

Article

## Wind Turbine Tower Vibration Modeling and Monitoring by the Nonlinear State Estimation Technique (NSET)

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**Abstract:** With appropriate vibration modeling and analysis the incipient failure of key components such as the tower, drive train and rotor of a large wind turbine can be detected. In this paper, the Nonlinear State Estimation Technique (NSET) has been applied to model turbine tower vibration to good effect, providing an understanding of the tower vibration dynamic characteristics and the main factors influencing these. The developed tower vibration model comprises two different parts: a sub-model used for below rated wind speed; and another for above rated wind speed. Supervisory control and data acquisition system (SCADA) data from a single wind turbine collected from March to April 2006 is used in the modeling. Model validation has been subsequently undertaken and is presented. This research has demonstrated the effectiveness of the NSET approach to tower vibration; in particular its conceptual simplicity, clear physical interpretation and high accuracy. The developed and validated tower vibration model was then used to successfully detect blade angle asymmetry that is a common fault that should be remedied promptly to improve turbine performance and limit fatigue damage. The work also shows that condition monitoring is improved significantly if the information from the vibration signals is complemented by analysis of other relevant SCADA data such as power performance, wind speed, and rotor loads.

**Keywords:** wind turbine; tower vibration; SCADA data; nonlinear state estimation technique (NSET); modeling; blade asymmetry

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## 1. Introduction

Vibration can be a good indicator of the operating conditions of a range of mechanical components and structures and thus can support condition monitoring of important wind turbine components such as the rotor, drive train and tower [1,2]. Analysis of vibration signals in both the time and frequency domain can be used to identify incipient failure of these components, but the vibration sensor and analysis methods for tower and drive train are different. For the tower, because the vibration frequency is quite low, a low frequency sensor (0–200 Hz) and an appropriate model based analysis method are used, while for the drive train bearing and gearbox, a high frequency acceleration sensor (3–20 kHz) and fast Fourier transform (FFT), Cepstrum methods are used [3]. However, there are two difficulties in the application of vibration analysis to wind turbines. First, large-scale wind turbines operate these days in a variable speed mode to optimize performance in relation to time changing wind speed and so the rotational speed of the rotor, gearbox and generator are changing significantly in time. Because the rotation speed of the gearbox is changing, the width of the vibration sidebands is not fixed, and this creates difficulties in locating the exact locations of gear or bearing faults. It is conventional as in [4] to use order analysis to deal with this problem, or equivalently azimuthal data sampling (rather than fixed time interval sampling) in which the rotor vibration is analyzed based on samples recorded at equidistant rotational angles instead of time equidistant samples. Second, there is strong aerodynamic and vibrational coupling between different turbine components and thus many interconnected factors may influence the vibration signatures. Rotor dynamics and control can for example, significantly influence tower vibration (TV). When the wind speed is above the rated one, the blade angle will normally be adjusted to maintain the rated power. This will result in changes to the aerodynamic forces acting on the rotor, and thus can lead directly to changes in tower vibration (both frequencies and amplitudes). It therefore makes sense to analyze vibration in wider context.

In recent years, wind turbine condition monitoring using supervisory control and data acquisition system (SCADA) data analysis is increasingly common. The SCADA system for a wind turbine records hundreds of important variables that can give a more comprehensive indication of the wind turbine health condition. The work reported in [5] starts from basic laws of physics applied to the gearbox to derive robust relationships between temperature, efficiency, rotational speed and power output. With this relationship, an abnormal rise in the gearbox oil temperature as represented in the SCADA data can be used to predict gearbox failure. In [6], the authors use SCADA data and data mining algorithms to predict possible wind turbine faults. The study reported in [7] used a neural network to construct normal operating temperature models of the gearbox and generator based on SCADA data. When the residual between the model prediction and the measured value becomes very large, a potential fault is identified. In this paper we also use SCADA data for tower vibration modeling and monitoring. The vibration signals in the SCADA system are analyzed alongside other related variables to give an improved assessment of the tower and rotor condition.

This paper is arranged as follows: Section 2 gives a detailed description of the NSET modeling methodology. Section 3 introduces the SCADA data used and analyzes which factors or variables are most important with regard to their influence on tower vibration. The above and below rated operational regimes are dealt with separately. Section 4 uses the NSET technique to construct the two required sub-models for tower vibration. In Section 5, the TVM is used to detect the blade angle error/asymmetry. The paper finishes with a discussion and conclusions in Section 6.

**2. Tower Vibration Modeling Method: Nonlinear State Estimation Technique (NSET)**

NSET is a non-parametric model construction method first proposed by Singer [8]. It is now widely used in the nuclear power plant sensor calibration, electric product lifespan prediction and software aging research [9–11].

