Kalman-Filter Based Data Fusion for Neutral Axis Tracking for Damage Detection in Wind-Turbine Towers

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KALMAN-FILTER BASED DATA FUSION FOR NEUTRAL AXIS TRACKING FOR DAMAGE DETECTION IN WIND-TURBINE TOWERS

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ABSTRACT

Wind Energy is seen as one of the most promising solutions to man's ever increasing demands of a clean source of energy. But there is a need to reduce the high initial costs for setting up and the maintenance costs. The maintenance cost may be lowered through the use of condition monitoring (CM) and structural health monitoring (SHM). SHM allows early detection of damage and allows maintenance planning which reduces the cost.

In this paper, change in Neutral Axis (NA) position is proposed as a metric for damage detection. A discrete Kalman filter (KF) is employed for the estimation of the NA in the presence of measurement noise from the strain sensors. The KF allows data fusion from the strain sensors and the yaw mechanism for the accurate estimation of the NA. Any change in the NA position may be used as an indicator for the presence and location of the damage. The study has been carried out on the simulated FE model of the wind turbine tower and indicates that NA tracking based on data fusion is sensitive to damage and robust enough to overcome the effects of measurement noise, and yawing of the nacelle.

KEYWORDS: *Structural Health Monitoring, Strain Sensors, Wind Turbine, Neutral Axis tracking, Kalman Filter*

INTRODUCTION

Ever since the industrial revolution, man's dependence on the fossil fuels as a source of energy has been on a rise. This dependence has increased even further in the last few decades, and so has the demand for energy. Unfortunately, the fossil fuels are not clean source of energy and pollute the environment. Over the last few years, there has been an increasing awareness about the environmental hazards posed by the extensive use of fossil fuels. As a result a search for clean source of energy has intensified. Wind Energy appears to be one of the leading sources of clean energy.

The use of wind energy has received an impetus due to the advancements in the field of materials engineering and manufacturing methods. Newer, bigger wind turbines which can harvest more energy from the wind currents are now possible. Furthermore, these wind turbines are more robust, and lighter in weight. The main hindrance for more widespread deployment of the wind turbines is the high initial costs for setting up of wind farms and its subsequent maintenance. These high initial costs make the energy more expensive than the conventional energy sources. The cost of generation being the biggest drawback of wind energy, there is a concerted effort to reduce it. This can be achieved by increasing the life-time of the wind turbines; reducing maintenance costs and ensuring high availability. The lifetime may be increased by ensuring a more robust design while the maintenance cost may be lowered and the high availability ensured through the use of condition monitoring (CM) and structural health monitoring (SHM) [1]. SHM allows early detection of damage and allows maintenance planning which reduces the cost [2]. Furthermore, it can allow us to avoid unnecessary downtime, hence increasing the availability of the system.

The SHM needs to be low cost, and suitable for continuous monitoring. These techniques are based on the concept that, the change in mechanical properties of the structure will be captured by a change in its dynamic characteristics [3]. The SHM process involves the observation of a system over time using periodically sampled dynamic response measurements from an array of sensors, followed by the extraction of damage-sensitive features from these measurements, and the statistical analysis of these features to determine the current state of the system's health. The SHM process requires use of sensors for data collection, filters for data cleansing, and central data processing units for feature extraction and post processing.

SHM has been a field of active research in the aerospace and offshore industry for several decades and many methods have been proposed and investigated. These methods have been able to detect and locate damage in a laboratory environment under controlled conditions. However when these methods were implemented for field validations or in real structures, the results obtained were not up to the desired level. The discrepancy between the expected and the measured results are mainly attributed to the uncertainty in the measurement environment with respect to noise, temperature and excitation mechanism for the structure. Hence there is a search for an SHM system which is able to detect damage in working conditions, and is robust enough to changes in ambient conditions and excitation. Furthermore, the method should be able to detect small levels of damage [4].

