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Norm-Optimal Iterative Learning Control for Wind Turbines During Grid Faults

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Abstract. Due to the increasing share of (offshore) wind turbines, more stringent requirements on power quality have been established. Importantly, the low-voltage ride-through grid requirement states that a wind turbine must remain connected to the electrical grid after a short intermittent grid fault. In the industry mainly gain-scheduled PID-controllers are used to mitigate the effects of grid faults on turbine operation, whereas more advanced solutions have been proposed in the literature such as model predictive control or multiple parallel PI-controllers. Remarkably, all controller implementations mentioned earlier are based on feedback control, where no feedforward strategies have been discussed in the literature. However, feedforward control could improve grid fault recovery performance by exploiting the relatively known fault characteristics by virtue of the specification in the Transmission System Operator requirements. Therefore, for the first time, a norm-optimal Iterative Learning Control (NO-ILC) algorithm is presented that solves these issues by learning the feedforward signal that optimally mitigates the effects of a grid fault. The NO-ILC algorithm applies model-free learning based on iterations, in which the framework of NO-ILC has been extended to include explicit input constraints. The goal of the NO-ILC is to reduce a (quadratic) cost function on specific input and output channels whilst conforming to specific input constraints by solving an optimisation problem, with, for this study blade pitch and rotor speed as respective input and output channels. It is shown that the NO-ILC algorithm can yield improved performance on a high-fidelity model, with a 45% decrease in the cost function used by NO-ILC compared to the nominal feedback control. The optimised feedforward signals resulting from NO-ILC can be used as an analysis tool to closer match the nominal grid fault feedback controllers response with that of NO-ILC, or directly applied as a library that can supplement the feedback controllers output during a grid fault.

1. Introduction

In recent years, the urgency of pursuing more renewable energy sources has become increasingly clear. There is not only a climate crisis but also a growing realisation that the European Union (EU) needs more independence from the global energy market. The energy market has been heavily affected by multiple diplomatic crises and the aftermath of the global pandemic. This, among other things, leads to the EU goal of 45% renewable energy use in 2030 compared to 22% in 2020 [1, 2]. The achievement of this goal can be done in part by increasing the use of (offshore) wind turbines (WTs). Growth in WTs is not limited only to the EU, as other markets have also increased wind energy production in recent years [3] and are committed to continue to do so in the coming years [4, 5].

Due to the increase in wind turbine energy production, the Transmission System Operators (TSOs) in multiple countries have defined stricter requirements on the operations of wind turbine parks to ensure stable operation of the grid. For the EU these requirements are summarised in [6], wherein the local TSOs can enforce some input within the limits of the document. One challenging type of requirement for WT operators is low-voltage ride-through (LVRT) requirements, also known as fault ride-through in the literature. The LVRT requirements define how the WT must operate during and after intermittent drop(s) of the grid voltage.

During a grid fault, a temporary torque imbalance is created which cannot be instantaneously compensated for due to the extreme short time scale of the grid event. This torque imbalance will lead to a temporary increase of rotor speed during the grid fault that may cause a shutdown of the wind turbine. After this initial increase in rotor speed, rotor speed oscillations occur that degrade power quality, which may not be accepted as per TSO requirements.

Multiple solutions have been proposed to limit the negative effects of a grid fault. In the works of [9, 10, 11] hardware based solutions are proposed where additional components such as a crowbar, a method to dissipate current to generate back EMF on the rotor, are utilised. These solutions will, however, require significant hardware cost on modern large-scale multi-MW wind turbines, reducing the desirability. Other solutions from industry, such as in [12, 13] add a second parallel PID-controller to the nominal controller that combined will generate the blade pitch rate and the blade pitch signal, respectively. In [14, 15] the gains of the PI-controller inside the phase-locked loop regulator, a type of regulator used to control the converters output current [16], are changed using a state machine based on grid measurements. It is unclear how effective these controllers are given the sparse documentation released, though it is likely that improvements are possible given that all of these control schemes are some variation of gain-scheduled PID-control, a relatively simple approach.