Assuming that there exist  $n$  variables or parameters of relevance for a particular process or device, then at time  $i$ , an observation of the variables can be written as an observation vector:

$$X(i) = [x_1 \quad x_2 \quad \dots \quad x_n]^T \tag{1}$$

Construction of a memory matrix  $D$  is the first step of NSET modeling approach. During a period of normal operation of the process or device,  $m$  historical observation vectors are collected covering the range of different operating conditions (such as high or low load, start up, before shut down, etc.) that the process or device is subject to, so as to construct the memory matrix  $D$  as:

$$D = [X(1) \quad X(2) \quad \dots \quad X(m)] = \begin{bmatrix} x_1(1) & x_1(2) & \dots & x_1(m) \\ x_2(1) & x_2(2) & \dots & x_2(m) \\ \vdots & \vdots & & \vdots \\ x_n(1) & x_n(2) & \dots & x_n(m) \end{bmatrix}_{n \times m} = \begin{bmatrix} D_{11} & D_{12} & \dots & D_{1m} \\ D_{21} & D_{22} & \dots & D_{2m} \\ \vdots & \vdots & & \vdots \\ D_{n1} & D_{n2} & \dots & D_{nm} \end{bmatrix}_{n \times m} \tag{2}$$

Each observation vector in the memory matrix represents an operating state of the process or device. With proper selection of the  $m$  historical observation vectors, the subset space spanned by the memory matrix  $D$  can represent the whole normal working space of the process or device. The construction of memory matrix  $D$  is actually the procedure of learning and memorizing the normal behavior of the process or device.

The work reported in [12] provides a systematic approach to data vector selection and memory matrix construction. The input to NSET is a new observation vector  $X_{obs}$  obtained at some time and the output from NSET is a prediction  $X_{est}$  for this input vector for the same moment in time. For each input vector  $X_{obs}$ , NSET will produce a  $m$  dimensional weighting vector  $W$  :

$$W = [w_1 \quad w_2 \quad \dots \quad w_m]^T \tag{3}$$

with:

$$X_{est} = D \cdot W = w_1 \cdot X(1) + w_2 \cdot X(2) + \dots + w_m \cdot X(m) \tag{4}$$

Equation (4) means that estimation in NSET is the result of a linear combination of the  $m$  historical observation vectors in the memory matrix  $D$ . The residual between the NSET estimation and the input is:

$$\epsilon = X_{obs} - X_{est} \tag{5}$$

The residual sum of squares for  $\epsilon$  is:

$$\begin{aligned}
 S(w) &= \sum_{i=1}^n \epsilon_i^2 = \epsilon^T \epsilon \\
 &= (\mathbf{X}_{\text{obs}} - \mathbf{X}_{\text{est}})^T (\mathbf{X}_{\text{obs}} - \mathbf{X}_{\text{est}}) \\
 &= (\mathbf{X}_{\text{obs}} - \mathbf{D}\mathbf{W})^T (\mathbf{X}_{\text{obs}} - \mathbf{D}\mathbf{W}) = \sum_{i=1}^n \left( \mathbf{X}_{\text{obs}}(i) - \sum_{j=1}^m w_j D_{ij} \right)^2
 \end{aligned}
 \tag{6}$$

In order to obtain the weighting vector  $\mathbf{W}$ , we need to minimize the residual sum of square and let the partial derivatives for  $w_1, w_2, \dots, w_m$  to be zero as follows:

$$\frac{\partial S(w)}{\partial w_k} = -2 \sum_{i=1}^n \left( \mathbf{X}_{\text{obs}}(i) - \sum_{j=1}^m w_j D_{ij} \right) D_{ik} = 0
 \tag{7}$$

Equation (7) can be written as:

$$\sum_{i=1}^n \mathbf{X}_{\text{obs}}(i) D_{ik} = \sum_{i=1}^n \sum_{j=1}^m w_j D_{ij} D_{ik} = \sum_{j=1}^m \left( \sum_{i=1}^n D_{ij} D_{ik} \right) w_j, \quad k = 1, 2, \dots, m
 \tag{8}$$

If Equation (8) is written in matrix form:

$$\mathbf{D}^T \cdot \mathbf{D} \cdot \mathbf{W} = \mathbf{D}^T \cdot \mathbf{X}_{\text{obs}}
 \tag{9}$$

From Equation (9), we can obtain the weighting vector as:

$$\mathbf{W} = (\mathbf{D}^T \cdot \mathbf{D})^{-1} \cdot (\mathbf{D}^T \cdot \mathbf{X}_{\text{obs}})
 \tag{10}$$

Substitution of Equation (10) into Equation (4) gives the model predicted vector as:

$$\mathbf{X}_{\text{est}} = \mathbf{D} \cdot \mathbf{W} = \mathbf{D} \cdot (\mathbf{D}^T \cdot \mathbf{D})^{-1} \cdot (\mathbf{D}^T \cdot \mathbf{X}_{\text{obs}})
 \tag{11}$$

From Equation (11), we can clearly see that the predicted vector is the linear combination of the historical observation vectors in the memory matrix, as mentioned above. In Equation (11),  $\mathbf{D}^T \cdot \mathbf{D}$  denotes the dot product between every two vectors in the memory matrix, and  $\mathbf{D}^T \cdot \mathbf{X}_{\text{obs}}$  the dot product between the new input vector and each vector in the memory matrix. Euclidean distance is the simplest way to identify the relationship (distance) between any two vectors, and within NSET is used an intuitive measure of the similarity between vectors and so, in order to give NSET a more direct physical interpretation, this norm is used as nonlinear operator and replaces the dot product in  $\mathbf{D}^T \cdot \mathbf{D}$  and  $\mathbf{D}^T \cdot \mathbf{X}_{\text{obs}}$  in Equation (11).

