $Y(z)$ is calculated:

$$H_{\hat{u}y}(z) = \frac{\hat{U}(z)}{Y(z)} = \frac{T\hat{X}_a(z)}{Y(z)} = T \left[I - (I - K_{SS}C_{a_k})A_{a_k}z^{-1} \right]^{-1} K_{SS}, \quad (11)$$

where $\hat{X}_a(z)$ is the z-transform of the augmented state vector and T is a matrix that selects the unknown torques from the augmented state vector. Secondly, the ratio between the z-transform of the measurements and the unknown torque is calculated:

$$H_{yu}(z) = \frac{Y(z)}{U(z)} = C_k(zI - A_k)^{-1}B_k + D_k. \quad (12)$$

Finally, the ratios in (11) and (12) are combined and evaluated on the unit circle (i.e. $z = e^{j\omega}$) to derive the FRF from the actual torques to the estimated torques: $H_{\hat{u}u}(e^{j\omega}) = H_{\hat{u}y}(e^{j\omega}) \cdot H_{yu}(e^{j\omega})$.

The AEKF shows a low-pass characteristic for the unknown torques [12]. For this reason, the bandwidth metric is chosen to be the value of $H_{\hat{u}u}(e^{j\omega})$ evaluated at $\omega = 100$ Hz, which is the upper frequency of interest. A high metric value indicates a performant sensor set. In contrast to the PBH metric, the bandwidth metric takes into account the noise properties of the sensors since the noise covariance matrices of the system are embedded in the steady-state Kalman gain matrix K_{SS} .

4.3 Sensor selection results

The results of the sensor selection algorithm show that the absolute encoder measurements are always removed from the sensor set last, regardless of the metric. This was expected because the position of the planet carrier (and planet gears) has a large influence on how the load affects the strain. Hence, an accurate position measurement is required to interpret the strain measurements.

The 10 most performant strain gauges chosen with the PBH metric are labelled in **Fig. 3**. The set is very similar if the bandwidth metric is used, with 8 out of 10 identical sensors, indicating the validity of the selected sensor set. The strain gauges are primarily placed around the torque arms of the gearbox, which are highly loaded parts of the

housing where the strain is directly affected by the torque. We also note that the selection algorithm favors the sensors on one side of the gearbox over the other. We believe that this is caused by small asymmetries in the FE model and consequently in the candidate sensor locations.

As a further experiment, we interrupted the selection algorithm when the measurement set has shrunk to 7 strain gauges (the reasoning behind this number is explained in section 5) and the encoders. We then manually removed the encoders from the measurement set one by one. In this experiment, the bandwidth metric predicts that the low speed shaft encoder can be omitted without greatly affecting the performance. This effect is not predicted by the PBH metric as the strain gauges have a lower contribution to this metric. These prediction will be verified in section 5.

Fig. 3. CAD image of the gearbox housing, including the candidate strain gauge location indicated with blue diamonds. The labels 1-10 indicate the most performant strain sensors as selected by the sensor selection algorithm using the PBH metric.

5 Virtual torque sensing results

In this section, the performance of the proposed virtual torque sensor, including the tuning method and sensor selection algorithm described before, is assessed numerically. The validation uses measurements generated by a reference simulation. Gaussian white noise is added to the simulated measurements to make the test case more realistic. The reference simulation consists of steady state operation at constant wind speed, including the oscillating aerodynamic torque (T_{aero}) described in section 3.1 (**Fig. 2**).

Fig. 4 shows estimated torque on the low speed shaft (**Fig. 4.a**) and on the high speed shaft (**Fig. 4.b**), using different sensor sets: The green curves show the estimation results using only encoder measurements (θ_{LSS} and θ_{HSS}), whereas the red curves show the estimation results using the high speed shaft encoder and seven strain gauges (θ_{HSS} and ϵ_7). The estimates are compared to the torque that is applied in the reference simulation (black curves).

The estimated low speed shaft torque lags slightly behind the reference. This lag is caused by the limited predictive power of the random walk input model. To reduce the estimation delay, more informative input models could be used, for example by exploiting the periodicity of the input torque or by building the input torque from a dictionary

of shape functions [23]. The lag can also be reduced without changing the input model by setting a higher value in the Q_u matrix, at the cost of increased noise in the estimates. This is exactly the trade-off that the tuning method of section 2.3 attempts to solve.

The strain measurements improve the estimation results especially for the high speed shaft torque. Without strain measurements, only the average torque trend is estimated whereas the strain gauges allow tracking the torque oscillation that occurs at $3 \times$ the rotation speed.

Table 1 lists the Normalized RMS Error (NRMSE) for the same sensor sets and additionally includes results for when both encoders are used. These results show that the encoder at the low speed shaft can be omitted without significantly affecting the estimation accuracy, as predicted by the bandwidth metric.

