Fault tolerant wind turbine production operation and shutdown(Sustainable Control)

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Abstract

Extreme environmental conditions as well as system failure are real-life phenomena. Especially offshore, extreme environmental conditions and system faults are to be dealt with in an effective way. The project Sustainable Control, a new approach to operate wind turbines (Agentschap NL, grant EOSLT02013) provides the concepts for an integrated control platform. This platform accomplishes fault tolerant control in regular and extreme conditions during production operation and shutdown.

The platform is built up from methods for the detection of extreme conditions and faults and from methods for operation and shut-down. The detection methods are largely model-based, which implies that event detection is derived from anomalous behaviour of outcomes from an observer, which can be an Kalman fiter. Various types of control approaches are included in the control methods. Often, more scalar feedback loops work together, the validity of which is motivated through frequency separation or orhogonality.

The detection and handling of extreme conditions and sensor failures elongates the operation. The application of optimizing techniques during production operation and during shut down can reduce the loads on the turbine significantly. A proof of principle on a multi MW wind turbine for optimzied production operation showed a typical reduction of fatigue damage equivalent loads between 10% and 30%.

Keywords: fault detection, gust detection, individual pitch control, fault tolerance, NMPC, optimal shutdown control.

1 Introduction

Nowadays, control has been well established as a driver for cost reduction of wind energy conversion. Usually, the associated control algorithms relate to production operation in stationary turbulent conditions without any deteriorated wind turbine behaviour (regular conditions). Unfortunately, extreme environmental conditions as well as system failure are real-life phenomena. Especially offshore, the need arises to deal in an effective way with [short-tem] extreme environmental conditions and with minor or more severe types of system failure. With this in mind, the project *Sustainable Control, a new approach to operate wind turbine* is being performed under grant EOSLT02013 of Agentschap NL (2006-2011). This project includes the development and integration of cornerstones that relate to control in four types of conditions:

- Optimised Feedback Control, for load reduction by advanced control methods when operation is in regular conditions;
- Fault Tolerant Control, for avoidance of standstill by controller reconfiguration in case of minor system failure;
- Extreme Event Control, for avoidance of high loads and shut-down under extreme conditions;
- Optimal Shut-down Control, for avoidance of unnecessary high loads and serial damage after serious system failure.

Figure 1 shows a functional layout of Sustainable Con-

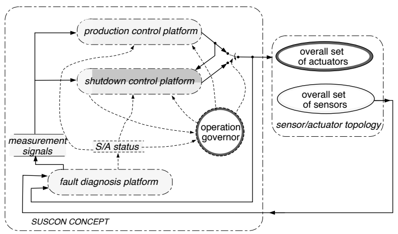

Figure 1: *Functional layout Sustainable Control*

trol. It includes platforms for production control, shutdown control and fault diagnosis. The dashed lines represent signals that govern the operation. The production and shutdown control platforms include monitoring and control methods; the fault diagnosis platform only monitoring methods. Sustainable Control is achieved by synchronized alternate operation of the methods: a combination of active methods on the platform relates to one of the listed cornerstones.

It is clear that this approach basicly differs from current isolated production and supervisory control.

The subsequent sections of this paper describe the different types of methods and the switching mechanisms, give a survey of conceived monitoring and control methods, address typicalities that relate to implementation, and show experimental and simulation results.

2 Sustainable control

Figure 2 gives a more detailed view on the functional layout, in which a symbiosis of fault diagnosis, production control and shutdown control is pursued.

Assume that currently no severe failure has occurred and that no extreme condition applies that requires immediate shut-down (hyper extreme condition). The wind turbine will then run in production operation. The main arbiter, that is to say the *operation governor*, will retransmit the control signals from the production platform to the actuators. Further, the shutdown platform receives the current control signal values in order to tune its internal condition for smooth 'take-over' when required.

All the time, the shutdown platform's unit for detection of hyper extreme conditions will be active. Their detection is signaled to the operation governer. It wil react by retransmitting the control signals from the shutdown platform instead of the production platform.

The subequent subsections describe the internal working mechanism of the platforms for fault diagnosis and control. This includes the functionality of the methods that are part of the platforms. The working of the methods itself is explained in the next section.

2.1 Fault diagnosis platform

Sensor and actuator faults are identified with model-based fault detection and isolation (FDI) methods. The detection is based on the residues from Kalman filters. These filters are arranged such that the behaviour of the residues in regular conditions can be distinghuised from that in faulty conditions. The sensor/actuator governor translates a fault into the status of the sensor/actuator topology. This status is read out by the operation governer and the control platforms through the S/A-status flag. In case of a non-severe failure, the operation governer will take no action. However, the production assembly governer may reconfigure the active extreme detection method and or control methods as well as the retransmission of measurement signals.