The nonlinear operator for Euclidean distance in n-space is simply:

$$\otimes(\mathbf{X}, \mathbf{Y}) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2}
 \tag{12}$$

When Equation (12) is used to replace the dot product in Equation (11), the result is:

$$\tilde{\mathbf{X}}_{\text{est}} = \mathbf{D} \cdot (\mathbf{D}^T \otimes \mathbf{D})^{-1} \cdot (\mathbf{D}^T \otimes \mathbf{X}_{\text{obs}})
 \tag{13}$$

In the construction of memory matrix  $\mathbf{D}$ , the Euclidean distance between every two observation vectors of the  $m$  vectors should be big enough to ensure that the condition number of  $\mathbf{D}^T \otimes \mathbf{D}$  is not

excessive. Otherwise, it will be very difficult to calculate the inverse matrix of  $\mathbf{D}^T \otimes \mathbf{D}$  and the NSET model may become ill conditioned.

If we are only interested in predicting one parameter such as  $x_n$  in the observation vector, then Equation (13) could be simplified as follows:

$$\begin{aligned} x_{n\text{est}} &= [x_n(1) \quad x_n(2) \quad \cdots \quad x_n(m)] \cdot \mathbf{W} \\ &= [x_n(1) \quad x_n(2) \quad \cdots \quad x_n(m)] \cdot \\ &\quad (\mathbf{D}^T \otimes \mathbf{D})^{-1} \cdot (\mathbf{D}^T \otimes \mathbf{X}_{\text{obs}}) \end{aligned} \quad (14)$$

In this case, the prediction for  $x_n$  is simply a linear combination of the  $m$  historic observation values of  $x_n$ . The Euclidean norm is used to calculate the similarity between the new input vector  $\mathbf{X}_{\text{obs}}$  and the  $m$  vectors of the memory matrix. Assuming that the new input measurement is most similar (in the Euclidian sense) to the vector  $\mathbf{X}(i)$  in memory matrix, then, the Euclidean distance between them is the smallest of all  $m$  possible distances and the weight  $w_i$  corresponding to  $\mathbf{X}(i)$  is the largest within  $\mathbf{W}$ . In summary, the vector in memory matrix that has the best similarity with the new input will contribute the most to the prediction for  $x_n$ .

When the process or device works normally, the input observation vector of NSET should be located in the normal working space that is represented by the memory matrix  $\mathbf{D}$ , and it is thus similar to some of the historical vectors in the memory matrix. In the case, the NSET estimation should be highly accurate. When problems or faults arise with the process or device, its dynamic characteristics will change, and the new observation vector will deviate from the normal working space. In this case the linear combination of the historical vectors in the memory matrix will not provide an accurate estimate of the input and the residual will increase in magnitude, sometimes very significantly.

NSET is quite different from the Artificial Neural Network (ANN), a very common data driven modeling method, in following two respects:

- (1) An ANN uses historical data to train the network. During the training, the network absorbs the information from the training data into the weights. After training the data is discarded. For each new input vector, the weights of the network remain constant and the prediction is the nonlinear combination of the variables in the input vector. And the weight for the network has no clear meanings. In contrast, with NSET modeling, for each new observation vector, the weights  $\mathbf{W}$  are individually generated by (14). Prediction with an NSET model is the linear combination of the historical observation data. The weights for NSET model show the similarity between the new input vector and vectors already in the memory matrix.
- (2) It is difficult to determine the structure for an ANN. In practice, it heavily depends on the user's experience to choose the number of neurons and the number of hidden layers. ANNs with a simple structure generally don't have enough modeling ability, while those having a complex structure will often over-fit the problem. NSET is a non-parametric modeling method and does not need a pre-determined structure. Good construction of the memory matrix alone will ensure satisfactory modeling accuracy. The modeling abilities for these two contrasting methods have been compared for a particular application [12], and confirm the comments above.