In the work of [17] a grid fault controller is presented using multiple parallel PI-controllers to control the converters output current. The optimal controller gains are found by employing particle swarm optimisation with the objective of reducing the absolute real part of the largest eigenvalue of the linearised system where all eigenvalues are kept strictly negative by a barrier function. Simulations show that this approach is valid for a grid fault of 0.5 V/pu, so 50% of nominal voltage. Note, however, that this approach puts emphasis on controller speed and assumes a linear model during optimisation, which could come at the expense of large overshoots of the output power. In the work of [19] a Model Predictive Control (MPC) on the generator side of the converter is presented where the grid side of the converter is controlled using vector control and the blade pitch by a PI-controller. The MPC-controller minimises a quadratic cost function of the difference in reference output voltage and the predicted next output voltage, where an optimal output current is calculated for the generator side of the converter. Simulations show that this approach is valid for grid faults of 0.2 V/pu with only small fluctuations on the grid current and converter DC-voltage, see also [18] for another MPC-based approach. In the work of [20] a sliding mode controller is presented that works on the error of real and reactive power. Using a small test setup it is shown to work for grid faults up to 0.35 V/pu, but with high amounts of oscillations or chatter, a known problem of sliding mode control [21]. The work of [22] employs a feedforward control scheme, the only one found, but this is on a wind turbine system with extra energy storage systems. Such additional energy storage systems allow for more flexible control strategies but at a higher installation cost.

Although there is a large body of work in grid fault controllers, no research has been performed on feedforward control for grid fault recovery. A feedforward strategy could be beneficial for faster recovery after a grid fault of which the fault characteristics are relatively well known by virtue of the specifications in the Transmission System Operator (TSO) requirements [8]. Therefore, in this work a norm-optimal Iterative Learning Control (NO-ILC) is used to iteratively learn the feedforward signal to optimally recover from a grid fault according to a

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predefined cost. The learnt feedforward signal is added to the feedback control signal of the nominal controller. NO-ILC has been used to establish an optimisation-based problem with the added benefits of the ability to include input constraints and its favourable convergence properties compared to conventional types of ILC, such as PID-type ILC [23].

The contributions of this work are:

(i) Exploiting NO-ILC to find the optimal feedforward signal to recover from a grid fault scenario.
(ii) Extending the NO-ILC algorithm to include explicit input constraints.

The structure of this article is as follows. Section 2 introduces the grid fault as used in this work. Section 3 introduces the NO-ILC algorithm by means of the respective cost function and input constraints. Section 4 shows how NO-ILC is implemented on a grid fault. Section 5 presents the results of the NO-ILC on a high-fidelity wind turbine model. Lastly, Section 6 presents the conclusion of the work.

2. Grid fault problem

During a grid fault the wind turbine must remain connected to the electrical grid despite a reduction in grid voltage. In Figure 1 the lower voltage limit for the grid fault during which the wind turbine must remain connected as per [6] is shown. During said grid fault, the maximum generator torque output is reduced proportional to the reduction in grid voltage to prevent exceeding current ratings of components such as the generator and transmission cables. This reduction in torque and the resulting rotor overspeeding can be illustrated by considering the following simple first order wind turbine model:

$$\begin{aligned} J_\mathrm{r}\,\dot{\omega}_\mathrm{r} &= T_\mathrm{r} - T_\mathrm{g}(u) \\ &= \frac{1}{2}\rho\pi R^3 \frac{C_\mathrm{p}(\lambda,\beta)}{\lambda} V^2 - \frac{u}{u_\mathrm{nom}} T_\mathrm{g}, \end{aligned} \tag{1}$$

in which ω_r is the rotor speed, T_r the rotor torque, $T_\mathrm{g}(u)$ the generator torque dependent on the

