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Robustness of an Economic Nonlinear model predictive control for wind turbines under changing environmental and wear conditions

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***Abstract*— In this work, the authors have assessed the robustness of an Economic Nonlinear Model-Predictive Controller (ENMPC) aimed at maximizing the power production of wind turbines. The scope of the paper is to quantify the sensitivity of this type of controller concerning wind conditions, climate, wind speed prediction unavailability, and aerodynamic performance degradation. A power production controller's robustness is crucial for the wind turbine industry due to the extreme variability of external conditions and the wear caused by long-term continuous operativity. Model-Predictive controllers are, in principle, more prone to robustness issues concerning standard controllers, a fact that limits their adoption on actual wind turbines. The analysis is performed with the fully-aeroelastic solver OpenFAST considering a wide set of realistic load cases. It is demonstrated that the ENMPC previously developed is robust to wind prediction unavailability and change in wind turbulence intensity. Conversely, it is not robust to the modelling error due to aerodynamic degradation. Indeed, a reduction in generated power concerning the reference controller is observed, especially for operating region two and end-life blades. Finally, a significant increase in power production is achieved considering the external temperature variation thanks to the ENMPC's direct handling of the generator temperature constraint.**

***Index Terms*— ENMPC, robustness, wind energy**

I. INTRODUCTION

The power controller strategy of a wind turbine greatly impacts the amount of energy it extracts from the wind. The objective of a power controller is to maximize energy production, maintaining the functioning point within the structural and electric envelope to guarantee safe, reliable and efficient production [1]. The standard wind turbine control strategy is usually segmented into four or more operating regions. In the simplest case, in region 1, below cut-in speed, the generator is inoperative, whereas, between cut-in and rated wind speed (region 2), the control strategy aims at maximizing the generated power, which is still lower than the generator rated power. In region 3, above rated wind speed, the controller acts to maintain rated power as wind speed increases. Finally, in region 4, the generator is shut down to prevent damage to the turbine. In region 2, several control strategies may be used [2], [3] for the maximum power point tracking problem (MPPT). The standard for large horizontal-axis wind turbines is represented by the optimal torque method, in which the generator torque is proportional to the square of rotor angular velocity, and the blade pitch (the other control variable) is kept constant to an almost-optimal value [4].

Although this technique is pretty easy to implement, it represents a suboptimal choice, especially when strong turbulence is present. Indeed, especially for large inertia rotors, the controller fails to achieve optimal rotor speed when the wind velocity suddenly changes [5]. In the last twenty years, many improvements have been proposed to the optimal torque method to alleviate its shortcomings. E.g., they include the reduction of the aforementioned constant [5], to the use of wind-speed estimation to correct the value of generator torque [6], and the use of adaptive control [7].

Another family of wind turbine control methods is the Nonlinear Model Predictive Control (NMPC). It can include nonlinear aerodynamic effects (such as stall), constraints on states and inputs and complex cost functions. Moreover, unlike the standard control approach, in NMPC, the two main control variables, collective blade pitch and generator torque are usually used together throughout the operating range. Usually, NMPC aims at tracking a predefined reference or static optimal set points [8]–[10]. When NMPC is formulated to maximize a cost function directly (e.g., generated power), it is referred to as Economic NMPC (ENMPC) [11], [12]. Few examples are available in the literature [13], [14] where an ENMPC to maximize power production is proposed. However, in [13] and in [14], the controller is not coupled with a high-fidelity solver to take into account modelling error fully. Note that in [14], the modelling error is only partially considered by adding an error on tower's main eigenfrequency. Moreover, the effect of a reduced time horizon is assessed in case of a limited prediction capacity of a nacelle LIDAR. However, the case of a complete lack of wind prediction is not considered.

Wind turbine controller robustness is a crucial issue, owing to the variability of atmospheric conditions (which may vary from calm winds to storms) and the long-term continuous operativity with relatively little maintenance. Wear and consequent degradation of aerodynamic and conversion performance is well-known, and it has been estimated that a wind turbine

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loses 12% of power output in a 20-years lifetime [15], a rate significantly faster than those of other energy production methods, including photovoltaic. Although this fact has an evident repercussion on the levelized cost of energy, it also may affect MPPT performance. For example, in the standard optimal torque method, the controller design requires the knowledge of the exact power curve of the turbine to evaluate the optimal constant of proportionality between torque and rotor kinetic energy. A misjudgment of this constant causes a loss of power and instabilities (usually solved through dedicated mechanisms). It is evident that, also if the optimal nominal value of the constant is known at the design stage (and this is hardly the case due to uncertainties), this value would become inadequate when the power curve modifies with turbine ageing [5], [16], [17]. Analyzing a new MPPT's robustness against internal and external factors is crucial in view of its use in real-world applications.