A non-severe failure can be the drop-out of a redundant blade root moment sensor, or even the drop-out of a non-redundant blade root moment sensor. In the first case, only the retransmission of measurement signals is adapted; in the second case, the detection of extreme production conditions will no more be based on all blade root moments, and individual pitch control will be excluded from production control or based on other measurement signals.

Severe failures concern strongly deteriorated functioning of pitch and yaw actuators, grid drop-out and combinations of sensor faults. In that case, the operation governer will signal to the shutdown platform to take over the control. The shutdown assembly manager in turn will reconfigure the shutdown control methods for appropriate use of control signals.

2.2 Production control platform

The production assembly governor combines methods for detection of extreme events and production control as allowed by the current status of the sensor/actuator topology. Extreme events are detected from the outputs of Kalman filters that are arranged for this purpose.

Optimal production control includes collective pitch angle adjustment and generator torque setting. The control actions result from a trade-off between objectives for rotor speed regulation, optimal energy yield and damping of drive-train torsion and tower bending. Further, optimal production is pursued through cyclo-stochastic individual pitch control (IPC). This IPC is centered around one and two times the rotational frequency (1p, 2p). It reduces the loads on the blades around these frequencies as well as the loads on the nacelle and tower around $3p$ and in very low frequencies. In addition, very low-frequent IPC is added for the sake of aerodynamic rotor balancing. A prioritisation algorithm divides available actuator capacity over collective and individual pitch control.

As long as the optimal production control unit applies, its internal condition is messaged to the unit for extreme production. The latter unit becomes active after the detection of an extreme event that still allows continuation of production operation. As from now, a completely different trade-off between control objectives will apply: extreme production control will focus on rotor speed limitation and reduction of extreme loads; energy yield and fatigue related damping are of minor importance. Further, the unit for extreme production control now messages its internal condition to the unit for optimal production control. This enables a smooth switch-back after the extreme conditions have ceased.

2.3 Shutdown control platform

The shutdown assembly governor combines methods for detection of hyper extreme events and shut down control as allowed by the current status of the sensor/actuator topology. Events that require shut down control are detected from gross values of direct measurement signals, the current status of sensors and actuators, and the residues of Kalman filters arranged

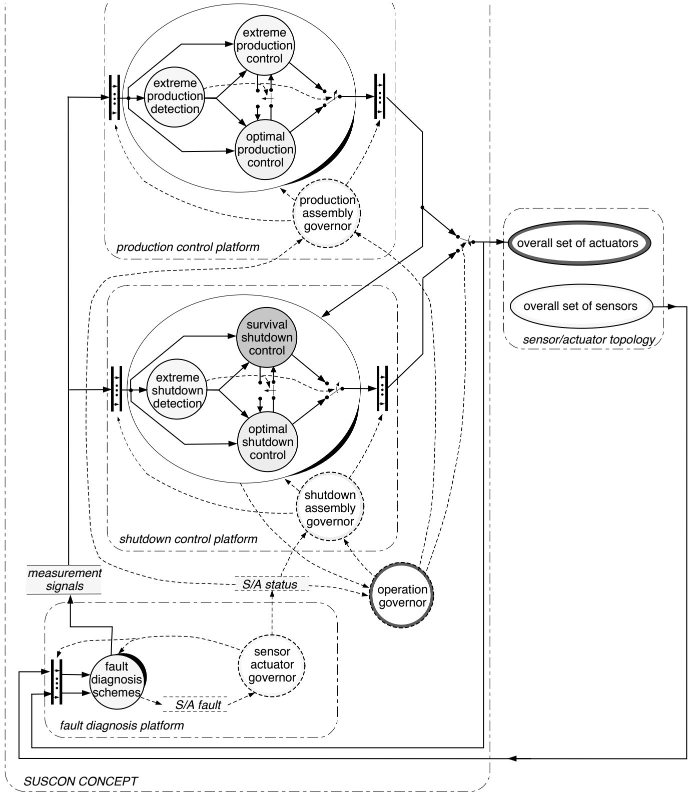

Figure 2: *Functional layout Sustainable Control (details)*

for the detection of extreme (external) conditions.

Assume for instance that one actuator stucks while no other failure or extreme external conditions occurs. This is a severe failure that requires immediate turbine shut-down. Because of the remaining 'mild' conditions, the shutdown can be optimized despite of asymmetric rotor loading. The latter follows from the unbalanced aeroydanamic pitch setting. The two valid pitch actuators and generator torque can be used such that smooth rotor deceleration is achieved while the effect on the tower by the asymmetric rotor loading is minimised. Even if also generator drop-out applies, this is still possible. For instance, non-linear model predictive control facilitates this.