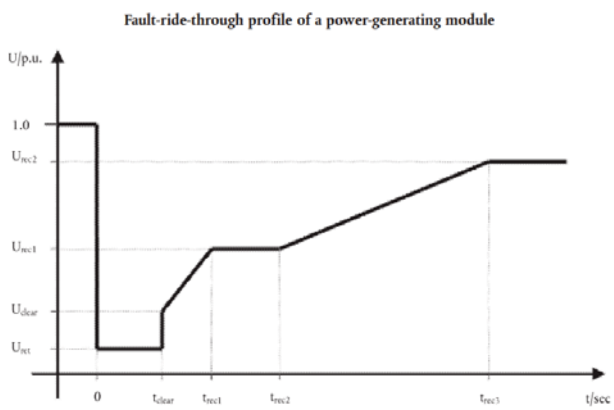

Figure 1. A lower limit of the grid voltage over time during which the WT's grid connection is required, with U/p.u. the relative grid voltage. If the grid voltage is below the specified level, the WT may disconnect from the grid, otherwise it has to stay connected to prevent cascading failures on the grid. The voltage levels and time points are TSO/country specific, where lower voltage levels and time scales impose a greater challenge on the WT's control. [6]

actual grid voltage u, u_{nom} the nominal grid voltage, ρ the air density, R the rotor diameter, C_{p} the power coefficient, $\lambda = \omega_{\mathrm{r}} R/V$ the tip speed ratio and V the wind speed. From the simplified model one can see that the generator torque is linearly effected by the magnitude of the grid fault drop u/u_{nom}. The rotor torque is however not directly affected by the grid fault that will lead to an imbalance in the generator and rotor torque if no action is taken. The goal of this paper is to synthesise the optimal feedforward signal to recover from a grid fault, using a form of iterative learning control described in the following section.

3. Norm-optimal ILC

Iterative Learning Control (ILC) is a technique that is used mainly to control the transient response of a system that operates repetitively. Or, in the words of Ahn et al., "an approach for improving the transient performance of systems that operate repetitively over a fixed time interval" [24]. This technique could be used, for example, to control a manufacturing robot or an autonomous vehicle that performs a repeating task, but also on non-repetitive tasks such as a grid fault.

In the ILC framework, the goal is to learn an optimal feedforward signal that can direct the system to a user-defined reference output signal. The creation of this optimal feedforward signal is done on the basis of the knowledge of previous attempts, which are more formally known as iterations. After each iteration j, an error $e_j[n] \in \mathbb{R}$ is calculated between the measured output $y_j[n]$ and the desired reference output $y_{\mathrm{d}}[n]$ for each point in the iteration. This is formulated as $e_j[n] = y_j[n] - y_{\mathrm{d}}[n] \, \forall \, n \in [0, N]$, with j being the iteration number, n the n-th sample in the iteration, and N the number of samples in a single iteration for which a feedforward signal is learnt. Based on the error e_j of the previous iteration, a new control signal is calculated using a learning rule which can often be represented as $\mathbf{f}_{j+1} = f(\mathbf{f}_j, \mathbf{e}_j) \in \mathbb{R}^N$ with $\mathbf{f}_j$ the feedforward input signal and f some learning function.

In Norm-optimal Iterative Learning Control (NO-ILC) not only feedforward control, but also feedback control is considered, as can be seen in Figure 2. The NO-ILC algorithm is used to iteratively minimise a (quadratic) cost function on (non)linear systems, where the optimal feedforward signal $\mathbf{f}_j$ is calculated after each iteration j. The optimal feedforward signal is added to the output signal of a feedback controller $\mathbf{u}_{j,\mathrm{fb}}$ to create a combined feedforward- feedback-control structure. The NO-ILC algorithm presented here is based on the work of [25] with an extension to include input constraints. Main advantages of the NO-ILC include monotonic convergence in one iteration for linear systems, easy formulation as an optimisation problem, and the ability to adapt the algorithm to include input constraints. In NO-ILC the following quadratic cost function is considered for minimisation:

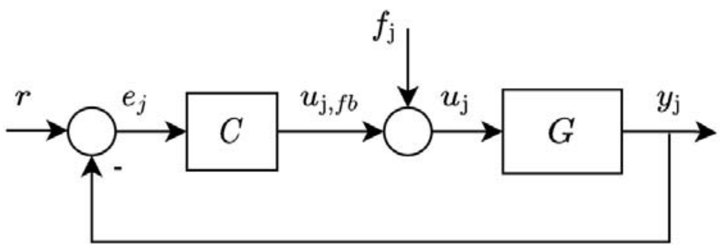

Figure 2. Block diagram of norm-optimal ILC where $\mathbf{f}_j$ is a learnt optimal input signal, C a feedback controller and G the systems input-output description. The signal $\mathbf{f}_j$ is synthesised by solving an optimisation problem that takes input constraints on signal $\mathbf{u}_j$ into account.

$$\mathcal{J}(\mathbf{f}_{j+1}) = \frac{1}{2}||W_{\mathrm{e}}\mathbf{e}_{j+1}||_2^2 + \frac{1}{2}||W_{\mathrm{f}}\mathbf{f}_{j+1}||_2^2 + \frac{1}{2}||W_{\Delta\mathrm{f}}(\mathbf{f}_{j+1} - \mathbf{f}_j)||_2^2 \tag{2}$$

where for SISO systems $\{\mathbf{e}_j, \mathbf{f}_j\} \in \mathbb{R}^N$ are the respective output error and feedforward input signal for iteration j of every time step, and $\{W_{\mathrm{e}}, W_{\mathrm{f}}, W_{\Delta\mathrm{f}}\} \in \mathbb{R}^{N\mathrm{x}N}$ weighting matrices on the output error, the feedforward input signal and the learning speed, respectively. The output error is defined with respect to the output and the reference signal by $\mathbf{e}_j = \mathbf{r}_j - \mathbf{y}_j$. For multivariable systems, the respective dimensions of $\mathbf{e}_j$ and $\mathbf{f}_j$ will have to be changed accordingly.

NO-ILC uses an offline calculated convolution matrix J of the impulse response of the closed-loop system from the feedforward input $\mathbf{f}_j$ to the system output error $\mathbf{e}_{j+1}$ to estimate the next output error. This convolution matrix effectively captures the effect of the feedback controller in the presence of the (optimal) feedforward signal. Using this convolution matrix J the next output error $\mathbf{e}_{j+1}$ is estimated by the linear estimate $\hat{\mathbf{e}}_{j+1} = \mathbf{e}_j - J(\mathbf{f}_{j+1} - \mathbf{f}_j)$ as proposed in [25]. In this work input constraints are included in NO-ILC. These constraints should be on the combined feedforward and feedback input signal for which the estimate $\hat{\mathbf{u}}_{j+1} = \mathbf{f}_{j+1} + \mathbf{u}_{j,\mathrm{fb}}$ will be used. The NO-ILC with input constraints can now be formulated as the following convex optimisation problem;

$$\begin{aligned} \mathbf{f}^*_{j+1} &= \arg\min_{\mathbf{f}_{j+1}} \mathcal{J}(\mathbf{f}_{j+1}) \\ \text{s.t.}\ \ & g(\hat{\mathbf{u}}_{j+1}) \leq 0 \end{aligned} \tag{3}$$

where $\mathbf{e}_{j+1}$ is replaced by $\hat{\mathbf{e}}_{j+1}$, and $g(\cdot)$ some function containing the input constraints. For the cost function as defined in Equation 2, the optimisation problem is convex given that the input constraint function is also convex.

4. Implementation

The NO-ILC algorithm as described in Section 3 has been implemented to learn the optimal feedforward signal for grid fault recovery on a high-fidelity wind turbine model. This high-fidelity wind turbine model is based on a 15 MW commercially-designed turbine, and is modelled in Bonus Horizontal axis wind turbine simulation Code (BHawC), a nonlinear aeroelastic software tool developed by Siemens Gamesa [26].