In the literature, the methods adopted to track an optimal reference power which includes the uncertainty of wind conditions, are mainly three: 1) polytope MPC, 2) tube-based MPC [18], [19] and 3) stochastic MPC [20]. The first two approaches treat uncertainty as a bounded disturbance, usually leading to a more conservative control strategy. In contrast, the third method optimizes the desired performance index satisfying probability constraints that incorporate the stochastic information of wind speed resulting in a compromise between the control objective and operation risk. However, the price to pay is a higher computational load. In [20], the stochastic and tube-based MPC are compared. Results show that both methods are promising optimal control strategies under wind speed disturbance, with stochastic performing better with substantial wind variability.

In this paper, the authors investigate the robustness of the ENMPC developed and described in detail in [21]. The parameters considered in the robustness analysis are related to blade degradation and atmospheric conditions (temperature, turbulence level and availability of information about incoming wind). Section II illustrates the reduced-order model on which the controller is based, section III briefly outlines the controller itself, whereas section IV reports the results of the robustness analysis.

II. Wind Turbine Nonlinear Reduced Order Model

The model-predictive uses the nonlinear reduced-order model (ROM) developed in [21]. Here the model is reported in brief for the reader's convenience. The model consists of two states (shaft angular velocity and mean wake induced velocity) turbine model with unsteady aerodynamics, coupled with a 1-DoF generator thermal model. The ordinary differential equations for wind turbine aeromechanics read:

$$J_{rot}\dot{\Omega} = \tau_{aer} - \tau_{gen} \tag{1}$$

$$m_a\dot{\lambda} = 2\rho\pi R^2\lambda(\lambda - V_w) + T \tag{2}$$

In the first equation, J_{rot} is the rotor/transmission/generator inertia (relative to low-speed shaft angular velocity Ω), τ_{aer} the aerodynamic torque, and τ_{gen} the generator torque (multiplied by the gearing ratio). In the second equation, $m_a = 0.637\rho(4\pi R^3/3)$ is the apparent aerodynamic mass, V_w is the wind speed, λ is the wake inflow at the rotor disk (which reduces effective wind speed when greater than zero), ρ is the air density, R is the rotor radius, and T is the rotor aerodynamic thrust. The aerodynamic torque and thrust can be expressed as:

$$\tau_{aer} = P_{aer}/\Omega = \rho\pi R^2 V_w^3 C_P/2\Omega \tag{3}$$

$$T = 1/2\rho\pi R^2(V_w - \lambda)^2 C_T \tag{4}$$

where P_{aer} is the aerodynamic power, V_w is the wind speed, and C_P and C_T denote the power and thrust coefficient.

For a computationally efficient application of the model, a map of the power and thrust coefficients is identified in terms of Ω, β and $(V_w - \lambda)$ (see [21]) through a preliminary numerical investigation based on the open-source OpenFAST tool [22].

Usually, the generator temperature is not considered by the controller. However, the generator can override the rated power for a considerable time before the generator rated temperature is reached, starting from a lower temperature. Following [21], a single-node model for the generator temperature is proposed:

$$\dot{\theta} = -k(\theta - \theta_0) + cP_{gen} \tag{5}$$

where θ_0 is the external temperature, and k and c are parameters to be identified. In this work, it is assumed $\theta_0 = 20°C$, $c = 6.67\ 10^{-8}\ °C/(Ws)$, and $k = \frac{1}{120}s^{-1}$ (this corresponds to a time constant of $120s$). In case of an external temperature lower than that considered during the design, the generator could work at a power higher than rated, increasing the power production. Conversely, a temperature higher than $20°C$ causes an overheating of the generator also for a power lower than rated. The inclusion of this state variable in the model gives the opportunity of increasing power production and of avoiding generator overheating at the same time.

