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Optimization with genetic algorithms of individual pitch control design with and without azimuth offset for wind turbines in the full load region

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Abstract: The reduction of fatigue loadings in wind turbines to increase their lifetime has become of special interest from a control viewpoint. Individual Pitch Control (IPC) is a well-known approach used to mainly mitigate periodic blade loads, and it is usually implemented with the assistance of the multi-blade coordinate (MBC) transformation, which transforms and decouples the measured blade load signals from a rotating frame into a non-rotating tilt-axis and yaw-axis. Nevertheless, these axes still show coupling between them in practical scenarios adversely affecting the system performance. Previous studies have demonstrated the benefits of including an extra tuning parameter in the MBC, the azimuth offset, in improving the performance achieved by the IPC. However, the tuning of this parameter and its real improvements that can be obtained compared to the IPC without this offset require more research. Here, two 1P+2P IPC, with and without additional azimuth offset, are designed and applied to the 5 MW reference turbine model developed by NREL using the FAST software as a simulation platform. The controller parameter tuning is formulated as an optimization problem that minimizes the blade fatigue load according to the Dirlik index and that is resolved through genetic algorithms. To fairly analyze the improvement entailed by the addition of the azimuth offset, both optimized IPC schemes, with and without azimuth offset, are compared qualitatively and quantitatively using a classical controller as the baseline case. From the simulation results, it can be stated that the optimal IPC scheme with azimuth offset compared with the IPC scheme without offset achieves improvements of around 11% in load reduction and pitch signal effort.

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Keywords: Control system design; control of renewable energy resources; wind turbine control; individual pitch control; genetic algorithms.

1. INTRODUCTION

Nowadays, the concern of global warming and climate change is a priority, which are promoting actions to reduce greenhouse-effect gas emissions. Considering that about 30% of these emissions are due to energy generation, wind energy has played an important role since the beginning as one of the main sources of renewable energy. The total global wind capacity in 2021 reached 837 GW, with China, the US, Germany, India, and Spain together accounting for 72%. Even so, according to the International Energy Agency's forecast, wind power capacity must increase to 3200 GW by 2030 to limit global warming to 1.5°C (Lee and Zhao, 2022). For this expansion to be financially affordable and competitive, wind turbines must operate more efficiently. From a control viewpoint, this can be achieved by improving the power captured from the wind and by reducing the different structural loads of the wind turbines, which increases their lifetime (Lara et al., 2023).

Traditionally, the speed controllers in the full load region of a wind turbine are based on a collective pitch control (CPC), which provides the same pitch value for the blades to reject the wind speed disturbances and keep the power output at its nominal value. However, currently, most wind turbines have control mechanisms that allow independent pitch control (IPC) for each blade. One important advantage of IPC is its capability to reduce fatigue loads on the rotor blades, the hub, and tower structure without significantly affecting the generated power. IPC is mainly used to reduce fatigue loads of the blades. The bending moment of each blade can be measured using sensors installed on them. However, these measurements are subjected to the corresponding rotating coordinate system of each blade. Most works on IPC use the azimuth-dependent multi-blade coordinate (MBC) transformation to transform the rotating moments of the blades into a non-rotating reference frame (Mulders et al., 2019). In this fixed frame, there are two azimuth-independent components of the moment: the tilt moment M_t and the yaw moment M_y. IPC is applied to reduce these two components, which are expected to be decoupled. However, in practical scenarios, the resulting transformed system still shows coupling between them (Mulders et al., 2019). Some authors use an azimuth offset as an additional tuning parameter to improve the decoupling of the multivariable system in the fixed frame. In (Mulders et al., 2019), the use of this offset in the implementation of IPC on first periodic (1P) harmonics achieves decoupling of the transformed system, showing beneficial effects on pitch performance and reduction of blade fatigue loading. In (Mulders and van Wingerden, 2019), the authors extend previous work and demonstrate the implications and importance of including azimuth offset for the mitigation of higher periodic harmonics, specifically 1P and second periodic (2P) loads.

Several studies combined the MBC transformations with more advanced control techniques, such as Linear Quadratic Gaussian, Model Predictive Control or H_∞ techniques.

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Computational intelligence methods are an increasing alternative to solve wind turbine control problems (Sierra-Garcia and Santos, 2021). In (Lara et al., 2021), an optimization with genetic algorithms (GA) is performed to tune the controllers of a wind turbine, minimizing the error of the generator angular speed and the tower fore-aft displacements. In (Mulders et al., 2020), authors used Bayesian optimization to tune the controller gains and azimuth offsets of an IPC scheme to minimize the blade fatigue 2P- and 1P-loads. The authors compared the results of this scheme with those achieved by the same scheme without azimuth offset, which obtains a worse performance; however, they did not optimize this last IPC scheme without offset. For a fair comparison and analysis, both IPC schemes with and without azimuth offset should have been optimized in this work according to the same cost function.

