Wind turbine control beyond the cut-out wind speed

Mate Jelavić[1], Vlaho Petrović[2], Mario Barišić[1], Ivana Ivanović[1]

[1] Končar Electrical Engineering Institute, Zagreb, Croatia

[2] University of Zagreb, Faculty of Electrical Engineering and Computing, Zagreb, Croatia

Abstract

This paper deals with control algorithms that enable wind turbine operation during very high wind speeds (higher than cut-out wind speed) commonly referred to as soft cut-out strategies. The objective of this work was to find a methodology that will allow for an easy implementation of such algorithms to existing (operational) wind turbines. Therefore it was necessary to develop a design methodology that will assure that design driving loads are not increased with new controller actions. This is done by a dynamic approach in which power or rotor speed setpoint is varied on-line based on the current wind turbine state and wind speed worst case prediction. Firstly a linear optimisation problem is formed for finding the worst-case short-term scenario. The worst-case scenario is defined by the wind turbine loads – the higher the loads, the scenario is considered to be worse. A fast and efficient way of solving worst-case prediction is found, which enables such algorithm to be implemented online.

1 Introduction

The common approach to wind turbine control at high wind speeds is the sharp cut-out at certain cut-out wind speed (typically 25 m/s) to protect the wind turbine structure from excessive loading. As wind power penetration increases and wind farms grow in size, such an approach is not adequate. It can lead to sudden shut down of the entire wind farm with very negative effects on the grid. Furthermore, it makes it very hard to predict energy output at high wind speeds – small error in wind speed prediction can lead to 100 % error in power prediction.

As it was proposed in [1], by reducing wind turbine power reference (instead of shutting it down) at high wind speeds, the mentioned downsides of the sharp cut-out can be avoided without significant increase in wind turbine loads. Such graduate reduction of wind turbine power reference in high wind speed is known in the literature as the soft cut-out strategy.

The soft cut-out strategies have been considered in literature [1, 2] and in practice with the common approach being the offline wind-power ramp shaping. The power reference is then selected based on the average measured wind speed or pitch angle during wind turbine operation. Although it has been shown that such control strategies can lead to improved wind turbine behaviour, wind turbine extreme loads are generally increased up to 5 % [1, 2]. Such an increase typically does not pose significant problem for new wind turbine designs and can be easily accounted for in the design process. However, if the soft cut-out strategy is to be applied to an existing (operational) wind turbine it would be optimal if no increase in loading would occur. An algorithm that can be easily and systematically designed and can assure that design driving loads will not increase is in the scope of this paper. Such an algorithm actively keeps the wind turbine in a state so that, even in a predicted worst case scenario of wind speed change, structural loads will not exceed predefined design envelope. Firstly, the worst-case loads are predicted on the defined time horizon, given current wind turbine state and expected wind speed characteristics. The worst-case loads are selected in an online optimization where all wind speed variations with the defined characteristics are assessed in order to find the one that gives the highest loads. After the worst case loads are predicted, the algorithm adjusts the power reference to keep the wind turbine in a safe state.

The paper is organised as follows: The mathematical model on which the proposed algorithm is based is described in Section 2. The worst-case prediction algorithm, which represents the core of the proposed control algorithm, is described in Section 3. In Section 4, the complete control algorithm for high wind speeds is described and the results are presented.

2 Wind turbine mathematical model

The algorithm was tested on the KONČAR K80 2.5 MW wind turbine. This turbine is direct-drive variable speed pitch controlled wind turbines with synchronous generator. In this section, simplified wind turbine mathematical model suitable for implementation to such wind turbines is described.

Since direct-drive wind turbine with rigid shaft is considered in this paper, the rotor speed dynamics can be described as:

$$J_t\dot{\omega} = M_a - M_g, \tag{1}$$

where ω is rotor speed, M_g is generator electromagnetic torque, M_a is aerodynamic torque and J_t is turbine moment of inertia. The aerodynamic torque can be described with quasi-steady relation:

$$M_a = \frac{\pi}{2}\rho_a R^3 C_Q(\lambda,\beta) v_w^2, \tag{2}$$

where ρ_a is air density, R is wind turbine rotor radius, v_w is effective wind speed, and C_Q is torque coefficient that describes the steady state dependence of aerodynamic torque on blade pitch angle β and tip speed ratio $\lambda = \frac{\omega R}{v_w}$.