III. Control Strategy

A. Reference controller

The standard controller of a Variable-Speed/Variable-Pitch wind turbine acts differently in the two main operating regions, region 2 and 3. Above cut-in speed but below rated wind (and then below rated power, region 2), the controller regulates generator torque proportionally to Ω^2 to keep optimal tip-speed ratio as wind speed increases. Here, the pitch is kept at a fixed optimal value. Above rated wind speed and below cut-off speed (region 3) the objective of the controller is to maintain generated power at rated value. The blade pitch is used as control variable in a PI controller to maintain rated angular speed. The generator torque is adjusted to have constant power, i.e. $\tau = P_{rat}/\Omega$. A transition region (2.5) is usually added to improve wind turbine performance about rated wind speed. For a more detailed description of the reference controller, see [4].

B. ENMPC formulation

In this work, the authors have used the ENMPC, developed and analyzed in detail in [21]. The ENMPC consists of a sequence of control actions defined through the solution of

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Optimal Control Problems (OCPs) over overlapping finite time intervals. Specifically, for every update time (T_u), the OCP over the time horizon (T_h) is initialized considering the available measurements and solved (see fig. 1).

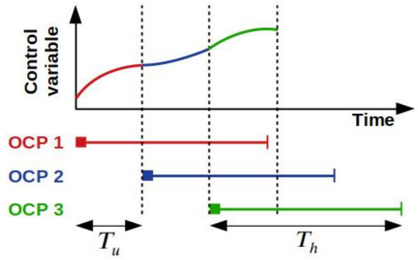

Fig. 1. NMPC timing. Overlapping OCPs determine the control variable.

The targeted objective is the maximization of aerodynamic power extraction under a set of constraints to avoid generator overheating and turbine overloading.

The constraints associated with the cost function minimization are 1) the collective pitch (control variable #1) β is constrained to avoid blade stall and to avoid extrapolation of the power and thrust coefficients, increasing the robustness of the controller; 2) the generator torque τ (control variable #2) is limited according to the installed generator; 3) the pitch rate $\dot{\beta}$ and the torque rate $\dot{\tau}$ are limited to obtain a feasible actuation law; 4) the generator has a significant thermal capacity, and hence the rated generator power can be overridden for a considerable amount of time; indeed, a generator thermal ROM is developed (see section II) and a constraint on the generator temperature, θ, is considered; 5) the electronics has reduced thermal capacity, and its rated power cannot be overridden, even for a short amount of time. A feasible approach is to oversize power electronics in terms of rated power concerning the generator to exploit the capacity of the generator to be overridden during functioning to extract more energy from wind gusts about rated wind speed. Then, a constraint directly given in terms of the generated power P^{gen} is considered to avoid damages to the power electronics. In a real-world application, the power electronics rated power should be set through an economic analysis (cost increase *vs* power production increase). In this work, the electronics rated power has been arbitrarily set 20% higher than the generator rated power; 6) a thrust constraint is included to avoid high loads on structures.
Thus, the ENMPC scheme over the horizon T_w reads:

$$\max_{\mathbf{u}} J = \int_{T_0}^{T_0+T_w} P_{\text{aer}} \mathrm{d}t \tag{6}$$

Equation (6) is subject to the dynamics defined in eqs. (1), (2) and (5) and to the constraints listed above. Note that the control variables are the second derivatives of actual controls (generator torque and blade pitch) to assure controls $C1$ continuity [21]. Since the ROM is nonlinear and based on maps evaluated on the entire functioning range, the controller does not require functioning regions and switching criteria.

This work uses the code PINS to solve the OCP [23]. It is developed by Trento University and is free for academic use upon request. PINS is based on an indirect method where the BVP is solved with the finite difference or collocation approach. The indirect method relates to Pontryagin Minimum Principle [24] to derive the necessary conditions of optimality [25]. A custom-designed, robust and fast nonlinear solver that exploits the problem structures of the discretized BVP is used. The executable of the controller, along with the interface with OpenFAST and the reference guide, has been made freely downloadable at `https://github.com/lpustin/ENMPC-for-Wind-Turbines`.

IV. Numerical results

The widely-used NREL 5 MW wind turbine [4] is the test case for applying the proposed control strategy. The high-fidelity dynamic response is simulated by the open-source software OpenFAST [22]. In [21], the assessment of the ENMPC performance on the same turbine has attested a significant increase in generated power between cut-in and rated wind speeds. One of the results of [21] is the sensitivity analysis on the effect of time horizon T_h and time update T_u on controller performance and computational effort. Here, the optimal values found in [21] are used, i.e. $T_u = 1$ s, $T_h = 30$ s. The time step is 0.2 s, sixteen times the time step used in OpenFAST.