In this paper, a Kalman Filter (KF) based methodology is proposed for the Neutral Axis tracking, which in turn is used as metric for damage detection of the tower structure. The KF incorporates the yawing of the nacelle to the wind direction and allows accurate tracking of NA even in changing loading direction. The NA is the property of the cross section of the tower independent of the bulk temperature effects, and the ambient wind loading. The position of the neutral axis can be assessed by measuring the strains on opposite surfaces of the tower in bending. The estimation of the NA of the tower subject to unknown loading both in magnitude and direction is presented here. The discrete KF [5] is employed for the estimation of the NA subject to wind loads in the presence of measurement noise from the sensors. The incorporation of data fusion allows greater confidence level in the damage detection and hence allows lower thresholds for damage detection, making it possible to detect lower levels of damage. The study is undertaken on a validated FE model of the 10MW wind turbine tower [6]. The robustness of NA tracking as a damage indicator has been studied for different damage extents, and different noise levels, and different conditions of yaw angle.

1 THEORETICAL BACKGROUND

1.1 Neutral Axis

The primary function of the tower structure is to support the hub, and the nacelle of the wind turbine. The nacelle and the hub are axial loads which are eccentrically loaded on the tower. This eccentric loading gives rise to axial compressive loads as well as bending loads as shown in Figure 1. The axial compression is uniform over the entire cross section while the bending loads will be tensile at one end and compressive at the other. Furthermore, the tower experiences wind loads which result in bending strains in the tower. The bending strains are given by (1)

$$\epsilon = \frac{M_b y}{EI} \tag{1}$$

where, ε is the longitudinal strain in bending, M_b is the net bending moment at the cross section due to wind loading and eccentricity, E is the Young's modulus and I is the area moment of Inertia, y is the distance from the NA [7].

Thus, one surface of the tower experiences, a combination of two axial compressions, (right side in Figure 1) while the other end experiences a combination of compressive load due to the weight and tensile load due to the bending, (left side in Figure 1). If the line connecting the two strain levels is extended, there will be a point where the strain experienced will be zero, which is identified as the Neutral Axis point. The neutral axis of the section is a function of the flexural rigidity of the structure, and does not depend on the applied bending loads, thus by, measuring the strains at the opposite edges of the beam, the neutral axis can be located, which in turn may be an indicator of the damage.

The Figure 1, explains the abbreviations used and the concept. The NA can thus be estimated based on the strain measurements.

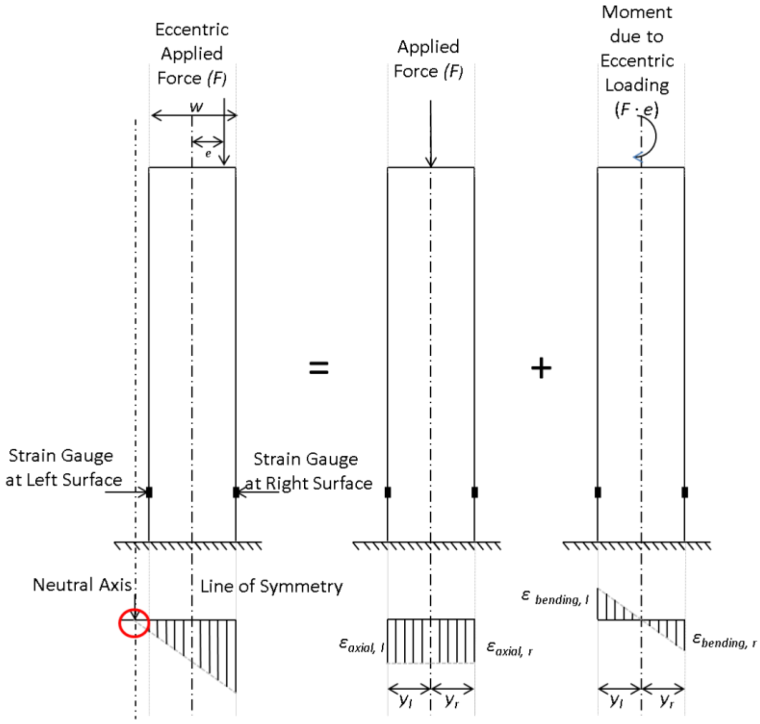


Figure 1: Flexural Strain Distribution over the beam cross-section subject to eccentric loading