The wind turbine tower fore-aft oscillations are modelled as:

$$M\ddot{x}_t + D\dot{x}_t + Cx_t = F_t, \tag{3}$$

where M, D and C are modal mass, damping and stiffness chosen to match tower top deflections, natural frequency and damping of the first mode of the tower oscillations. Aerodynamic thrust force F_t is modelled with quasi-steady relation similar to (2):

$$F_t = \frac{\pi}{2}\rho_a R^2 C_t(\lambda,\beta) v_w^2, \tag{4}$$

where C_t is thrust coefficient that describes the steady state dependence of aerodynamic thrust force on blade pitch β and tip speed ratio λ.

The blade pitch actuator dynamics is described with second order differential equation:

$$a_2\ddot{\beta} + a_1\dot{\beta} + \beta = \beta_r, \tag{5}$$

where β_r is the blade pitch reference angle defined by rotor speed (i.e. power) controller. Coefficients a_2 and a_1 are dependant on the machine since larger wind turbine must have slower pitch actuation dynamics.

3 Worst-case prediction algorithm

In this section, the prediction of the worst-case scenario for the wind turbine on a given time horizon is described. Worst-case scenario can be arbitrarily chosen, e.g. as maximal rotor speed or load (either peak value or a mean value) or even linear combination of several loads on a given horizon. Based on a linearised wind turbine model and the expected wind speed spectrum, the prediction is formed as linear optimisation problem, where all possible wind speed variations with given characteristics are assessed and the one that produces the worst-case scenario (e.g. that produces the maximal load value) is chosen.

3.1 Mathematical model used for prediction

Since the prediction is formed as a linear optimisation problem, wind turbine mathematical model from Section 2 has to be linearised, discretised and written in the state space form. Note that all values defined in this subsection and used in the remaining of the paper represent deviations from the operating point values – symbol Δ is omitted on purpose to obtain better readability.

The state vector $\tilde{x}_k$ describing the wind turbine dynamic behaviour is chosen as:

$$\tilde{x}_k = \left[x_{t,k} \quad \dot{x}_{t,k} \quad \omega_k \quad e_{I,k}\right]^T, \tag{6}$$

where e_I represents discrete time integral (i.e. accumulation) of the rotor speed reference tracking error:

$$e_{I,k} = e_{I,k-1} + T_s\left(\omega_{ref,k} - \omega_k\right), \tag{7}$$

where ω_{ref} is rotor speed reference and T_s is the sampling time.

Furthermore, the wind turbine mathematical model is augmented with rotor speed control loop for high wind speeds (pitch controller). Since gain scheduled PI controller is used, it can be written as:

$$\beta_{r,k} = K_P\left(\omega_{ref,k} - \omega_k + \frac{1}{T_I}e_{I,k}\right), \tag{8}$$

where K_P and T_I are gain scheduled PI controller parameters.

The proposed algorithm is intended to work only during high wind speeds, when the generator electromagnetic torque is typically kept constant. Therefore the generator electromagnetic torque is omitted from the linearised wind turbine model.

Therefore the input vector is chosen as:

$$\tilde{u}_k = \left[v_{w,k} \;\; \omega_{ref,k}\right]^T, \tag{9}$$

and the complete linearised mathematical model can be written as:

$$\begin{aligned} \tilde{x}_{k+1} &= A_{\mathrm{WT}}\tilde{x}_k + \left[B_{\mathrm{WT},v} \;\; B_{\mathrm{WT},\omega}\right]\tilde{u}_k, \\ y_k &= C_{\mathrm{WT}}\tilde{x}_k + \left[D_{\mathrm{WT},v} \;\; D_{\mathrm{WT},\omega}\right]\tilde{u}_k. \end{aligned} \tag{10}$$

The output variable y_k in (10) can be chosen arbitrarily, depending on how the worst-case scenario is defined.

Since the proposed algorithm has to evaluate all possible wind speed variations and choose the worst one, it is necessary to augment wind turbine mathematical model with the wind speed mathematical model:

$$\begin{aligned} x_{\xi,k+1} &= A_\xi x_{\xi,k} + B_\xi \xi_k, \\ v_{w,k} &= C_\xi x_{\xi,k} + D_\xi \xi_k, \end{aligned} \tag{11}$$

where x_ξ is state vector and $\xi \sim \mathcal{N}(\bar{\xi}, \sigma_\xi^2)$ is Gaussian noise defined by its mean value $\bar{\xi}$ and variance σ_ξ^2. Such a noise can be considered as an excitation for the wind speed mathematical model, while model matrices are chosen in order to match expected wind speed spectrum $G_{sp}(j\omega)$:

$$G_{sp}(j\omega) \approx C_\xi \left(e^{j\omega T_s} I - A_\xi\right)^{-1} B_\xi + D_\xi, \tag{12}$$

where I is identity matrix of appropriate dimensions.