In this work, its robustness is investigated with respect to 1) wind speed prediction error (section IV-A); 2) wind turbulence (section IV-B); 3) blade degradation (section IV-C); 4) external temperature (section IV-D); The analyses are performed over a set of load cases (LC) covering the entire functioning range. The baseline turbulence is the 'B' IEC Kaimal, and a power-law wind shear with an exponent equal to 0.2, and a surface roughness length of 0.03 m are used.

A. Controller performances without the wind speed prediction

In principle, the developed ENMPC requires predicting the effective wind speed on the optimization time horizon. However, wind speed prediction (obtained by LIDAR sensor [26] for direct wind measurement or using a predictor based on previous measurements [27], [28]) is often inaccurate, due to advection and measurement error, in the former case, or estimation error, in the latter. The current wind speed (plus a white-noise error with amplitude 0.2 m/s) is considered to assess the effect of a lack of knowledge of incoming wind in the whole optimization time horizon. Current effective wind speed can be obtained with an observer by available measurements on wind turbines (an open-source implementation is available in ROSCO [29]). Confirming the preliminary results presented in [21], fig. 2 shows that the ENMPC power production with and without the incoming wind speed data availability is similar for all the LCs, if a sufficiently short time update (T_u =1 s, see [21] for the tuning of this parameter) is used. Moreover, fig. 2 depicts the blade pitch Standard Deviation (SD), that can be considered an indicator for the control effort. In the operating region 2, the reference controller keeps the pitch constant, according to the control philosophy. In the other cases, the ENMPC pitch SD is lower than that of the reference controller with and without the wind prediction. Such a smooth

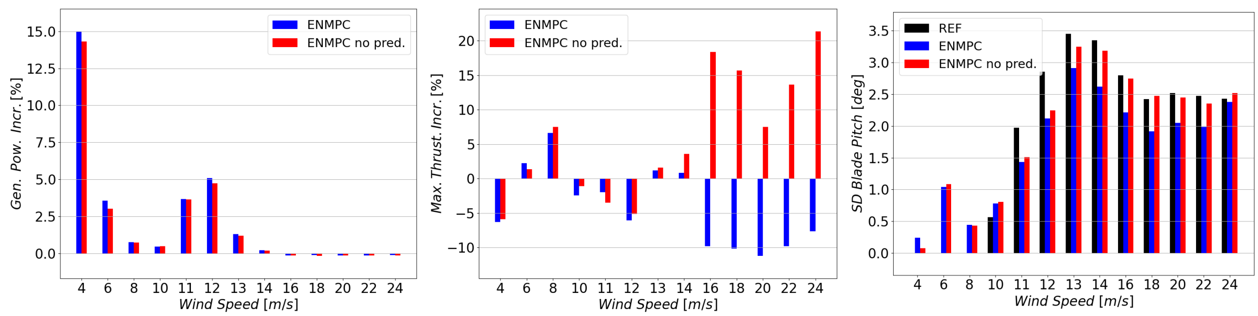

Fig. 2. Generated power increment, maximum thrust increment and control effort (standard deviation of blade pitch), considering the exact knowledge of effective incoming wind over the whole time horizon (blue bars) or considering the wind speed constant, i.e. without knowledge of future wind (red bars).

control law is achieved thanks to the fact that there is no strict constraint on angular speed, and the first derivative continuity of the control law. Moreover, in the ENMPC without wind prediction case, the blade pitch SD is higher (especially for the operating region 3 LCs) than in the ENMPC with wind prediction. This is attributable to the need of the controller to recover from the wrong prediction on state evolution caused by the wind misjudgment. Finally, in the case without wind speed prediction, the maximum thrust peak is higher than in the case with prediction. However, the thrust constraint is not violated (the maximum thrust is reached only for the rated speed, 12 m/s), and the thrust oscillations are not included in the objective function. A future investigation could include, especially for operating region 3, a term for penalizing thrust oscillations in the objective function.

B. Controller robustness with respect to the wind turbulence level

In IEC [30] standard, three levels of turbulence ('A', 'B', and 'C') are defined, with 'A' being the most turbulent. Usually, actual sites have lower turbulence level than the IEC standard, which is conservative and designed for certification purposes. Instead, it is fundamental to assess site turbulence levels to provide an accurate estimation of Annual Energy Production. A power maximization controller needs to be effective with all the turbulence levels to be adopted in real-world applications. This work assesses the controller performance in all the IEC turbulence categories , comparing the generated power and the maximum thrust peak with respect to the reference controller in the same conditions.