When NSET is used for wind turbine condition monitoring, the operational time span covered by NSET model (*i.e.*, from which the memory matrix is selected) should be carefully considered. The

ambient temperature and wind speed distribution can be quite different according to the time of year, and this is certainly true of wind turbine studied here, which is located in Zhangjiakou, north of Beijing where there are pronounced seasonal variations. Such meteorological parameters have a significant influence on the operation of wind turbine components. In order to achieve satisfactory model accuracy, the time span covered by the NSET model should not be too long, and ideally should be constrained to be within a particular season. This does mean that an NSET model would have to be constructed for each season, and although this adds to the effort required, the task should not be onerous once the procedures for model construction are in place. A related issue is whether the memory matrix should be renewed to reflect new operation conditions for wind turbine. It is attractive to add to the memory matrix new vectors representing more extreme external conditions than might have been available when the matrix was first formed, but care must be taken to ensure that the wind turbine is still operating normally. The danger is that faulted operation is incorporated into the matrix, making it then less likely to identify future faults as anomalies. These difficulties concerning renewal or amendment of the memory matrix relate to whether we can distinguish an observation vector representing a normal operating condition from one associated with a fault. The former could be added to the memory matrix while the later should be rejected. Principal Components Analysis (PCA) could perhaps be used to distinguish these two categories of observation vectors.

### 3. Wind Turbine SCADA Data Preparations and Tower Vibration Analysis

The machine studied in this paper is a GE model 1.5S LE 1.5 MW-rated variable pitch, variable speed wind turbine, located in Zhangjiakou, northwest of Beijing. The cut-in and rated wind speeds for wind turbine are 3 m/s and 12 m/s, respectively. The SCADA system records all wind turbine parameters every 10 min. This 10-minute resolution data is a time-averaged value. Each record includes a time stamp, power, wind speed, blade angle, tower and drive train vibration amongst many others. The accelerometer for measuring tower vibration is mounted at the top of tower, where it meets the nacelle. The accelerometer for drive train vibration (DTV) is mounted on the high-speed shaft bearing. 10-minute SCADA data from the wind turbine from March to April 2006 was used, and there were 8784 10-minute records, covering a period of 61 days. Data quality was good and there were no missing records during this period.

For a large-scale wind turbine, there are several different operational regimes reflecting different wind speed ranges. When the wind speed is between cut-in and rated ones, the wind turbine runs in a Maximum Power Point Tracking (MPPT) regime. In this regime, the blade angle is usually fixed (at around two degrees depending on the blade design) and the rotational speed for rotor is controlled to be proportional to wind speed in order to maintain operation at  $C_{pmax}$  and thus maximize energy capture. When the wind speed is above the rated wind speed, the wind turbine is controlled to operate at a fixed (rated) power output regime. In this control regime, the power is limited electronically through the variable speed drive converter to rated power, while at the same time the wind turbine's aerodynamic power is kept constant on average by adjusting the blade angle to limit the rotor speed within an acceptable range. In these two operating regimes, the tower vibration signals recorded by the SCADA are of course quite different. Figure 1 shows trends of tower vibration and related variables from 25/03/2006 to 29/03/2006. Figure 2 shows trends from 17/04/2006 to 22/04/2006. The physical units used for tower vibration and related variables are shown in Table 1.

Figure 1. Trends for tower vibration and related variables with below rated wind speed.

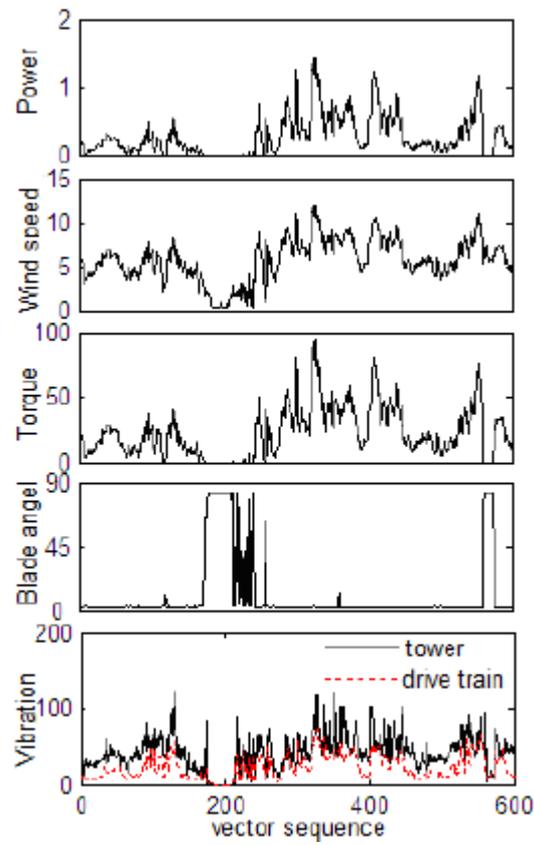
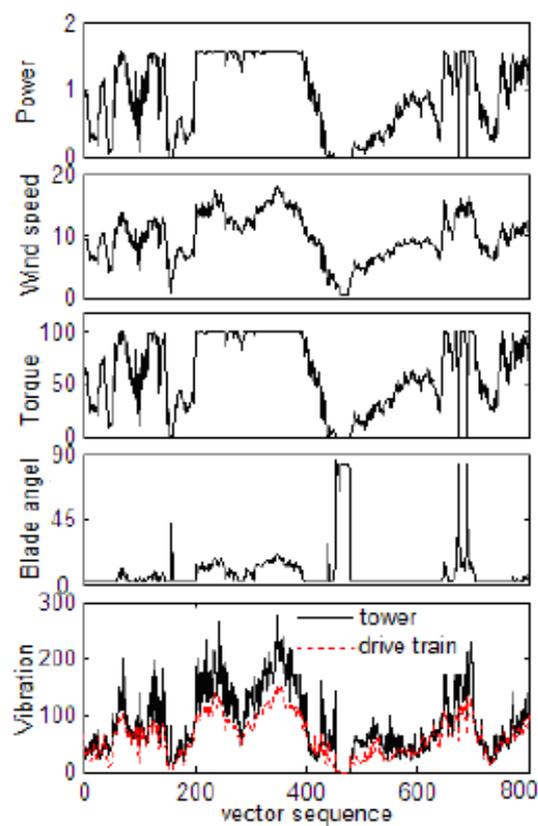