Another severe failure could be 'free yawing' caused by free running yaw motor rotors. Under remaining mild conditions, this can also be processed through optimized turbine shut-down. Cyclic pitch angle adjusment allows for the generation of an aerodynamic yawing moment. An aerodynamic yaw servo system can be established on that principle. This allows for good yaw alignment in the first phase of turbine shutdown and steadily yawing out of the wind in the second phase.

During optimized tubine shutdown, the unit for survival shut-down will receive the belonging internal status. If for instance an extreme wind gust coincides with one stucking pitch actuator, it will be usually desired to shut-down the wind turbine as fast as possible. As from now, survival shut-down control will take-over optimal shut-down control. Again, the ceasing of the extreme condition could allow for optimized turbine shutdown. For this reason, the survival shutdown unit messages its condition to the optimal shutdown unit. Be aware that a 'moderate gust' from say 10 to 15 m/s may induce survival shutdown in case of large asymmetric rotor loading by actuator stuck.

3 Fault diagnosis

Sensor and actuator faults are identified with model based fault detection and isolation (FDI) methods as developed in SUSCON at TU Delft. Specifically, TU Delft developed algorithms for Generalized Maximum Likelihood Ratio Tests (GLRT) and mixed H_∞/H_- index observers for FDI in blade moment sensors and pitch and yaw actuators [1], [2].

The point of departure is that both sensor faults and actuator faults can be detected from so called 'prediction errors' in the measurement signals, which are called the residues ($\underline{r}$). The residues are obtained as the difference between measurent values $\underline{y}(n)$ on a certain time instance n and the according prediction $\underline{\hat{y}}(n)$. The predicted, or estimated measurements $\underline{\hat{y}}(n)$ are based on measurement and control signal values up to time instance $n-1$ through a so called 'observer'. This observer estimates the state vector $\underline{\hat{x}}(n)$ of the wind turbine model. The general format of the observer scheme is as follows:

$$\begin{aligned} \underline{\hat{x}}(n+1) &= A\,\underline{x}(n) + B\,\underline{u}(n) + L\,(\underline{y}(n) - \underline{\hat{y}}(n)) \\ \underline{\hat{y}}(n) &= C\,\underline{\hat{x}}(n) + D\,\underline{u}(n) \end{aligned} \tag{1}$$

with $\underline{u}$ the control signal [vector]. The residue is then simply obtained as

$$\underline{r}(n) = \underline{y}(n) - \underline{\hat{y}}(n) \tag{2}$$

Be aware that it is assumed that the true dynamic state $\underline{x}(n)$ of the wind turbine and the measurement signals $\underline{y}_{\text{valid}}$ in failue-free conditions evolve as per the following state space model:

$$\begin{aligned} \underline{x}(n+1) &= A\,\underline{x}(n) + B\,\underline{u}(n) + B_{\text{d}}\,\underline{d}(n) \\ \underline{y}_{\text{valid}}(n) &= C\,\underline{x}(n) + D\,\underline{u}(n) + D_{\text{d}}\,\underline{d}(n) \end{aligned} \tag{3}$$

with $\underline{d}$ the disturbance signal [vector], which is dominated by wind speed variatons We thus assume that the fault-relevant dynamic behaviour of the wind turbine is represented by this linear dynamic model. Of course, the model parameters will vary in time because of changing working conditions. However, an invariant linear model is supposed to be a fairly good approximation of reality on time scales of seconds to tens of seconds.

The measurements $\underline{y}$ will deviate from the failure-free measurements $\underline{y}_{\text{valid}}$ by the direct effect of sensor failure but also by the indirect effect of actuator failure. This will cause a deviating behaviour of the estimations $\underline{\hat{y}}$ and so also of the residues $\underline{r}$.