At low wind speed, the controller performs better with the less turbulent "C" case (see fig. 3), whereas nearing rated wind speed, a higher turbulence level gives a greater power increment with respect to the reference controller. Indeed, as described in [21], the ENMPC power increase in region 2 is related to the combined action on generator torque and collective pitch and to the capability to predict wind turbine dynamics in response to incoming wind. At low speed, the error between the ROM predicted wind turbine dynamics and the high fidelity OpenFAST dynamics decreases with lower turbulence, and the ENMPC performances increase. At higher wind speed, the superior capability to exploit wind gusts with respect to the standard controller more than compensates for

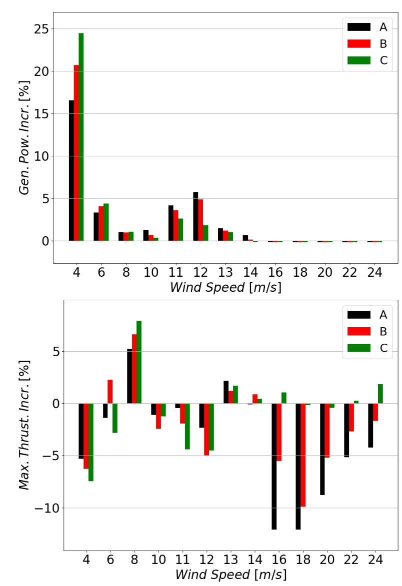

Fig. 3. Increment of mean generated power and of the maximum aerodynamic thrust peak (concerning the reference controller). The three IEC categories of turbulence ("A", "B", and "C", with "A" being the most turbulent) are shown.

the reduced ROM predictive capability, resulting in improved performance.

Instead, near rated wind speed (operating region 2.5, 12 m/s), the advantage of using the ENMPC is greater for higher turbulence levels, thanks to handling the generator thermal constraint. Indeed, as described in [21], near-rated wind speed, the power increment achieved with the controller is related to its capability to override rated power for short transients (until the generator temperature reaches the rated value). In such a way, contrary to the reference controller, the ENMPC may exploit wind bursts above rated wind speed. Such bursts are stronger for higher turbulence.

In fully developed operating region 3 , the advantage of using the ENMPC is null since the mean generated power cannot exceed the rated one without violating the thermal constraint. As the reference controller, the ENMPC can maintain the rated power for all the turbulence levels.

Although reference controller doesn't take rotor thrust into account, and the proposed one only considers a constraint on it, some interesting considerations on the two controllers may be drawn. The behaviour in region 2 and 3 are indeed clearly

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different. In region 2, there isn't a sharp advantage of one of the two controllers, with any level of turbulence. On the contrary, in region 3, the proposed controller gives a clear advantage in terms of maximum thrust, which decreases as the wind speed increases and that is greater for higher level of turbulence. This is probably due to the fact that the reference controller uses the blade pitch as a control variable only in region 3. It is well known that using pitch to control angular velocity gives rise to an increase of vibratory level [31]. In addition, the proposed controller doesn't impose a strict constraint on rotor angular speed, allowing a +20% variation with respect to the rated value of the standard controller. This may reduce the use of collective pitch.

C. Controller robustness with respect to the wind turbine aerodynamic degradation

Wind turbine blades are exposed to precipitations of a variety of forms and abrasives airborne particles can accrete and erode the surface, especially at the leading edge. This can reduce blade performances and be a critical issue for model predictive control. Indeed, the Reduced Order Model prediction error increases and thus the controller performance can drastically decrease. However, a short update time, as for the case without wind speed prediction, can mitigate the effect of ROM error. In [17], the effects of leading edge erosion on wind turbine blades are analyzed. We have chosen two of the examined cases, the 'A2' case (only pits on the leading edge) and the 'C4' case (end-life blade with pits, gouges and delamination). Since the airfoil used in [17] isn't the same as the NREL 5MW wind turbine, the lift and drag coefficients are proportionally scaled. This approximation is suited for estimating the overall trend in Annual Energy Production. According to Tab. 3 in [17], for the case 'A2', the lift coefficient is decreased by 10%, and the drag one is increased by 80%. For the 'C4' case, the lift coefficient is decreased by 15%, and the drag one is increased by 400%.