Figure 2. Trends for tower vibration and related variables with some operations above the rated values.



**Table 1.** Physical units for SCADA variables.

Variable name	Physical unit	Notice
Tower vibration	mm/s <sup>2</sup>	Bandwidth: 0–200 Hz
Drive train vibration	mm/s <sup>2</sup>	Bandwidth: 3–20 kHz
Power	MW	Rated: 1.5 MW
Wind speed	m/s	Rated: 12 m/s
Torque	%	Rated: 880 kNm
Blade angle	degree	Below rated: 2

### 3.1. Tower Vibration Analysis below the Rated Wind Speed

Below rated wind speed, the pitch angle of this GE turbine is fixed at 2 degrees. From Figure 1, we can find that the following variables have a great influence on tower vibration magnitude.

- A. *Wind speed.* Wind speed is stochastic and produces time varying forces and loads on the rotor. Most relevant to this analysis are the torque and thrust, both approximately proportional to wind speed squared below rated. Even below rated, the higher the wind speed the larger magnitude tower vibration, as shown in Figure 1. This is because the amplitude of thrust variation increases with wind speed, and wind speed standard deviation also increases with wind speed, assuming roughly constant turbulence intensity.
- B. *Torque and power.* At  $C_{pmax}$  regime, torque will increase approximately with wind speed squared as indicated above, output power with wind speed cubed. Torque and power reflect how hard the wind turbine works. The higher torque and power is, the higher the rotating speeds for rotor and drive train become that will lead to increased tower vibration.
- C. *Drive train vibration.* Drive train for wind turbine includes main bearing, gearbox, and generator bearing. Because the drive train is located in the nacelle, vibration of the drive train will be transmitted to the supporting structure, in this case through the yaw bearing to the tower and will directly influence tower vibration.

In Figure 1, at point 175 (27/03/2006 02:14:05 AM), the wind turbine went through an emergency shut down and the blade pitched from 2 degrees to 90 degrees to provide aerodynamic braking of the rotor as is normal for such an emergency stop (in this case, a remote manual stop). During such an event the aerodynamic forces on the rotor reverse over a very short period of time (typically less than 10 s) as it moves from turbine mode to propeller mode. This results in a large impulse force on the tower.

### 3.2. Tower Vibration Analysis above the Rated Wind Speed

Regarding Figure 2, we are interested in the period when the wind speed is above the rated value, that is, from points 199 to 400. During this period, the wind turbine is operating at constant power output regime. From Figure 2, we can see that the blade angle is regulating in accord with the wind speed. In this operating regime, the tower vibration is closely related to the following variables:

- A. *Blade angle.* When the wind speed is above rated, the blade pitch for the GE model 1.5SLE is increased to regulate power. With an increase in blade pitch angle beyond the stall point, the aerodynamic lift coefficient blade decreases and the drag force coefficient increases rapidly. The

net effect is a significant increase in thrust and this result in increased tower deflection and vibration amplitudes.

B. *Wind speed.*

C. *Drive train vibration.*

The reasons for selecting wind speed and drive train vibration related to tower vibration are same as Section 3.1. In this operational regime, torque, output power, and rotational speed are approximately constant and thus have little influence on tower vibration.

A closer look at the magnitude of the difference between the tower vibration (TV) and drive train vibration (DTV) in Figure 2 reveals something interesting. This difference is relatively small when the blade angle is fixed, that is, when the wind turbine runs at  $C_{pmax}$  regime but the difference becomes considerable when the blade angle is changing, from data points 199 to 400, that is when the turbine is operating in the rated regime. The reason for this phenomenon lies with the main bearing characteristics. When the wind speed is low the thrust force on the rotor and tower is also small, and most of the load transmits to the drive train so that the vibration difference between them are small. In contrast, when the wind speed is high, the regulation of blade angle results in significant and rapid changes in thrust; this directly excites tower/rotor mode vibration. In this situation, the main bearing thrust ring structure, if suitably designed only a small part of the total load is transmitted to the drive train. As a result, the tower vibrates significantly while the drive train vibration remains similar to that approaching rated power.