Likelihood ratio test for residues
When we focus on detection of failures of blade root flap moment sensors, the measurement vector y in the above mentioned model and related observer needs only to contain blade root flap moment sensors. Then, the wind speed variations that dominate the disturbance signal $\underline{d}$ can be modeled as blade (root) effective wind speed signals; one or two per blade. If only axial wind sped variations are taken into account, then only one wind speed signal per blade applies. A power spectrum matrix formulation for these blade effective wind speed signals is given in [5]. The existence of such a power spectrum matrix allows for the deriavation of a linear state space model (wind model) that generates the wind speeds in $\underline{d}$ from completely uncorrelated Gaussian distributed noise $\underline{e}$ (white noise):

$$\begin{aligned} \underline{x}_{\text{w}}(n+1) &= A_{\text{w}}\,\underline{x}_{\text{w}}(n) + B_{\text{w}}\,\underline{e}(n) \\ \underline{d}(n) &= C_{\text{w}}\,\underline{x}_{\text{w}}(n) + \underline{e}(n) \end{aligned} \tag{4}$$

It is clear that we can add this wind model to the above wind turbine model formulation by Eq 3. This yields a so called augmented model. From this model, we can derive an observer as per Eq 1 which now directly relates to (three) Gaussian white noise sources $\underline{e}$. This is typed as a Kalman filter in innovation form (innovation filter).

In failure-free conditions, the innovation filter yields residues $\underline{r}(n)$ that are equal to the Gaussian white noise values $\underline{e}(n)$. In case of sensor failure, the residues will definitely deviate from $\underline{e}(n)$. If the sensor value suddenly drops to zero, the evolution of the residue in addition to its 'failure-free value' $\underline{e}$ can be approximated by the output of a state space model that is driven by a fault with a given amplitude A. This the so called failure signature model.

Because $\underline{e}$ is Gaussian white noise, it is possible to derive probality density functions of the residue in case of a sensor fault and the failure-free case. In particular, the both *joined* probability density functions can be derived in a straightforward way over a window that preceeds the current time instance n. Further, their *ratio* can be *maximized* over the fault amplitude A.

The resulting *Generalized Maximum Likelihood Ratio* (GLR) will grow very rapidly after a sensor fault. A threshold test is made for detection (GLRT). It appears that very fast detection is enabled; specifically, ca 1 second for blade root sensor failure. It is clear that GLRTS for assumed potential failure of all relevant sensors are to be performed. A detailed treatment is given in [2]. The on-line determination of GLRTs over a moving time window may become quite a computational burden.

Effectively, an involved GLRT agrees with a threshold test for the ratio between the auto-correlation of the residues and its cross-correlations with assumed normalized sensor failure. These correlations are determined over a relatively short moving time window.

Threshold values for residues
As an alternative to the likelihood ratio approach, H_∞/H_- index observers have been developed for fast sensor and actuator fault detection of yaw motor failure [1], [3]. The advantage of this approach is that only on-line evaluation of the observer scheme by Eq.

1 is required. This observer approach was applied for yaw motor failure detection in [4].

In the H_∞/H_- index approach, it is pursued to compute the observer 'feedback matrix' L in such a way that the disturbances $\underline{d}$ (mainly wind) and yaw motor fault f *effectively* influence the residue $\underline{r}$ through a pair of complementary filters such that:

- the one filter will respond up to a certain maximum on any normalized disturbance in failure-free conditions ('valid-maximum' γ);
- the other filter will respond not lower than a certain minimum in case of the normalized failure condition ('failure-minimum'β).

The measurable residue $\underline{r}$ can thus be considered as the sum of the outputs of both filters.

It is clear that we can detect a failure in a straightforward way if we succeed to design this filter pair such that the

> product of the maximum occurring excitation size and the valid-maximum γ (H_∞-index)

is lower than the

> product of the minimum occuring fault size and the failure-minimum β (H_- index).

Of course, the chance that such a filter pair exists is lower when the 'natural motion' in the measurement signals is strong. Unfortunately, this is the case for wind turbines because of the variations in the wind speed. Further, the computation of these filters is very cumbersome although it can be performed offline. The numerical procedure involves three linear matrix inequalities that are to be simulatenously satisfied, of which two relate to β and γ while the third guarantees the stability of the filters. As a consequence, acceptable computational effort is only achieved when the number of first order differential equations of the wind turbine model amounts to ca. 8 or lower.

As an alternative, it can be tried whether the use of only the first filter, which responds below or up to the H_∞ index at normalized excitation, would suffice for failure detection. This was done for the detection of yaw motor error and appeared very successful. The sensitivity of the residues to 'missing yawing actions', which should be performed due to yaw moment excitation from turbulence, appeared very high. This allowed for the definition of a clear threshold: residues from turbulence in failure-free conditions are amply below the threshold while they almost instantaneously grow very strong in case of yaw motor failure.

Figure 3 shows the 'residue-outcome' of the H_∞ algorithm in a simulation for yaw motor failure from 80 s, with an IEC extreme wind direction change (45degr) between 50s and 55s. The residue responds significantly stronger on yaw failure than on direction change.