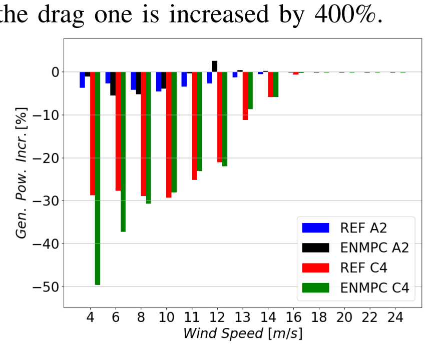

Fig. 4. Increment of mean generated power (with respect to the reference controller without aerodynamic degradation) for the ENMPC and the reference controller considering different levels of aerodynamic degradation (see tab. 3 in [17]).

In operating region 3, the ENMPC and the reference controllers can maintain the rated power (see fig. 4) for both the degradation cases, thanks to the large availability of wind power. In the operating region 2.5 and for low degradation, the ENMPC outperforms the standard controller, exploiting the thermal transient to override rated power. However, both controllers have significantly lower performance for a highly degraded blade. Finally, in operating region 2, the ENMPC power production is lower than the reference controller for both levels of damage. The ROM can be updated online during blade ageing to reduce the effect of modelling errors. Recently, several model identification methods for uncertain or evolving systems have been proposed, using machine learning techniques or nonlinear model predictive controllers applied to online model discrimination [32], [33].

D. Controller performances in the presence of external temperature variation

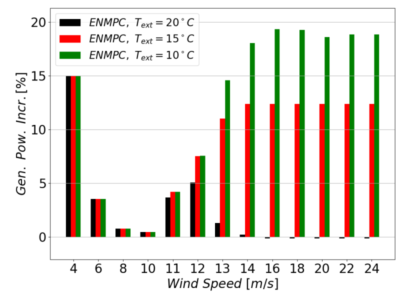

Fig. 5. Increment of mean generated power concerning the reference controller. Three external temperatures are analyzed.

In [21], for the first time to the author's knowledge, a controller directly handling the generator thermal constraint has been developed. Here, the controller performances with an external temperature variation are analyzed. Indeed, if the external temperature is lower than the design one, the generator heat exchange increases, and it is possible to increase generated power. Note that a strict constraint on maximum instantaneous generated power (20% the rated power) is imposed to protect the electronics (see [21]). The sensitivity analysis aims to show the potential of including external temperature in the control strategy. Future investigations will focus on a thermal high-fidelity model coupled with OpenFAST to confirm and accurately assess the generator power increment. Three cases of external generator temperature are analyzed: 1) the rated $T_{ext} = 20°$C case, where, in steady conditions, the generator reaches reference temperature for rated power. This is the condition considered in the previous analyses; 2) two lower external temperature cases, $T_{ext} = 15°$C and $T_{ext} = 10°$C cases.

Figure 5 depicts the increment of the mean generator power for the three cases. As expected, the external temperature does not affect the power production in the operating region 2. Indeed, the generator temperature constraint is not active for low wind speed. Conversely, for the operating region 3, the generator temperature constraint is active, and power production increases with external temperature lower than reference one, 20°C. Finally, for 12 m/s and 11 m/s LCs (where rated wind speed is exceeded for a limited amount of time), the generator temperature constraint is active only for the $T_{ext} = 20°$C. Therefore the increased generator cooling is sufficient in $T_{ext} = 15°$C and $T_{ext} = 10°$C cases to avoid the generator temperature constraint activation, and the same optimal solution and power production are achieved (see fig. 5).

V. Conclusions

The robustness of the ENMPC developed in [21] is investigated to make the controller more ready for real-world applications. The controller is coupled with the fully-aeroelastic solver OpenFAST, and a comprehensive set of load cases are considered in all the operating regions of interest of the wind turbine. First, considering the unavailability of wind speed prediction, the controller has proven to be robust. Indeed, only a slight decrease in generated power is observed. Secondly, three wind turbulence intensities are considered. In all the examined cases, the controller increases power production, without particular problems in terms of closed-loop stability. Then, a medium and a severe case of leading edge erosion are analyzed. Below region 3, the controller is heavily affected by blade damage, especially for low wind speed. An online-tuned ROM can reduce modelling error, and can help to increase generated power in the presence of blade damage. Finally, since the controller handles the generator temperature constraint directly, a significant increase in power production is achieved when the external temperature is lower, particularly in operating region 3.

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