Now the complete mathematical model with state vector $x_k = \left[\tilde{x}_k^T \;\; x_{\xi,k}^T\right]^T$ and input vector $u_k = \left[\xi_k \;\; \omega_{ref,k}\right]^T$ can be written as:

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k, \\ y_k &= Cx_k + Du_k, \end{aligned} \tag{13}$$

where model matrices are:

$$\begin{aligned} A &= \begin{bmatrix} A_{\mathrm{WT}} & B_{\mathrm{WT},v}C_\xi \\ 0 & A_\xi \end{bmatrix}, \\ B &= \begin{bmatrix} B_{\mathrm{WT},v}D_\xi & B_{\mathrm{WT},\omega} \\ B_\xi & 0 \end{bmatrix}, \\ C &= \begin{bmatrix} C_{\mathrm{WT}} & D_{\mathrm{WT},v}C_\xi \end{bmatrix}, \\ D &= \begin{bmatrix} D_{\mathrm{WT},v}D_\xi & D_{\mathrm{WT},\omega} \end{bmatrix}. \end{aligned} \tag{14}$$

3.2 Formulation of optimization procedure

Worst-case prediction algorithm has to assess all expected wind speed variations on a given horizon and choose such wind speed that brings the wind turbine in the worst possible condition. The expected wind speed variations are defined by the wind speed spectrum (12) and by the Gaussian noise exciting wind speed model $\xi \sim \mathcal{N}(\bar{\xi}, \sigma_\xi^2)$.

First, we define vectors:

$$\begin{aligned} X &= \left[x_1^T \;\; x_2^T \;\; \cdots \;\; x_N^T\right]^T, \\ Y &= \left[y_0^T \;\; y_1^T \;\; \cdots \;\; y_{N-1}^T\right]^T, \\ V_\xi &= \left[\xi_0 \;\; \xi_1 \;\; \cdots \;\; \xi_{N-1}\right]^T, \\ \Omega_r &= \left[\omega_{ref,0} \;\; \omega_{ref,1} \;\; \cdots \;\; \omega_{ref,N-1}\right]^T, \end{aligned} \tag{15}$$

where N is length of prediction horizon. Now, the wind turbine mathematical model over the prediction horizon can be written as:

$$\begin{aligned} X &= \mathbf{A}x_0 + \mathbf{B}_V V_\xi + \mathbf{B}_\Omega \Omega_r, \\ Y &= \mathbf{C}x_0 + \mathbf{D}_V V_\xi + \mathbf{D}_\Omega \Omega_r, \end{aligned} \tag{16}$$

where matrices $\mathbf{A}$, $\mathbf{B}$, $\mathbf{C}$ and $\mathbf{D}$ are constructed directly from state space model matrices (14).

Before formulating the optimization procedure for finding the worst-case scenario, we have to define what worst-case scenario is. To this end, linear combination of wind turbine mathematical model outputs is used, i.e. performance index $J = h^T Y$ is defined, where vector h defines the linear combination of outputs to be used. The vector h is constructed to include all the design driving loads in the criterion. The higher values of J indicate the worse wind turbine condition, meaning that worst-case prediction can be formulated as linear optimisation problem:

$$\begin{aligned} \underset{V_\xi}{\text{maximize}} \quad & h^T \mathbf{D}_V V_\xi \\ \text{subject to} \quad & e^T V_\xi = e^T \bar{V}_\xi = N\bar{\xi}, \\ & \left(V_\xi - \bar{V}_\xi\right)^T \left(V_\xi - \bar{V}_\xi\right) \leq N\sigma_\xi^2. \end{aligned}$$

Optimization constraints follow from the distribution of excitement variable $\xi \sim \mathcal{N}(\bar{\xi}, \sigma_\xi^2)$, where the first constraint ensures the mean value, and the second constraint ensures the variance of the excitation variable. Note that in the first constraint, vector $e = [1 \;\; 1 \;\; \cdots \;\; 1]^T$ is used for calculation of the mean value. Also note that vector $\bar{V}_\xi$ is introduced in both constraints and it represents the expected value of the vector V_ξ. The most straightforward approach is to choose $\bar{V}_\xi = e\bar{\xi}$, i.e. that all its components are equal to the mean value of the excitation signal. But also any knowledge about future wind speed can be incorporated into $\bar{V}_\xi$ as well, e.g. if the wind gust is predicted [3, 4] etc.