From Figures 1 and 2, we can see that the variables that have greatest influence on tower vibration levels are quite different in the two distinct wind turbine operational regimes. And so the tower vibration model (TVM) should comprise two distinct sub-models corresponding to the two different turbine control regimes.

#### **4. Tower Vibration Modeling Using Nonlinear State Estimation Technique (NSET)**

The TVM is used to describe the complex relationship between tower vibration and the parameters that govern its behavior. In this paper, the TVM is constructed with use of the established Nonlinear State Estimation Technique (NSET) applied to SCADA data obtained when the wind turbine was working normally. This model can then be used as a reference to help detect incipient failure when contemporary data indicates a significant change in operational characteristics. NSET integrates the modeling variable (such as tower vibration) and its related variables (such as wind speed, power, torque, *etc.*) as a “related variable set”. And at a sampling time, variables in the “related variable set” make an observation vector. After the TVM is constructed with NSET, by giving a new observation vector, the TVM NSET model can make a prediction for the tower vibration. The residual being the difference between the prediction and actual value for the tower vibration will reflect the deviation between the new input vector and the normal TVM. The magnitude and characteristics of the residual can be used to identify possible incipient failure for components such as the wind turbine rotor.

##### *4.1. Tower Vibration Modeling with NSET Method*

Following the above section, the key steps for vibration modeling with NSET are in sequence: selection of the relevant variables to make up the observation vector and construct the memory matrix

$D$  using the SCADA data obtained from the wind turbine during periods of normal (healthy) operation. Historic data as shown in Figures 1 and 2 are used to validate the TVM. SCADA data from March to April but excluding these two sets used for validation, written as data set  $M$ , are used to model the tower vibration. As mentioned before, tower vibration has different influential variables in different operating regimes. Therefore, data set  $M$  is divided into two subsets  $M_1$  and  $M_2$ .  $M_1$  includes the records which wind speed is between cut-in and rated wind speed, while records in  $M_2$  are those which wind speed is between rated and cut out wind speed.  $M_1$  and  $M_2$  are used respectively to construct the sub-models for below and above the rated operation.

#### TVM for Wind Speed Below the Rated (Sub-Model A)

With the analysis in Section 3.1, the observation vector for regime below rated is made up from variables with the greatest influence on tower vibration, including the tower vibration parameter itself. It is perfectly acceptable in a NSET model to include the desired model output parameter such as tower vibration itself in the observation vector which is shown as Table 2.

**Table 2.** Observation vector below rated wind speed.

<b>Working condition</b>	<b>Variables in the observation vector</b>
below the rated (MPPT regime)	wind speed, torque, power, drive train vibration, tower vibration

For each record in subset  $M_1$ , the variables in Table 2 are selected to make up the historical observation vector. In total, the number of the historical observation vector available in  $M_1$  is 5369. The second and critical step for NSET modeling is to selecting  $d_1$  (usually about several hundreds) representative historical observation vectors from the vectors available so as to form the memory matrix  $D_1$ . [12] has reported a systematic memory matrix construction method.

#### TVM for Wind Speed above the Rated (Sub-model B)

Following the analysis in Section 3.2, observation vectors above rated take to include the following variables (Table 3).

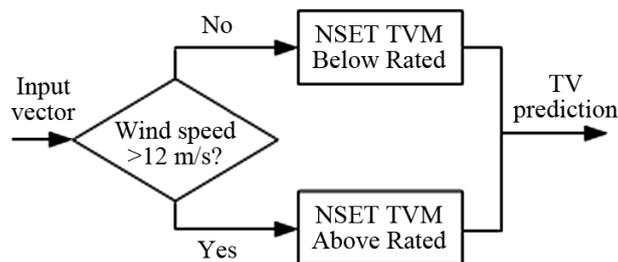
**Table 3.** Observation vector above rated wind speed.

<b>Working condition</b>	<b>Variables in the observation vector</b>
above the rated (output leveling regime)	wind speed, blade angle, drive train vibration, tower vibration

One thousand forty seven (1047) historical observation vectors above the rated wind speed are available in  $M_2$ . With the same constructing method used before,  $d_2$  historical observation vectors are selected to form the memory matrix  $D_2$ .

After the construction of memory matrices  $D_1$  and  $D_2$ , one or other of the two sub-models can be used to provide a prediction for any new input observation vector. In this paper, because we are only interested in the prediction for tower vibration alone, Equation (14) will be used to give the prediction result. Figure 3 shows how these two sub-models work together to give a prediction for tower vibration.