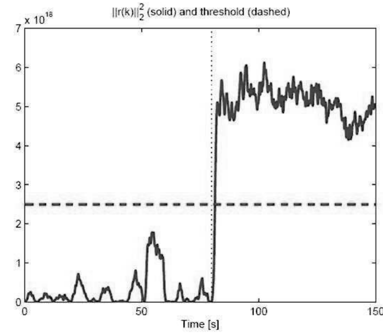

Figure 3: *Yaw motor failure detection by a H_∞ observer*

4 Production control

4.1 Extreme condition detection

Extreme conditions are detected from wind speed estimates or residues of a Kalman filter. The Kalman filter is derived from an augmented turbine model model with 'wind dynamics', similar to that for fault detection in the previous section. ECN developed detection algorithms that are based on the cumulated sum of the wind speed estimates or on generalized maximum likelihood ratio tests (GLRTs) for the residues. Detailed descriptions are in [6]and [7].

CUSUM tests for wind speed estimates
Let a uniform rotor coherent wind condition variation be typed as 'regular gust'. A regular gust is primarily observable as a fast, simultaneous change of the blade effective wind speeds. The gust detection method in [6]directly relates to this fast simultaneous change through a cumulated sum (CUSUM).

The used *extended* Kalman filter has parameters that depend on the rotor azimut position. It estimates instantaneous values of the blade wind speeds and the wind direction angle from measurements of the flapwise and leadwise blade root moments. For this purpose, the disturbance model includes three state variables for the blade wind speed and one for the wind direction (general form by Eq 4).

Figure 4 shows the simulated 'input' blade effective wind speeds and wind direction (blue/black) and the related estimations (red/grey) for a combined extreme gust and wind direction change.

The CUSUM based detection of gust occurrence exists in the exceedence of a threshold h by the CUSUM measure ϵ, which

- is mainly the time-integral of $\hat{u}-u$, the difference between the instantaneous and moving average values of the wind speed estimates;

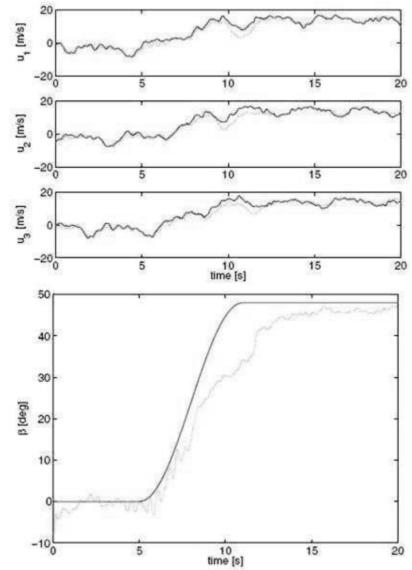

Figure 4: *Wind speed and direction at 15m/s gust and 48^o direction change (red/grey: estimations*

- is smoothly pulled down to zero with constant rate of change ν.

Proper choices of threshold h, moving average window size k_0 and recovering speed ν allow for a good speed/accuracy trade-off: no false alarms; gust detection before any significant rotor speed increase.

Likelihood ratio tests for residues
Likelihood ratio tests can be performed for the residues $\underline{r}$. These tests allow for the identification of anomalous behaviour $\underline{r}$ that relates to gusts.

Say, an extreme wind speed or wind direction change occurs. The evolution of the residue $\underline{r}$ *in addition to* its 'gust-free value' $\underline{e}$ can then be approximated by the outputs of the turbine state space model by Eq 3 that is driven by an assumed related gust evolution with amplitude A. Of course, we measure the overall values of the residues.

The white, Gaussian character of $\underline{e}$ now allows to derive expressions for the joint probality density functions of the residue in case of the occurence of the assumed gust and in the gust-free case; the attribute 'joint' pertains to the simultaneous consideration of the time points in a fixed-length window of which the end point moves with the current time instance n. The ratio of these joint probability expressions can be analytically *maximized* over the fault amplitude A. The resulting *Geralized Maximum Likelihood Ratio* (GLR) will grow very rapidly during the occurrence of a gust *of which the normalized evolution is fed through in the probabality density function ratio.*

It is known that rotor uniform wind speed changes affect the thrust force and driving rotor torque while uniform wind direction changes affect the tilting rotor torque and horizontal force. So it is clear that residue analysis for different measurement signals is needed for different rotor coherent wind condition changes (gust classes). Six wind classes are distinghuised in [7]. Next to the uniform gust and change of wind direction, these include the fast change of a backing and veering wind, of a jet stream, of a partial wake condition, and of a sloping wind.