3.3 Online solver for worst-case optimization problem

For the worst-case prediction to be used online, it is necessary to guarantee fast and reliable solving of the optimization problem described in the previous subsection. Although there are fast solvers described in the literature as well as examples of implementations of online optimizations [5], it was decided against using standard solver for linear optimization problems. Instead, specific structure of the proposed optimization problem is used in order too ensure that finding of solution is as fast as possible.

Generally, linear optimization problems always have solution in the direction defined by the optimization criterion [6]. In our case, the direction is defined by the vector $\mathbf{D}_V^T h$. Therefore, the optimization is equivalent to finding the farthest point in the direction of the vector $\mathbf{D}_V^T h$, that does not violate the constraints. In other words, the solution to the linear optimization problem, if bounded, will always lie on at least one constraint.

Let us now analyse the constraints. The constraint that ensures the mean value ($e^T V_\xi = N\bar{\xi}$) defines a hyperplane on which the solution must lie. The other constraint defines a hypersphere with centre in point $\bar{V}_\xi$ and radius $\sigma_\xi \sqrt{N}$. Therefore the optimal solution has to be on the intersection of the hyperplane defined by the mean value $\bar{\xi}$ and variance σ_ξ^2. It should be noted that the centre of the hypersphere $\bar{V}_\xi$ also lies on the hyperplane $e^T V_\xi = N\bar{\xi}$.

Described geometric structure can be exploited for fast finding of optimal solution. First the projection of the vector $\mathbf{D}_V^T h$ on the hyperplane $e^T V_\xi = N\bar{\xi}$ has to be found:

$$g = \mathbf{D}_V^T h - \left(e^T \mathbf{D}_V^T h\right) e. \tag{17}$$

Then the optimal solution V_ξ^* is found by moving from $\bar{V}_\xi$ in the direction of vector g exactly the amount of the hypersphere radius $\sigma_\xi \sqrt{N}$:

$$V_\xi^* = \bar{V}_\xi + \frac{\sigma_\xi \sqrt{N}}{g^T g} g. \tag{18}$$

Relations (17) and (18) ensure that V_ξ^* is the optimal solution to the optimization problem described in the previous subsection. It is obvious that optimization is reduced to vector algebra, where the direction of the solution is defined by the wind turbine mathematical model and optimization criterion (and therefore it can be calculated offline), while the hypersphere centre $\bar{V}_\xi$ and radius $\sigma_\xi \sqrt{N}$ are defined by the expected wind conditions and should be updated during wind turbine operation. Since the online part of the optimization problem can be reduced to finding appropriate direction of vector g based on current operating point and to summation of two vectors (18), the proposed worst-case scenario prediction can be executed extremely fast.

Figure 1 shows the optimization procedure described with (17) and (18). For visualisation purposes, the simplified optimization problem that uses the prediction horizon with only three samples is shown in the figure (hence it can be shown in 3D). The intersection of two contraints (plane and sphere) results in blue circle. Therefore points of the blue circle represent the wind speed deviations with the same mean value $\bar{\xi}$ and variance σ_ξ^2 – in other words, the optimal solution is located on the blue circle as well. The vector $\mathbf{D}_V^T h$ shows the direction where optimisation criterion increases, so the vector's projection on the plane containing blue circle points directly to the optimal solution.

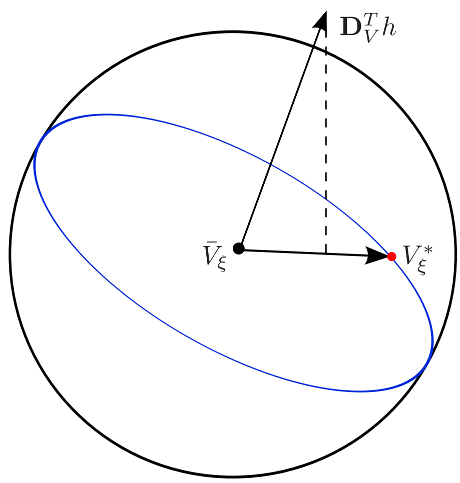

Figure 1: Visualisation of the simplified optimization problem.