**Figure 3.** NSET modeling and prediction for tower vibration.



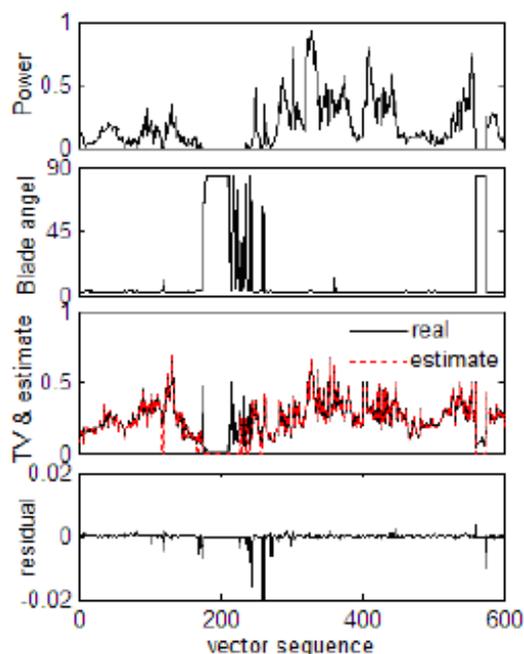
4.2. Validation for the NSET Tower Vibration Models

Using the memory construction method as outlined in [12], the memory matrix  $D_1$  is formed of 432 vectors, and  $D_2$  has 261 vectors.

Validation Case 1:

The 600 records shown in Figure 1 are used to validate the TVM. During this period, wind speed is below the rated and only sub-model A is required for prediction of the tower vibration. Note that when the turbine is shuts down, the TVM cannot function and the prediction is thus zero. The validation result is shown in Figure 4. Note that in this figure, the pitch angle is shown in natural units (degrees) for ease of interpretation, rather than the scaled value between 0 and 1 for other parameters.

**Figure 4.** Validation for sub-model A.

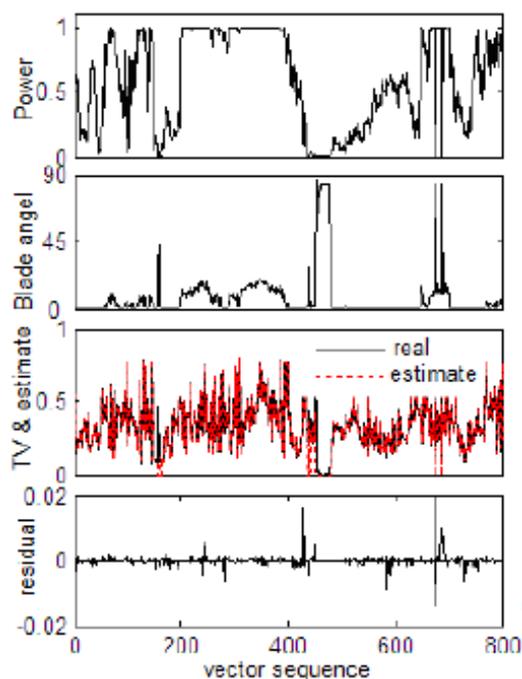


From Figure 4, we can see that when the wind turbine shuts down or starts up, the blade angle will pitch to the 90 or 2 degree setting (such as at points 175, 243, 260, 562, and 575). Because the blade pitches very quickly, the corresponding large change in aerodynamic loads result in abnormally large vibration magnitudes and large NSET model residuals. After removing these above points, sub-model A has a good prediction for tower vibration.

## Validation Case 2:

The 800 records shown in Figure 2 are used to validate the TVM for above rated operation. The records of this period cover wind speed both below and above the rated. Sub-models A and B work together to give the prediction for tower vibration according to the logic of Figure 3. Validation is shown in Figure 5. After removing the isolated large residuals caused by wind turbine shut downs and starts ups (such as at points 427, 674 and 688), the combination of these two sub-models demonstrates satisfactory modeling accuracy.

**Figure 5.** Validation for sub-model B.



## 5. TVM Used for Rotor Condition Monitoring

The analysis of Section 3 above shows that the rotor aerodynamic characteristics have a significant impact on tower vibration. Incipient rotor failure might be expected to lead to abnormal rotor aerodynamics and these changes could be detected through close monitoring and analysis of tower vibration. The TVM captures essential aspects of the relationship between the tower vibration and the key turbine parameters during normal healthy operation. When changes indicative of incipient failure of rotor occur, this normal relationship between the variables in the observation vector will change and deviate from the TVM. As a result, the TVM will no longer give an accurate prediction of tower vibration; the residual between the NSET model prediction and the measured values will become significant. Standard hypothesis testing [13], can be used to determine whether the differences are statically significant.

Blade angle asymmetry is a common kind of rotor fault and can lead to unacceptable fatigue damage. When this fault occurs, the blade angles for the three blades become different from each other leading to asymmetry of aerodynamic loading. If wind turbine runs in this way for extended periods, the unwanted asymmetric loads can cause serious damage to the drive train and even the supporting structure. Blade angle asymmetry could be detectable using the TVM developed in Section 4.