Fig. 4. Torque estimation results for the low speed shaft (**Fig. 4.a**) and high speed shaft (**Fig. 4.b**) of the gearbox with different sensor sets.

Table 1. Normalized RMS Error (NRMSE) of simultaneous estimation of low - and high speed shaft torque with different sensor sets

	θ_{LSS} and θ_{HSS}	θ_{LSS} , θ_{HSS} and ϵ_7	θ_{HSS} and ϵ_7
Low Speed Shaft Torque NRMSE [%]	1.37	1.27	1.28
High Speed Shaft Torque NRMSE [%]	0.12	0.022	0.023

While the sensor selection algorithm can indicate the most valuable sensors set of a given size, it does not assess the required amount of sensors. This question is addressed in **Fig. 5**, where the NRMSE is plotted against the amount of strain sensors. Every result in this graph is simulated using an optimized sensor set. Up to here we have shown results for 7 sensors (**Fig. 4** and **Table 1**), and by looking at **Fig. 5** it is clear that we are very close to the highest accuracy possible with this amount of sensors. However, good results can also be achieved with fewer sensors, and the final choice regarding the number of sensors will depend on the application and a trade-off analysis

between number of strain gauges and accuracy. It may also be desirable to install more sensors than strictly required, as redundancy improve robustness in case of sensor failure.

Fig. 5. NRMSE of the low speed shaft torque (**Fig. 5.a**) and high speed shaft torque (**Fig. 5.b**) in function of the number of strain sensors.

6 Conclusions

This paper has introduced a virtual load sensing approach to estimate the torques on the low- and high speed shaft of a wind turbine gearbox. The virtual torque sensor combines encoders on the shafts and strain measurements on the housing with a physics-based model. This approach avoids expensive and intrusive direct torque sensors. The measured torque can be used to optimize the gearbox design as well as for control, monitoring and maintenance strategies.

The model used in this paper consists of a torsional drivetrain model and a Finite Element (FE) model of the gearbox housing. The torsional model is a simplified lumped-parameter representation of the drivetrain and gearbox, and includes the aerodynamic torque oscillation due to wind shear and tower shadow. The FE model is statically reduced to limit the computational burden. This reduced model is linked to the torsional drivetrain model by solving the quasi-static equilibrium of the shafts for the bearing forces. The resulting model can simulate the torsional dynamics of the drivetrain as well as the strain response on the housing.

A sensor selection algorithm was used to determine the most performant sensor set for the virtual torque sensor. It starts from a large pool of sensors including encoders on the low- and high speed shaft of the gearbox and 200 possible strain gauge locations on the housing. Using a performance metric, the least performant sensors are removed one-by-one. We used two different performance metrics, one based on the Popov-Belevitch-Hautus (PBH) observability matrix and another based on the theoretical bandwidth of the virtual torque sensor. Our results show that both performance metrics result in a similar sensor set consisting of both encoder measurements and strain gauges placed primarily around the torque arms of the gearbox. The sensor selection algorithms

favour strain gauges on one side of the gearbox, we expect this to be a numerical effect caused by slight asymmetry in the FE model. This will be further investigated in future work. The bandwidth metric also predicted that the low speed shaft encoder could be removed without degrading the accuracy significantly.

An Augmented Extended Kalman Filter (AEKF) is used to combine the model predictions and the measurements in order to estimate the unknown torques. The settings of the AEKF have been tuned using an automated method, thereby avoiding a time-consuming manual tuning procedure.

The performance of the virtual torque sensor was tested using measurements generated in a reference simulation. We showed that with encoder measurements on the high speed shaft and 7 strain gauges placed on the housing we can accurately estimate the unknown torques, achieving a Normalized Root Mean Squared Error (NRMSE) of 1,27 % and 0,02 % for the low- and high speed shaft torque, respectively. Without strain gauges, the estimation accuracy degrades: the NRMSE increases to 1,37 % and 0,12 % for the low- and high speed shaft torque, respectively. A further analysis of the estimation results with different amounts of strain gauges showed that sensor set with 7 strain gauges achieves a result that is very close to the highest accuracy possible with our approach. The amount of strain gauges could also be reduced if a small performance degradation is acceptable. These results show the potential of the virtual torque sensing approach and the validity of the methods for tuning the AEKF and optimizing the sensor set.

Future steps include an experimental validation, focusing on the level of accuracy that can be achieved in the presence of uncertainties such as mechanical tolerances and imperfect sensor placement. Furthermore, the approach will be extended to estimating non-torque input loads. This extension will involve more advanced gearbox models and additional sensor types.

7 Acknowledgements

This research is supported by the Flanders Innovation & Entrepreneurship Agency within the V6LoadS project. Furthermore, the Research Fund KU Leuven is gratefully acknowledged for its support.

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