The total involved measurement signals are the thrust force and driving torque, the yawing rotor torque and vertical force, and the tilting torque and horizontal force. Alternatively, load measurements can be done in a rotating frame, as long as a non-singular relationship exists with the six rotor loads. Of course, it can be decided to detect gust from less classes. In that case the according rotor loads can be left out the detection algorithm. Note that the wind (disturbance) generating model as per Eq 4 is to match to the considered load signals.

For a certain gust class, it is of course allowed to perform a GLRT for more than one assumed evolution of the related normalized gust (gust class evolution prototype [GCP]). GCPs for a uniform gust can be a '1 minus cosine' evolution and a 'mexican hat'; details are in [7].

Figure 5 gives an example of GLRT based detection of a uniform gust that starts at time instance 120 s. The left hand boxes show the enveloping time frame

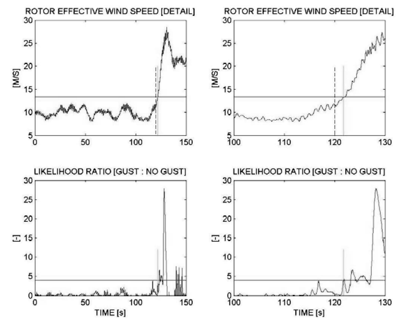

Figure 5: *Gust detection by likelihood ratio test*

whereas the right hand boxes show details around the start of the gust. The solid horizontal line in the lower plots identifies the detection threshold; the solid vertical line the time instance of detection. The upper right plot tells that detection occurs after a 'fast moving average' wind speed increase of ca. 1.5 to 2 m/s. The nearly exceedance of the detection threshold at 118 s proves the probability of 'over detection'. An other choice for the length of the moving window may release this ambiguity at the cost of a slightly later gust detection.

Effectively, an involved GLRT agrees with a threshold test for the ratio between the auto-correlation of the residues and its cross-correlations with assumed normalized extreme event evolution. These correlations are determined over a relatively short moving time window.

4.2 Optimal production operation

Optimal production operation is pursued through a combination of [extended] basic control and cyclo-stochastic individual pitch control; see e.g. [8], [9], [10]and [11], [12], [13]. This way of operation is supported by (i) fast adapting distribution of availabe actuator capacity over the different control functions, and (ii) slowly settling individual pitch angle additions for compensation of rotor unbalance; see e.g. [14], [16], [15]. Proof of principle experiments have been performed on an protoptype mulit-MW industrial wind turbine.

Basic control with extensions for damping
The conventional controller is typical and contains two loops: pitch control for generator speed regulation (active above-rated only) and generator torque control for power regulation (according to optimal-λ QN-curve below-rated, and constant power above-rated). Both loops act on the rotor speed, which is usually filtered with a (subset of a) series of a low-pass filter at the 3P frequency, a band-stop filter around the first tower sideward frequency $f_{\rm sd}$ and a band-stop filter at the first collective lead-lag frequency $f_{\rm ll}$. The pitch controller is a PI compensator in respect of the pitch *angle*, designed to achieve a gain margin of 0.5 or more and a phase margin of 45 degrees. Additions for dynamic inflow compensation and filtered wind speed estimation & feedfworard can apply.

The active damping can include the first torsional mode of the drive-train (if a gearbox is present), the foreaft tower bending mode and the sideward tower bending mode. The first and third damping options are accomplished through generator torque variations; the second one through collective pitch variation.

Within the SUSCON project experimental model verification has been performed through comparison of transfer function from adopted model descriptions and from identification experiments; the latter were obtained with well chosen test signals on the pitch angles and the generator torque. The experimentally obtained and the model-based results on a multi MW prototype wind turbine showed astonishing good agreement in relevant frequency ranges [17].

Multi-rotational mode IPC
Individual pitch control in integer multiples np of the rotational frequency (multi-rotational mode IPC) for 3 bladed wind turbines can be simply based on [P]I-feedback in transformed coordinates. These transformed coordinates are weighted sums of corresponding variables on the 3 blades, in which the weighting factor for the variable on a specific blade is a harmonic function in n times the azimut angle of the blade [12]. The multi-blade coordinates after an np-transformation directly relate to the $n^{\rm th}$ rotational mode of the wind. This implies that low-frequency regulation of an np-multi-blade coordinates agrees with reduction of blade loads around the np-frequency [18], [5]. Very recent developments prove that stacked linear time invariant model models can be applied for subsequent stability analysis when designing multi-rotational mode IPC.