1.2 Kalman Filter

The KF is a set of mathematical equations that provides an efficient computational (recursive) solution of the least-squares method. Theoretically, KF combines a system's dynamic model (physical laws of motion) and measurements (sensor readings) to form an estimate of the systems varying quantities (system state) that is better than the estimate of the system obtained by measurement alone, [8]. Figure 2 concisely explains the implementation of the KF.

In the present application, the state estimate variable is a 3×1 vector consisting of the ratio, $\frac{2x}{w}$ (referred to as Neutral Axis Estimate - NAE) which in undamaged condition should remain constant independent of the applied loads. x is the location of the neutral axis and the other variable tracking the constant 1. This constant for tracking 1 is incorporated to ensure, accurate system depiction, and formation of square measurement matrix which allows faster computations. The third component of the vector is the variable θ for the yaw angle. It is a linear estimate of the measurement from the sensor. The measurement update matrix takes into consideration the observability of the neutral axis based on the locations of the sensors.

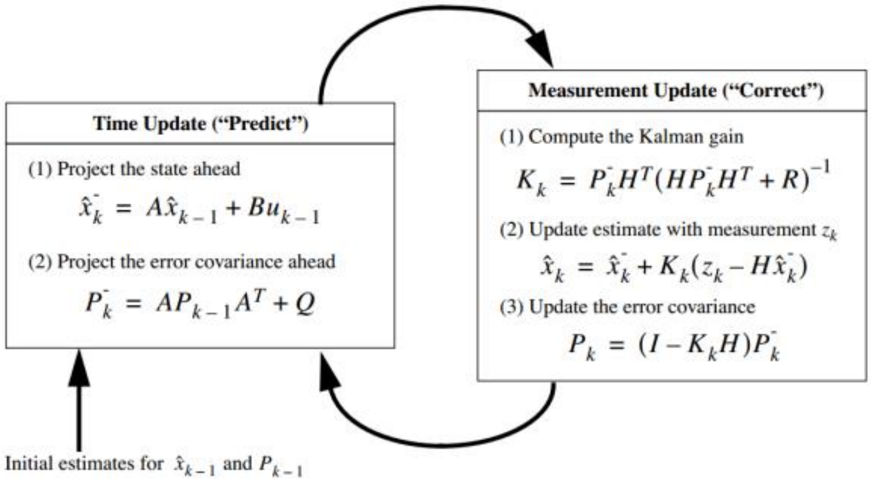


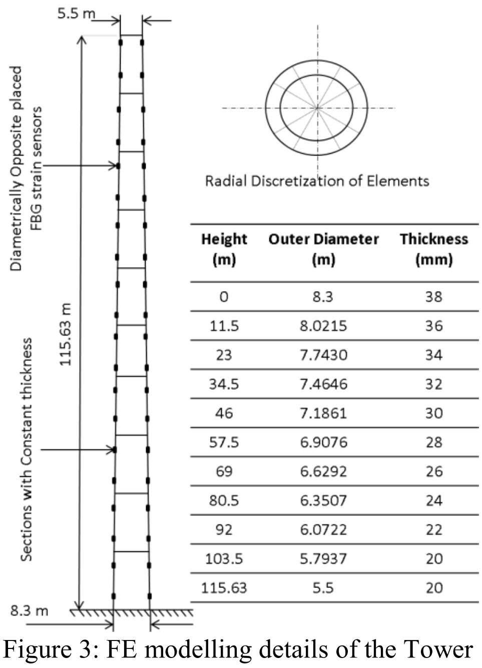
Figure 2: Flow Chart for the implementation of the KF [7]

where, x is the estimate of the state, A is the state transition matrix, B is the control matrix, u is the control variable, P is the state variance matrix, Q is the process variance matrix, K is the Kalman gain, H is the measurement matrix, z is the measurement variable, the 'super minus' indicates a priori estimate while the subscripted k indicates the time step.