The quadratic cost function as in Equation 2 is employed. The blade pitch is considered as the controllable input, and for the output error the rotor speed error has been considered. In this work an 80% voltage reduction of 300 ms with gradual rise and descent is considered, as can be seen in Figure 3. Input constraints on the absolute blade pitch value and the rate of change have been included as follows:

$$\begin{aligned} \mathbf{f}^*_{j+1} &= \arg\min_{\mathbf{f}_{j+1}} \mathcal{J}(\mathbf{f}_{j+1}) \\ \text{s.t.}\ \ & u_{\min} \leq \hat{\mathbf{u}}_{j+1} \leq u_{\max}, \\ & \left|\hat{\mathbf{u}}^{2:N}_{j+1} - \hat{\mathbf{u}}^{1:N-1}_{j+1}\right| / T_{\mathrm{s}} \leq u_{\Delta\max} \\ & \left\{\mathbf{f}^{1:n_1}_{j+1}, \mathbf{f}^{(n_1+n_2):N}_{j+1}\right\} = 0 \end{aligned} \tag{4}$$

with T_{s} the discrete-time sample rate, and $\{u_{\min}, u_{\max}, u_{\Delta\max}\} \in \mathbb{R}$ the limit values of the asymmetric absolute rate constraint and symmetric rate of change constraint, respectively. The superscript in Equation 4 denotes which time-steps of the vector are used, with the subscript still

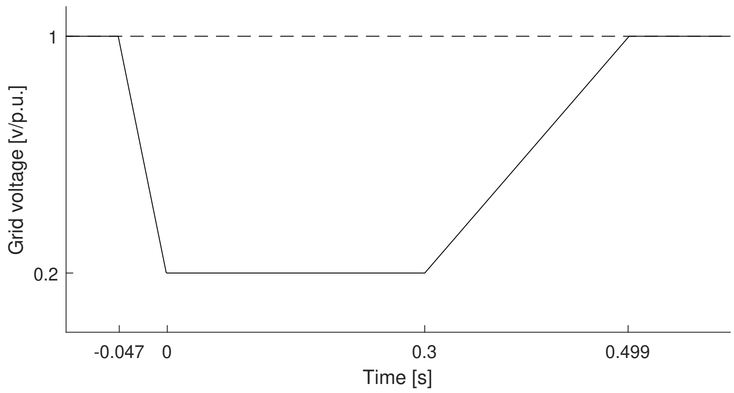

Figure 3. The grid fault profile during which the wind turbine needs to stay operational and connected to the electrical grid, that is used in this paper. The voltage level is measured relative to the nominal voltage. The ramp-down and ramp-up rates are compliant with internal Siemens Gamesa testing with a fault time of 0.3 seconds. The NO-ILC algorithm will be active from time is zero to 7 seconds.

indication the iteration index. The third constraint ensures that learning does not start before the grid fault, and is of finite duration, where n_1 is the first sample where the grid fault has full magnitude and n_2 the number of samples for which learning occurs with $n_1 \leq n_1 + n_2 \leq N$. The third constraint in Equation 4 ensures simple integration of the feedforward signal with the feedback signal without unwanted transients by ensuring that the first and last feedforward inputs are zero as only in a finite period of feedforward signal is used.

The optimisation problem is solved using a quadratic optimisation algorithm in MATLAB, where after each iteration of NO-ILC learning a new BHawC simulation is started using the latest iteration of the feedforward signal. In the first iteration the feedforward signal is zero, $\mathbf{f}_1 = \mathbf{0} \in \mathbb{R}^N$, and as such will represent the nominal controller.

5. Results

This section presents the results of the NO-ILC implemented to find the optimal feedforward signal for grid recovery. For the output error $\mathbf{e}_{j+1}$, the rotor speed error against a static reference signal is considered. Since a deterministic model has been used, matrix $W_{\Delta \mathrm{f}}$ has been set to zero. The other weighting matrices are diagonal matrices with the following magnitude, $W_\mathrm{e} = 10$ and $W_\mathrm{f} = 1$, where the output error has the highest penalty. The learning of the feedforward signal starts after the grid fault occurs, in the first sample with the full magnitude of grid fault, and with a total learning time of seven seconds.