Note that the 1p multi-blade harmonic load amplitude relates to the steady state and low-frequent yaw and tilt moments caused by shear, tower shadow and turbulence; the 2p amplitude relates to 3p-variations in the yaw and tilt moment. Besides, the very low frequent '0p' amplitude, which is caused by rotor unbalance, relates to low-frequent shaft bending moments and 1p yaw and tilt moment variations. A balancing concept that is insensitive to measurement offsets has been developed [15], [14].

A prioritisation algorithm divides available actuator capacity over collective and individual pitch control [14], [16]. Limits for IPC apply that arise from the spare actuation part left by prioritized collective pitching. The key property of the prioritisation algorihm exists in the limitation of the *multi-blade coordinates of planned cyclo-stochastic individual pitch control actions*. These multi-blade coordinate use to vary not too fast and correspond with the amplitude of the pitch actions around an np frequency. Further they give a very good impression of the desired division of IPC effort in tiltwise and in yawwise orientation. So the concept of limitation of the multi-blade pitch coordinates allows for

- well regarded division of spare pitch capacity with respect to reduction of yaw and tilt oriented loads;
- smooth limitation of IPC harmonics because only the allowed size of the amlitude will slowly vary and *not the instantenous pitch value*.

Similar reasoning with respect to desired pairs of multi-blade pitch coordinates that relate to different rotational modes and with respect to desired position range, speed and acceleration of the IPC actions, proves that the same concept of multi-blade pitch coordinate limitation can be applied repeatedly.

Figure 6 shows for six time spans normalized perpendicular shaft bending moments, derived from blade moment measurements on a multi-MW prototype wind turbine. The (blue) first, third and fifth 'bar'

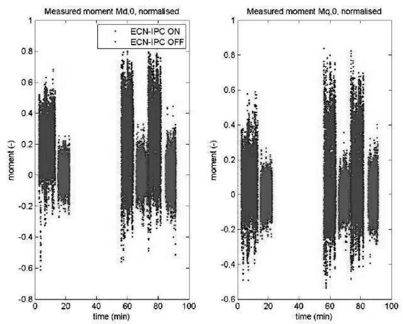

Figure 6: *Normalized equivalent shaft bending moment measurements on a multi-MW wind turbine*

represent measurements without IPC while IPC in 0p, 1p and 2p is included in the (red) 'bars' 2, 4 and 6. The 'bars' represent relatively fast signal variations; the (0p)-IPC zeroes the average values (rotor balancing) while the (1p,2p) -IPC significantly reduces the variations. Typically, reduction of the fatigue damage equivalent loads between 10% and 30% appeared from the measurements.

IPC reconfiguration at sensor failure
A common fear when IPC is applied pertains to the effect of a failing blade root moment sensor. Fast GLRT-based detection as discussed in Ch 3 guarantees that severe asymmetric blade loading will get no time to settle: IPC can be switched off only one or two seconds after the failure occurred; thereafter, pitch synchronisation is easy to establish.

However, detailed examinations of 1p IPC show that drop-out of one sensor has two direct effects, *the consequences of which are well manageable*:

- the low-frequent size of the multi-blade coordinates will be reduced by 33%;
- a large 1p component will enter in the multi-blade coordinates.

The reduced low-frequent size will only make the 1p load reduction 33% less effective. This can be compensated for by a higher feedback gain.

The large 1p component will be fed through as (steady state) offsets in two of the three pitch angle, which causes rotor unbalance. If rotor balancing is applied that can accomdate large offsets in the blade root moment sensor, then the mentioned unbalance will be compensated for. The method described in [15]can handle this.

The large 1p component will not be fed through as 2p-additions to the pitch angle variations because of the polar symmetry.

4.3 Extreme production operation

The Kalman filter for gust detection through CUSUM tests by [6]provides estimations of the instantaneous wind speeds and wind direction (§4.1). These estimations are linked to a dedicated algorithm for gust suppression and wind direction tracking. Once an extreme event is detected, the EEC algorithm (i) limits the rotor speed by fast collective pitching and maximal generator torque setting; and (ii) reduces 1p blade loads through IPC as soon as the rotor speed is sufficiently bounded.