## Blade Angle Asymmetry Detection

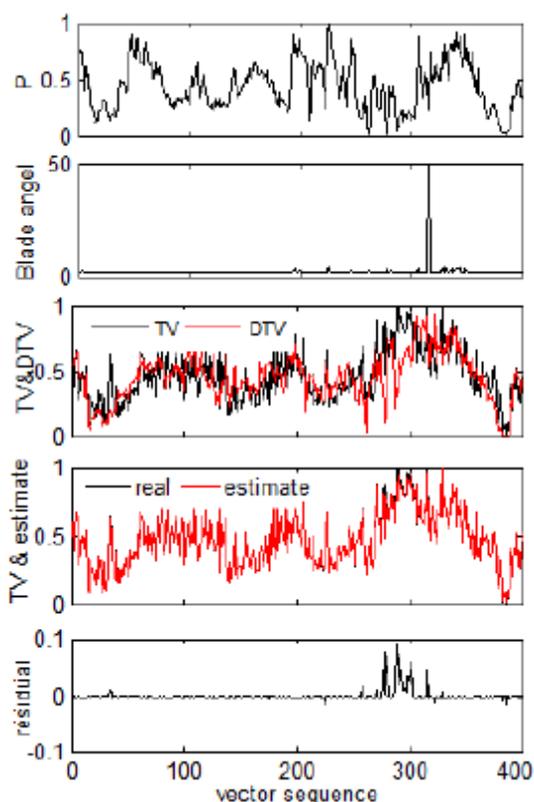
For the wind turbine studied here, at 10:51 on 01/04/2006, the turbine underwent an emergency shut down due to excessive blade angle asymmetry. Information regarding this shutdown was recorded by the SCADA system and is shown in Table 4.

**Table 4.** Failure data.

Wind turbine ID	Date	Time	Failure code	Failure Text
15401801	01/04/2006	10:51:57	144	Blade angle asymmetry
15401801	01/04/2006	10:51:57	184	Shut down

We select 400 records around this failure as input vectors for the TVM constructed in Section 4 (starting 316 data points prior to shutdown). The trend for tower vibration residuals and trends for other related variables are shown in Figure 6.

**Figure 6.** Trends for blade angle asymmetry.



The failure mentioned above occurred at point 316, and the blade angle pitched to 90 degrees as part of the emergency stop. In the trends for tower vibration and drive train vibration, the difference between these two are small before point 275. But after point 275, the tower vibration was much higher than before and the difference between the two was sharply increased. This abnormal change in the relationship between these variables is detected in a timely manner by the TVM and the residuals change in a statistically way after this point. With proper setting of the alarm threshold value or using moving window method as in [12], the rotor failure such as blade angle asymmetry can be robustly detected before serious damage is caused to the wind turbine. How to set the threshold for failure

detection is not the purpose for this paper and readers can refer to papers [12,13] for more details on threshold determination. Using the moving window method, this blade angle asymmetry was detected at point 279, well ahead the wind turbine shut down at 316.

## 6. Discussion and Conclusions

This paper has characterized wind turbine tower vibration, both below and above the rated wind speed. The NSET method has been used to model the dependence of the tower vibration on the most influential parameters under normal operational conditions. The derived tower vibration model has been used to detect one specific kind of rotor fault: blade angle asymmetry. The following conclusions can be drawn:

- (1) For wind turbine condition monitoring, it can be misleading to analyze the vibration signal alone. Because of the strong impact of wind on a turbine and the coupling amongst the different wind turbine components and vibrational modes, vibration analysis must take other related factors into account to give a more accurate representation of the turbine so as to be useful for condition monitoring and diagnostics. For example, it is essential when analyzing a wind turbine rotor, to take both wind speed and rotational speed into account.
- (2) The results presented have demonstrated that tower vibration must be analyzed in the context of the rotor and its different operational regimes. Since the aerodynamic forces acting on the rotor are very sensitive to the blade angle, blade angle asymmetries will lead to significant differences in the thrust on individual blades. The unbalanced thrust force on the rotor will excite the supporting tower structure and cause the tower's behavior and vibration to deviate from the normal operational condition. Therefore, monitoring the tower vibration provides a useful method for detecting rotor aerodynamic asymmetries caused for example by poor blade pitch adjustment or blade pitch control faults. NSET has been shown to be an effective technique to model the relationship between tower and rotor dynamics. The NSET tower vibration model (TVM) is able to accurately represent the relationship between rotor loads and tower vibration and thus to detect incipient rotor faults (in this case blade asymmetry) in a timely manner. Admittedly only one example of successful fault identification has been presented in this study, and this cannot prove that all such faults would be identified in a timely and thus useful manner. Access to much larger data sets is required in order to provide a statically significant sample of faults for detection, and this is work in progress. Nevertheless, the methodology presented here is underpinned by an engineering knowledge of the turbine and how it is operated, and this together with the successful fault identification allows the conclusion that the technique has promise and merits further development. It is also worth noting that blade pitch asymmetry is not the only means by which off axis aerodynamic loads could be generated that could be seen as abnormal, in contrast to wind shear which is of course to be expected. Other conditions that would create abnormal off axis loads could include poor yaw control, damage to individual blades, and blade icing. All of these faults should in principal be detectable using the methodology presented here, and will be the subject of future research.

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