The learning of the NO-ILC algorithm is presented in Figure 4, where the first iteration represents the nominal feedback controller. The addition of the optimal feedforward signal yields a 45% reduction in the cost function $\mathcal{J}(\mathbf{f}_\mathrm{end})$ and a 32% reduction of the rotor speed errors l^2-norm. Although the tower-bottom moment was not included as an objective in the cost function, the reduction in rotor speed excursions resulted in a 4% reduction of the tower-bottom moment errors l^2-norm, where the tower-bottom moment is defined as the moment of the tower structure at the interface of the tower and the foundation perpendicular to the rotor blades. The fact that the tower-bottom moments l^2-norm has not increased indicates that the mechanical loading of the turbine has not increased, even though it is not inside the cost function. Compared to the nominal controller, the NO-ILC significantly reduces the oscillations of the rotor speed. This reduction in oscillation is not only for the 7 seconds in which the feedforward signal is active but also after this time indicating a smooth transition between combined feedback-feedforward

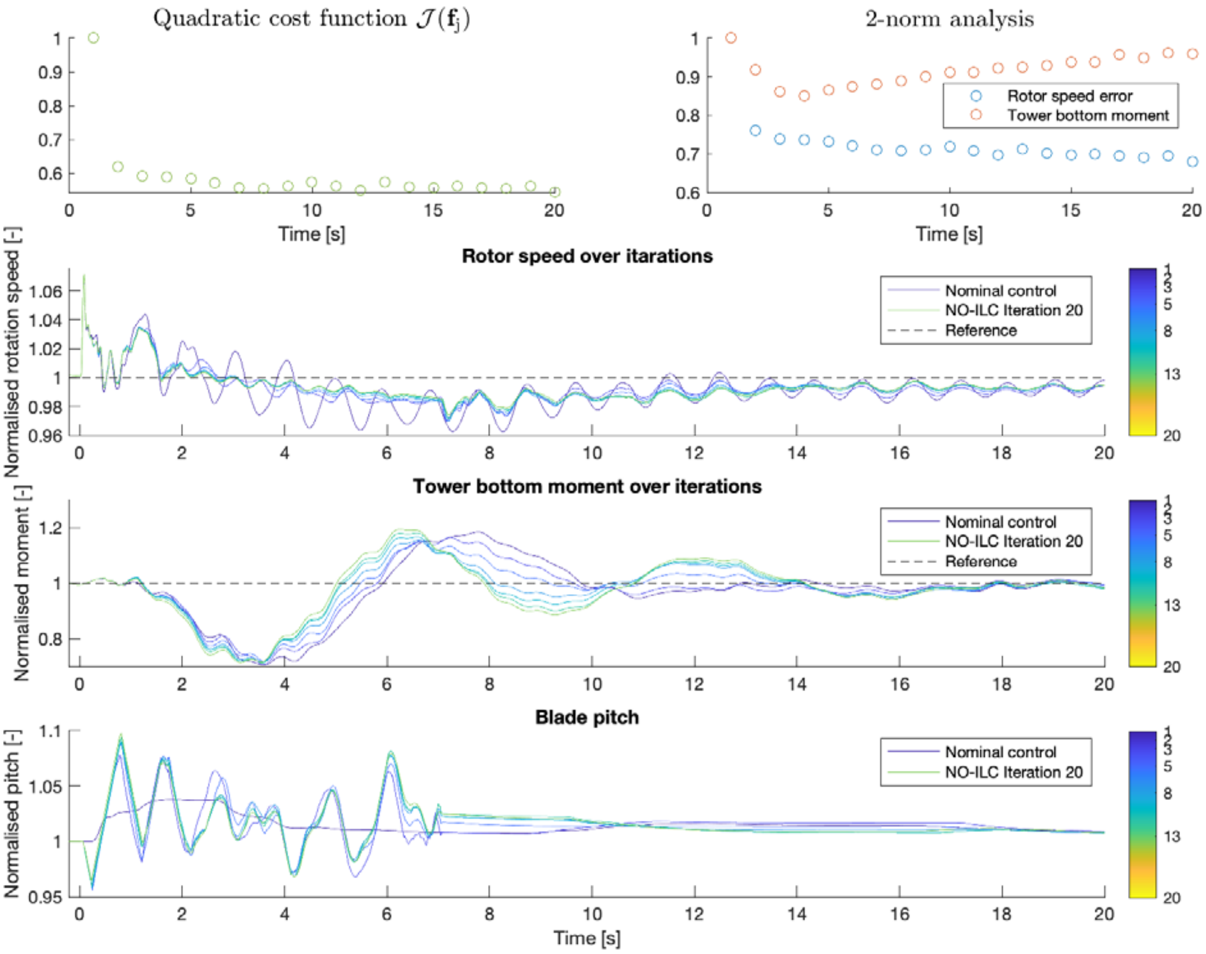

Figure 4. Comparison of norm-optimal ILC and a nominal feedback controller for a grid fault to 0.2 V/pu for 300ms on a high-fidelity simulation model. Top left shows cost function $\mathcal{J}(\mathbf{f}_\mathrm{j})$, top right the l^2-norm of the rotor speed and tower bottom moment. The color of the bottom three plots indicates the iteration number as indicated in the color bar.

and strict feedback control after the grid fault.

Cost function $\mathcal{J}(\mathbf{f}_j)$ converges almost in a single iteration and in near-monotonic fashion, even though the used model is nonlinear. This indicates that the linear approximation used inside the optimisation algorithm works sufficiently well for this application. The feedforward addition also significantly reduces the amplitude of periodic oscillation after the grid fault has occurred which is advantageous for fatigue load reductions.