Figure 7 shows the rotor speed and flapwsie blade root moments during the extreme conditions as per figure

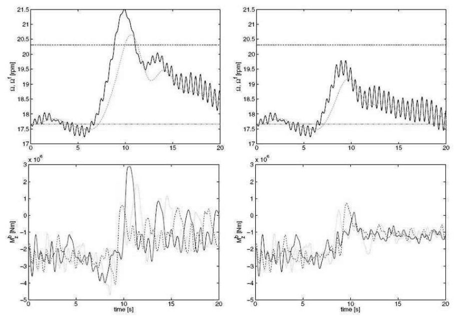

Figure 7: *Rotor speed and blade root moments without (left) and with (right) IPC-supported extreme event handling*

4. In the upper graph, the smooth line represents the filtered rotor speed. The dramatic effect of dedicated event handling becomes clear (right vs left plot). The belonging pitch effort is shown in Figure **??**

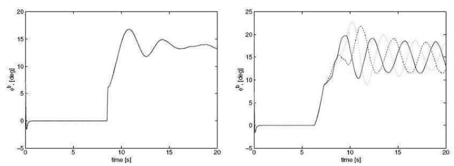

Figure 8: *Pitching effort during extreme conditions without (left) and with (right) IPC-supported extreme event handling*

5 Shutdown control

5.1 Hyper extreme condition detection

The described detection methods in §4.1 can be applied in similar way for the detection of hyper extreme conditions. Further, logic reasoning applies as concerns the actions to be undertaken in case of combinations of exreme conditions and or failures.

5.2 Optimal shutdown control

Model predictive control for smooth shut down
Dotx Control Solutions achieved a promising optimal shutdown result with non-linear model predictive control (NMPC). The developed approach includes a prediction of the wind turbine behaviour over a finite, but considerable time window relative to the actual time time instance. For a given cost function and given constraints, the optimal control input series over that window will be computed; only the first one will effectuated. On the next time-step this procedure is restarted. A very advantageous property of NMPC is that hard constraints can be satisfied exactly *without additional limitation procedures.*

Since turbine shut-down is significantly a deterministic control problem, such repeately performed predictions are certainly valuable: a good set of control signals will result for the current time instance.

Figure 9 shows the foreaft tower moment after pitch actuator stuck. Two 'chaotic-like' pitch actions largely damp the tower resonance (left plots) that would arise when only steady pitching speed applies in the valid actuators (right plots).

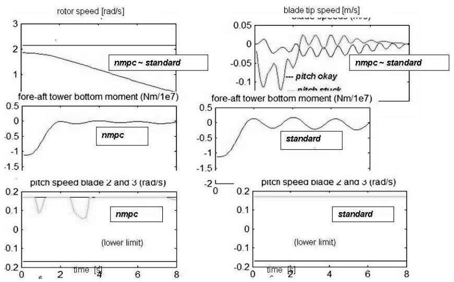

Figure 9: *Wind turbine shut down at pitch actuator stuck*

A disadvantage is the computational burden: the optimization process in the determination of the prediction over the time windos is highly iterative. Further, non-linear MPC requires relinearization of the model at each micro-time step in the prediction window. This implies the need for as simple as possible models that yet represent enough structural dynamics behaviour

Controller reconfiguration at yaw actuator failure
Now consider yaw motor failure and reconfiguration of yaw control through individual pitch control (IPC). This can typically happen and be required during shut-down. TU Delft dealt with this problem [4]. Figure 10 shows sufficient tracking capability of IPC

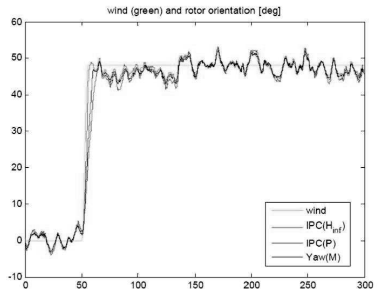

Figure 10: *IPC based yawing after IEC extreme wind direction change*

based yawing for an extreme wind direction change of 48°; the required pitch speeds and acceleration lay well within firm, but realistic limits (< 10°/s, < 20 °/s²).

Thus, fault tolerant yaw control appears a realizable option. The simulations further include realistic turbulence, shear and tower shadow.

5.3 Survival shutdown control

When no optimal shut-down strategy can be applied then nothing is left but using all means in a commonsense sensitive way. Wind turbine manufactures use to implement this case on the base of ample experience.

6 Conclusions

A plurality of methods for the detection of faults and extreme conditions and for the control in regular, extreme and shut-down conditions has been presented. It can be concluded that well tuned, alternate operation of such methods can optimize the operation of the turbine in terms of yield and loads.

The detection and handling of extreme conditions and sensor failures elongates the operation, and thus enhances the yield.

The application of optimizing techniques during production operation and during shut down can reduce the loads on the turbine significantly. A proof of principle on a multi MW wind turbine for optimzied production operation showed a typical reduction of fatigue damage equivalent loads between 10% and 30%.

Implementation of the methods in a so called Sustainable Control platform then provides four types of control: Optimized Feedback Control, Fault Tolerant Control, Extreme Event Control and Optimal Shutdown Control.

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