2 FINITE ELEMENT MODELLING

The proposed methodology was verified on a simulated FE model of the DTU 10 MW Reference Wind Turbine. The model was simulated in commercial FE modelling software ABAQUS [9] based on the design data in the reference [6].

The tower is a 115.630 m tall hollow steel structure. The outer diameter varies linearly from 8.3 m at the base to 5.5 m at the top of the tower. The tower is divided in 10 sections where the wall thickness is constant in each section, but gradually decreasing from the bottom to the top. The tower is encastred at the bottom (Figure 3). The tower is made from steel S355 with a Young's modulus of 210 GPA, Poisson's ratio 0.3 and the density 8500 kg/m^3 (8% increase of the density to account for the secondary structural components).



Height (m)	Outer Diameter (m)	Thickness (mm)
0	8.3	38
11.5	8.0215	36
23	7.7430	34
34.5	7.4646	32
46	7.1861	30
57.5	6.9076	28
69	6.6292	26
80.5	6.3507	24
92	6.0722	22
103.5	5.7937	20
115.63	5.5	20

Figure 3: FE modelling details of the Tower

The nacelle and hub loads were applied as point loads, at specified eccentricity and height indicated from the design specifications. The wind loads were simulated as random loads using Euro-codes, [10]. A peak wind pressure was selected and applied on the surface area facing the wind, in order to compute the force. The force increases according to the power law along the height of the tower. The blades, however, were assumed to be pitched into a full aerodynamic brake position to ensure minimal rotor motion and consequent change in mass distribution, which may affect the NA [11].

3 NUMERICAL SIMULATIONS

3.1 Effect of Yaw on Neutral Axis Location

The yaw of the nacelle results in changing of the load distribution experienced by the tower. In ideal conditions, the axial load experienced will not change, while the bending loads due to the eccentricity changes. The location of the NAE due to the limited observability changes with the change in yaw angle and is plotted in Figure 4.

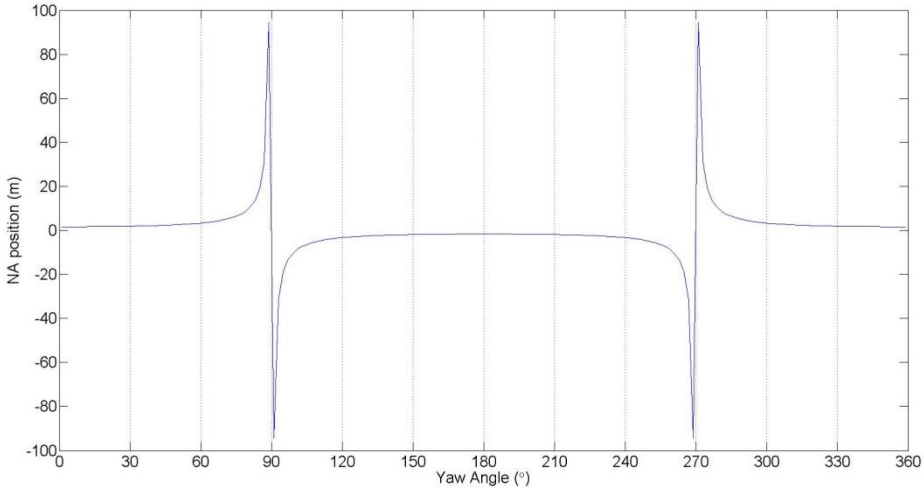


Figure 4: Plot of NA location against Yaw Angle

As can be clearly seen in the Figure 4, the location of the NA undergoes significant changes, and hence as such needs to be monitored quantity for robust damage detection.