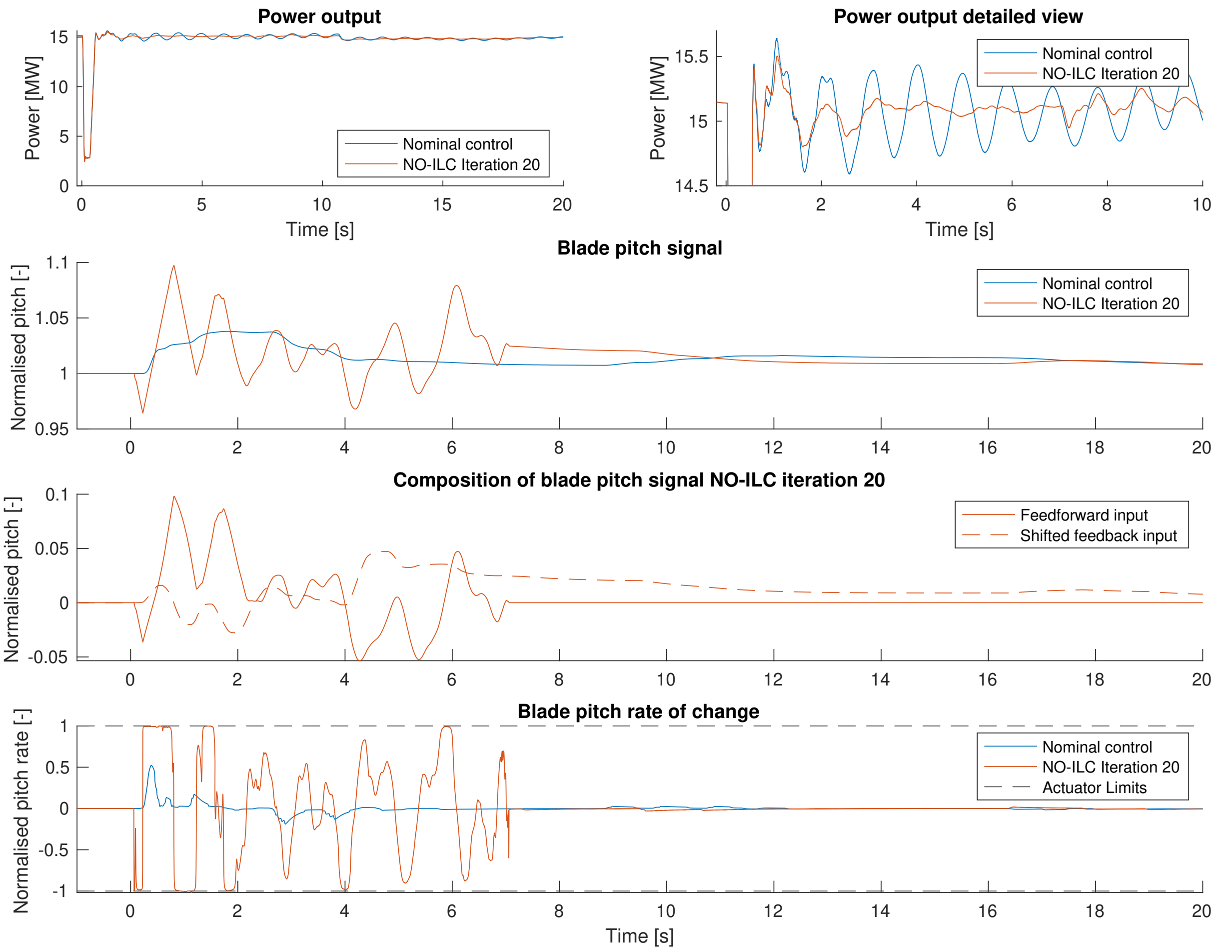

Figure 5. Comparison of norm-optimal ILC and a nominal feedback controller for a grid fault to 0.2 V/pu for 300ms on a high-fidelity simulation model. The power output is shown at the top, with in the middle the blade pitch signal, and in the bottom the blade pitch rate of change.

Comparison of the NO-ILC algorithm with the nominal feedback controller is presented in Figure 5. The difference in power output quality after the grid fault by use of the NO-ILC algorithm is evident with a 40% decrease in l^2-norm for the power output error from 0.5 to 10 seconds after the grid fault has settled. This increase in power quality can largely be contributed to the improved rotor speed response when using the NO-ILC algorithm. A contributing factor in the superior performance of the NO-ILC algorithm compared to the nominal controller is that the NO-ILC makes full use of the available pitch actuator limits after the grid fault, as can be seen in Figure 5. The new blade pitch input mostly adds periodic contributions that dampen the rotor speed oscillations, where the NO-ILC can be tuned to trade-off between actuation effort and rotor speed regulation.

6. Conclusion

This paper shows the potential to improve the nominal control strategy in case of grid faults. The NO-ILC algorithm has been successfully adapted to work for grid faults with the inclusion of input constraints. The cost function $\mathcal{J}(\mathbf{f}_{\text{end}})$ converges near the final value in a single step as promised by NO-ILC, where true single-step convergence can be expected for linear systems. The fast convergence of the cost function and the adherence of the input constraints indicate that the use of a linear model in the impulse response is sufficient on a nonlinear wind turbine model. Simulations show that NO-ILC significantly reduces output error oscillations, with a 45% decrease in the cost function $\mathcal{J}(\mathbf{f}_{\text{end}})$. For practical implementation of NO-ILC two directions are suggested:

(i) Improve nominal feedback control by matching its output closer to the optimal input signal acquired by a NO-ILC algorithm.

(ii) Create a library of optimal feedforward signals using NO-ILC that can be supplemented to the feedback signal based on the turbine state and external conditions to recover from similar grid faults.

Use case (i) could be implemented as is, but for use case (ii) the NO-ILC algorithm will have to be tested on a wider scenario of grid faults and objective functions with automatic grid fault detection. In addition, a test using stochastic grid fault and turbine conditions could be conducted, where one could study how the optimal feedforward signal correlates with external and internal states, and study the effects on the turbines output with a mismatch in learnt conditions and deployed conditions for the optimal feedforward signal.

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