4 Active load reduction beyond cut out wind speed

In this section, the control algorithm that actively keeps the loads in the design envelope, even when wind speed is higher than cut-out value, is presented. The principle scheme of the proposed control algorithm is shown in Fig. 2. The core of the algorithm is worst-case prediction algorithm described in the previous section, where the highest expected mean value of the tower bending loads is predicted. If the predicted loads exceed the design envelope loads, the wind turbine power (i.e. rotor speed) reference is reduced in order to achieve lower wind turbine loads. By changing the rotor speed reference, both tip speed ratio λ and pitch angle β are changed, which enables us to find new operating point with lower loads (and lower energy output as well).

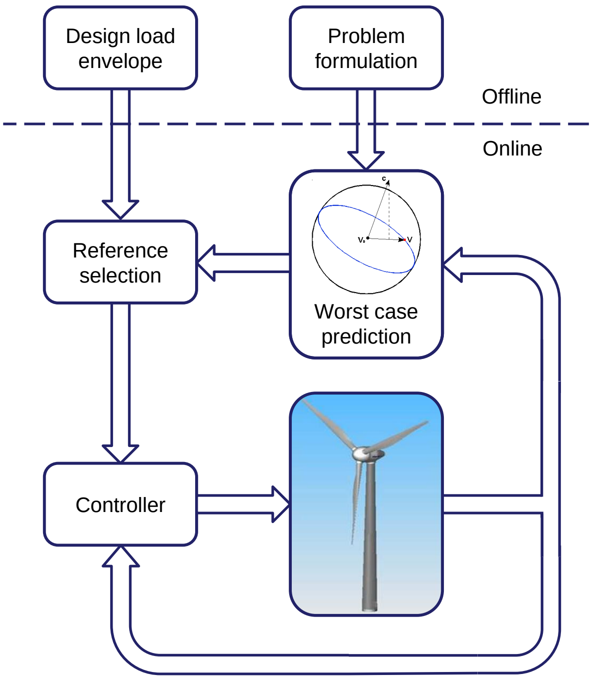

Figure 2: Principle scheme of the wind turbine control beyond cut out wind speed.

4.1 Rotor speed reference selection

Rotor speed reference selection is based on the design loads envelope, linearised mathematical model and worst-case prediction of the wind turbine loads. The worst-case prediction and the new rotor speed reference are calculated every 2 s.

First, easily measured wind turbine signals (measured pitch angle, rotor speed, tower top acceleration and nacelle wind speed measurement) are fed to Kalman filter which estimates current wind turbine and wind speed state vector $\hat{x}$ according to (13). The $\hat{x}$ represents the beginning of the horizon used for worst-case load prediction.

The worst-case prediction algorithm is used to predict the maximal mean tower bending loads on a horizon of 2 s. Once the worst-case wind speed deviations V_ξ^* are predicted, the worst-case load criterion can be written using (16):

$$J^* = h^T Y^* = h^T \mathbf{C}\hat{x} + h^T \mathbf{D}_V V_\xi^*. \qquad (19)$$

Note that influence of the rotor speed reference value is omitted from (19), i.e. predicted loads assume no change in rotor speed reference.

The rotor speed reference is kept constant on the entire horizon:

$$\Omega_r = (\omega_{ref}^* - \omega_{\mathrm{OP}})e, \qquad (20)$$

where ω_{OP} is rotor speed value in the chosen operating point. Therefore the rotor speed reference value ω_{ref}^* that keeps the predicted loads on the reference value J_{ref} (defined by the design envelope) is calculated directly from (16):

$$\omega_{ref}^* = \omega_{\mathrm{OP}} + \frac{J_{ref} - J^* - J_{\mathrm{OP}}}{h^T \mathbf{D}_\Omega e}, \qquad (21)$$

where J_{OP} is load criterion value in the operating point. The rotor speed reference ω_{ref}^* is not allowed to be higher than rated rotor speed – if higher value is calculated from (21), then the rated rotor speed is used as the reference.

4.2 Concept validation

The proposed control concept has been validated by a simulation campaign according to IEC-61400-1 for the class IA wind turbine performed in aeroelastic code GH Balded [7].