3.2 Kalman Filter for NA estimation

The KF is a powerful tool for the estimation of the state variables especially in the presence of measurement noise. So, the use of KF will improve the estimation. Figure 5 shows the relative performance of the KF for the estimation NA compared to the direct estimation method. As seen in the Table 1, the standard deviation of the KF based estimation is order of magnitude lower than the direct estimation method, especially in the presence of measurement noise.

Table 1: Statistical Performance of Estimators

Noise level	KF Estimation Standard Deviation (mean) (NAE)	Direct Estimation Standard Deviation (mean) (NAE)
0%	0.0048 (-0.2700)	0.0111 (-0.2702)
5%	0.0049 (-0.2698)	0.0163 (-0.2720)
10%	0.0049 (-0.2708)	0.0212 (-0.2724)

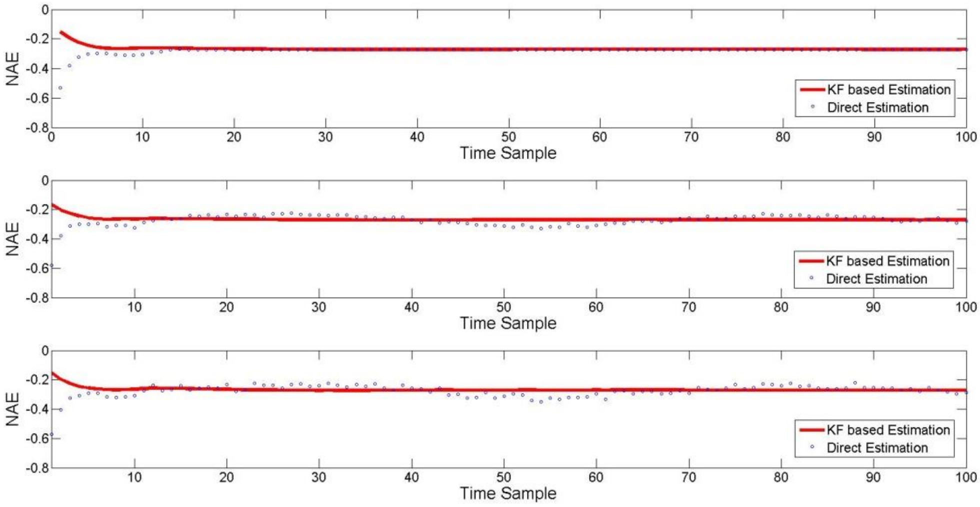


Figure 5: Comparison between direct and KF methods

Also, due to the presence of measurement noise, the mean of the prediction changes, this in turn will directly affect the accuracy of the damage detection methodology. Hence, the use of KF estimator is necessary. The noise indicated is added in the measurement of strains as well as the yaw angle.

3.3 NA based Damage Detection

As explained in section 2.1, the NA of the cross-section of the tower is the property of the condition of the structure and may be used as a damage indicator.

In order to validate the use of NA as damage indicator, artificial damage was introduced in one element of the tower, by reducing the flexural rigidity of that particular element by 20%. Reduction of Flexural Rigidity is a valid damage simulation strategy as indicated by [12]. The reduction of flexural rigidity may be treated equivalent to loss of material thickness due to corrosion or cracking and is a commonly used strategy for global level damage simulation in bridge structures [13]. The simulated damage was detected by comparing the NAE of the damage and the undamaged element.