The proposed controller was compared to the classic control strategy with sharp cut-out at 25 m/s wind speed and to the standard soft cut-out strategy with static power ramp down. Design driving loads envelope was chosen equal to the case with classic controller. The wind turbine behaviour was analysed in terms of fatigue loading, ultimate loads and energy yield.

Fatigue loads, calculated using rainflow counting method, showed no significant change. Similar behaviour was reported by other authors treating the

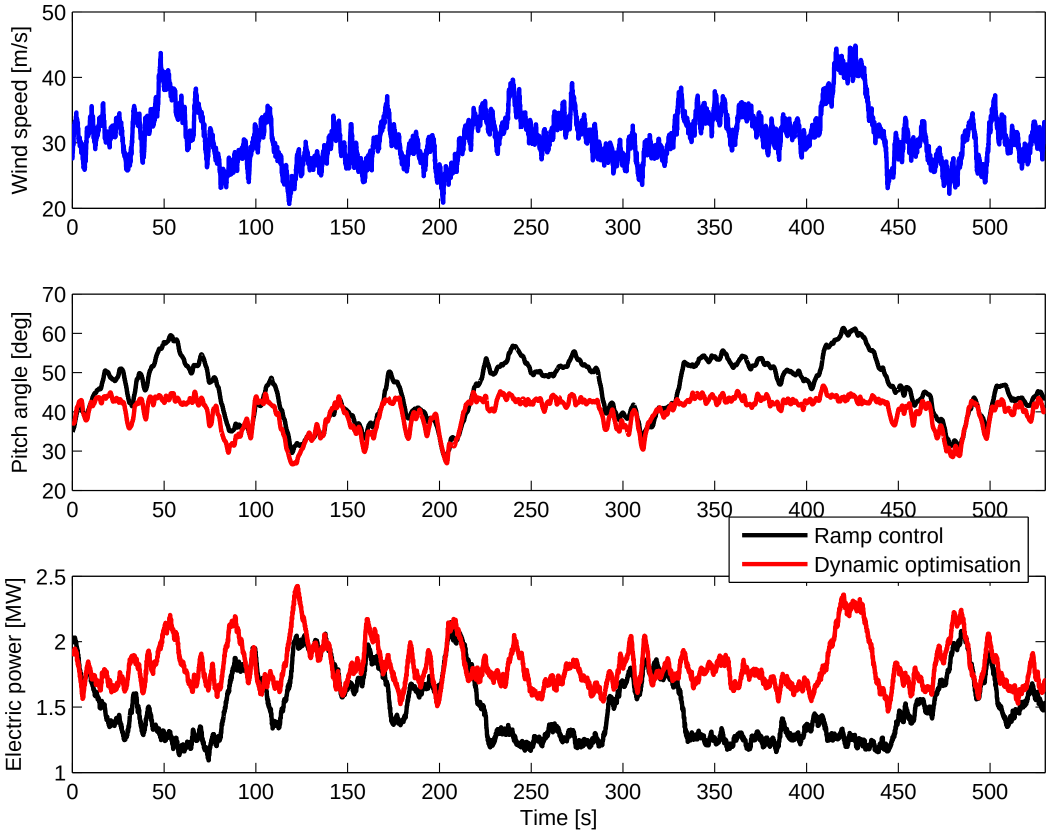

Figure 3: Comparison of standard soft cut-out strategy (ramp control) and proposed dynamic optimisation.

soft cut-out strategies [2]. The reason for this is the fact that the wind turbine spends relatively small amount of time operating in the high wind speed region. Therefore this extension of the operation region brings relatively small number of extra load cycles over lifetime. Moreover, the amplitude of these loads is not excessive since it was a criterion for the algorithm design. On the other hand soft cut-out strategy reduces number of shut downs and start ups compared to the classic sharp cut-out strategy what is favourable in terms of fatigue loading. The design driving loading for the wind turbines in scope is torsional (M_z) and resultant bending (M_{xy}) at the blade root, yaw bearing and tower and (M_x), (M_{yz}) for the hub respectively. The design driving loads were either not changed or slightly reduced (1-4 %). The ultimate loads were not changed in cases when their maximum values have been obtained for idling or parked conditions at extreme wind speed (e.g. 50 years recurrence period). These cases were not influenced by the described algorithm. At the other hand the observed slight reduction in loading comes from the fact that the described algorithm becomes active somewhat below cut-out wind speed, thus reducing extreme loads occurring at this wind speed.

The wind turbine energy yield was increased by 0.9 % due to fact that the wind turbine operation region has now been extended. Compared to the standard soft cut-out strategy with static power ramp down, the proposed algorithm showed certain increase of 0.3 %. It is due to the dynamic nature of the algorithm that takes into account the actual wind turbine operation state and wind speed properties. It allows the control algorithm to "push" the turbine towards normal (rated) operation point at any occasion that will not bring the turbine in danger. This is clearly depicted in Fig. 3. The described behaviour results in smaller pitch angle excursions what is also favourable for wind turbine operation.

Resultant static power characteristics obtained by standard ramp cut-out and proposed dynamic approach are shown in Fig. 4.

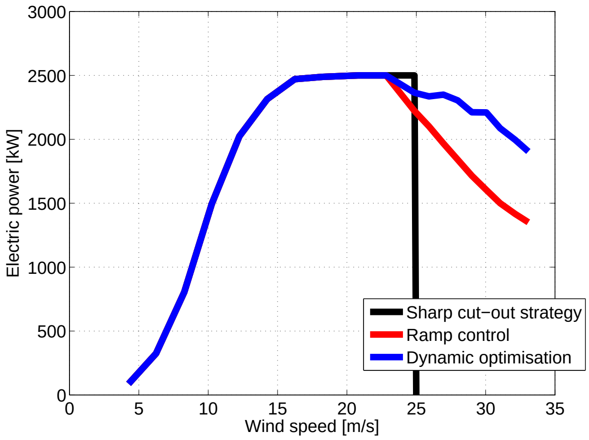

Figure 4: Comparison of static power sharacteristics.

5 Conclusion

This paper presents a new approach to the wind turbine control during high wind speeds. Instead of commonly used predefined wind-power ramp a dynamic approach is proposed that relies on the wind turbine state estimation and worst case wind speed prediction. The algorithm assesses all wind speeds with defined characteristics and chooses the one that produces the maximal loads. Wind turbine power or rotor speed setpoint is then adjusted to ensure that even in such an extreme event design driving loads will remain in the predefined envelope. This allows for an easy application of the presented algorithm to the existing (operational) wind turbines. Namely, design driving loads envelope can be chosen from the baseline case with classic control algorithm (usually sharp cut-out at certain wind speed). The described algorithm will assure that the design driving loads are not increased and no design modifications are necessary.

Since worst case predictions are done through linear optimisation, a fast and efficient way of solving such optimisations is found. This allows for an easy implementation of the algorithm to any standard wind turbine controller what is also very important for its application to existing wind turbines.

The algorithm was validated in simulation campaign according to IEC 61400-1 performed in GH Bladed for KONČAR K80 2.5 MW direct drive wind turbine. Neither fatigue nor ultimate loads increased compared to the baseline case with sharp cut out at 25 m/s. Furthermore it was also shown that slight increase in annual energy yield can be expected compared to baseline case, while in comparison to the static wind-power ramp control smaller power and pitch angle variations are obtained.

Acknowledgement

This work has been financially supported by Croatian Science Foundation under grant No. I-4463-2011 (MICROGRID) and by the European Community Seventh Framework Programme under grant No. 285939 (ACROSS). This support is gratefully acknowledged.

References

[1] H. Markou and T. J. Larsen, "Control strategies for operation of pitch regulated turbines above cut-out wind speeds," in *European Wind Energy Conference and Exhibition EWEC 2009*, vol. 6, 2009.

[2] E. Bossanyi and J. King, "Improving wind farm output predictability by means of a soft cut-out strategy," in *European Wind Energy Conference and Exhibition EWEA 2012*, 2012.

[3] V. Spudić, M. Marić, and N. Perić, "Neural networks based prediction of wind gusts," in *European Wind Energy Conference and Exhibition EWEC 2009*, vol. 6, 2009, pp. 4037–4045.

[4] S. Kanev and T. Van Engelen, "Wind turbine extreme gust control," *Wind Energy*, vol. 13, no. 1, pp. 18–35, 2010.

[5] V. H. Quintana, G. L. Torres, and J. Medina-Palomo, "Interior-point methods and their applications to power systems: a classification of publications and software codes," *IEEE Transactions on Power Systems*, vol. 15, no. 1, pp. 170–176, 2000.

[6] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge University Press, 2004.

[7] E. A. Bossanyi, "GH Bladed – Theory Manual, Version 3.81," Garrad Hassan, Tech. Rep. 282/BR/009, November 2008.