Table 2: NA Based Damage detection in presence of Noise

Sensor Location (m)	% Relative Change in NAE			
	0% Noise	1% Noise	5% Noise	10% Noise
2.875	-0.0177	-0.0694	-0.2029	0.5403
8.625	-0.1546	-0.1266	-0.3123	0.3565
14.375	-0.0820	-0.0576	-0.1811	0.1504
20.125	-0.2128	-0.2161	-0.3438	-1.0455
25.875	-0.0252	-0.0508	-0.0135	0.5836
31.625	-0.4384	-0.4577	-0.4394	0.7286
37.375	-0.9947	-1.0899	-1.0932	-1.1910
43.125	5.4836	5.4674	5.4675	5.3286
48.875	-1.0367	-1.0491	-0.9949	-0.7893
54.625	-0.4416	-0.5153	-0.6243	-0.1339
60.375	-0.0422	0.0151	-0.1978	0.1797
66.125	-0.2413	-0.2820	-0.2334	-0.3370
71.875	-0.1271	-0.0716	0.1087	0.3750

77.625	-0.1664	-0.1475	-0.1069	-0.0487
83.375	-0.0417	-0.0639	-0.0125	-0.2715
89.125	-0.0770	-0.1277	-0.0120	-0.4831
94.875	0.0101	0.0301	0.1279	-0.2785
100.625	-0.0121	-0.0271	-0.3458	0.1291
106.375	0.0584	0.0463	0.0330	0.0299
112.440	-0.0368	0.0684	0.1646	0.7457

The damage is detected if the change in the NA estimation of the damaged and undamaged state is more than a specified threshold, which is determined on engineering judgment. As can be clearly observed, even in the presence of measurement noise, there is significant difference in the change of the NAE of the damage element and the others, so the chances for a false detection are quite minimal and as such a lower threshold may be possible 5% in the current case. The use of yaw tracking allows this higher confidence and as such is an advantage for detecting lower levels of damage.

3.4 Sensitivity to Severity of Damage

Ideally the damage metric should be able to detect even minor changes in the system, but in actual practice these changes are often masked, by changes in ambient condition changes and measurement noise. Hence the sensitivity to damage is investigated

Table 3: Performance of NA with changing severity of damage

Damage Extent	**Undamaged NAE**	**Damaged NAE**	**% change in estimate**
5%	7.008	7.160	2.169
10%	7.008	7.276	3.825
15%	7.008	7.374	5.215
20%	7.008	7.479	6.717
25%	7.008	7.593	8.340

Table 3 indicates the percent change in the NAE with change in the damage severity. It can be seen that damages above 15% damage can be easily detected through the tracking of NA, and as such the methodology promises to be better than the conventional vibration based damage detection methods, which are unable to detect such low levels of damage in presence same levels of measurement noise [12].

4 CONCLUSIONS

The paper proposes data fusion of strain measurements and yaw angle for NA tracking which in turn is used as a damage indicator. The study first establishes the merits for the use of KF for NA tracking estimation. This KF based NA estimation is then used to detect damage in the simulated tower structure of the 10MW DTU RWT.

The study indicates that the NA is a property of the condition of the structure and remains relatively unaffected by the measurement noise. Furthermore, the robustness of the metric has been studied in the presence of measurement noise. Further sensitivity studies for varying severity of damage have been investigated. From the results obtained it can be seen that the NA based tracking is a promising SHM methodology which promises to be low cost. Furthermore, it is sensitive to lower levels of damage which are not detected through the conventional vibration based methods [12]. Furthermore, by incorporating data fusion, the confidence level in the damage detection is increased, thus allowing lower thresholds for damage detection

The present study aims at giving a proof of concept and the validity of the use of data fusion for NA tracking for damage detection in tower structures in the presence of yawing. The authors acknowledge that the actual loading conditions in-service, and the, pitching and the rotation of the blades may increase the complexity for the use of the metric, and hence has been earmarked as an area of further research. In addition more realistic damage scenarios, like fatigue induced cracks, need to be simulated and the sensitivity of the method needs to be validated in these scenarios.

In nutshell, the study presents a brief study and a proof of concept of the use of data fusion for NA tracking and its use as damage detection metric. The obtained simulated results show promise and as such, the methodology needs to be validated through experimental validation.

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