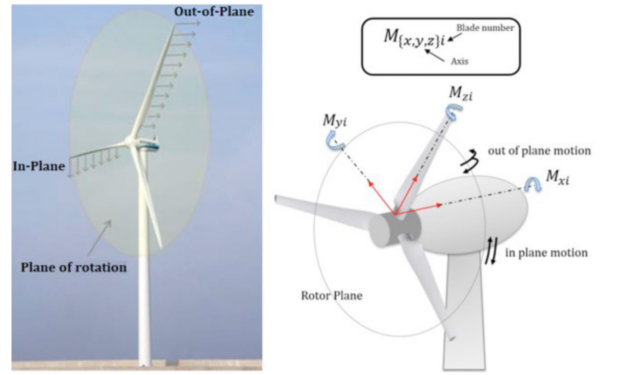
In this paper, an IPC scheme is used to reduce the 1P and 2P blade loads of a wind turbine of 5 MW in the full load region. Specifically, the IPC parameters are tuned to reduce the blade fatigue loading according to the index Dirlik (Ragan and Manuel, 2007). The tuning procedure is performed by means of optimization with GA. Two IPC cases (the schemes with and without azimuth offset ψ_o) are optimized, analyzed, and compared. The results of both configurations are compared with those achieved by a classical baseline PI controller as CPC without IPC. Conclusions about the real improvement provided by the azimuth offset are derived.

The remainder of the paper is organized as follows: Section 2 provides background on IPC implementation. In Section 3, the proposed methodology and the optimization procedure are described. Section 4 shows a comparative analysis of the results of the proposed controllers and the baseline controller and verifies the improvements obtained by using azimuth offset. Finally, conclusions are summarized in Section 5.

2. BACKGROUND ON MBC TRANSFORMATION AND IPC

This section briefly presents the general formulation of IPC and MBC transformations for n-P harmonic reduction in blade loading in wind turbines with three blades. The individual aerodynamic loads on wind turbine blades can be categorized into two components: in-plane and out-of-plane. They mainly arise at multiples (n-P) of the turbine rotational speed. As shown in Fig. 1a (Jeong et al., 2012), the in-plane component is tangential to the plane of rotation and the out-of-plane (OoP) component is normal to it. These moments are initially measured in the corresponding rotating coordinate system of each blade, as shown in Fig. 1b (Cheon et al., 2019), where the blade OoP bending moment at the blade root is called My_i (i is the blade number 1, 2, or 3). In the n-MBC transformation for the n-P harmonic, the rotating OoP bending moments of the blades are collected in the vector $\mathbf{M}(t)=[M_1(t)\ M_2(t)\ M_3(t)]^T$ and supplied to the forward MBC transformation matrix $\mathbf{T_n(\psi)}$ to obtain in the fixed frame the corresponding azimuth-independent tilt and yaw moments, $M_{t,n}(t)$ and $M_{y,n}(t)$, respectively, as shown as follows:

$$\begin{bmatrix} M_{t,n}(t) \\ M_{y,n}(t) \end{bmatrix} = \boldsymbol{T}_n(\boldsymbol{\psi})\, \boldsymbol{M}(t) \tag{1}$$



(a) (b)

Fig. 1. (a) Components of aerodynamic loads on wind turbine blades: tangential to the plane of rotation (or in-plane) and normal to it (or out-of-plane). (b) rotating coordinate system of the i-th blade, where M_{xi} represents the in-plane bending moment of the i-th blade and M_{yi} is its out-of-plane moment.

The vector $\boldsymbol{\Psi}$ is the array with the three azimuthal angles, one for each blade, where a zero value for an angle indicates the vertical upright position. The expression of the forward transformation matrix is given in (2), where n=1 for the 1P harmonic and n=2 for the 2P harmonic.

$$\boldsymbol{T_n} = \frac{2}{3}\begin{bmatrix} \cos(n\psi_1) & \cos(n\psi_2) & \cos(n\psi_3) \\ \sin(n\psi_1) & \sin(n\psi_2) & \sin(n\psi_3) \end{bmatrix} \tag{2}$$

Subsequently, the fixed frame tilt $\beta_{t,n}(t)$ and yaw pitch $\beta_{y,n}(t)$ angles are computed by the IPC block for each n-P harmonic. These non-rotating pitch signals $\beta_{t,n}(t)$ and $\beta_{y,n}(t)$ are transformed into the rotational frame to obtain the three pitch components $\beta_{IPC1,n}(t)$, $\beta_{IPC2,n}(t)$, and $\beta_{IPC3,n}(t)$, as shown in (3). This transformation is computed using the reverse MBC transformation, $\boldsymbol{T_n^{-1}}$, which is defined according to (4). The parameter $\psi_{o,n}$ is the azimuth offset for the n-P harmonic. The offset can be used to improve the decoupling of the tilt- and yaw-axis components in the fixed frame. The n-P pitch components are added to provide the final IPC signals $\beta_{IPC1}(t)$, $\beta_{IPC2}(t)$, and $\beta_{IPC3}(t)$.

$$\begin{bmatrix} \beta_{IPC1,n}(t) \\ \beta_{IPC2,n}(t) \\ \beta_{IPC3,n}(t) \end{bmatrix} = \boldsymbol{T}_n^{-1}(\boldsymbol{\psi} + \psi_{o,n}) \begin{bmatrix} \beta_{t,n}(t) \\ \beta_{y,n}(t) \end{bmatrix} \tag{3}$$

$$\boldsymbol{T}_n^{-1} = \begin{bmatrix} \cos[n(\psi_1 + \psi_{o,n})] & \sin[n(\psi_1 + \psi_{o,n})] \\ \cos[n(\psi_2 + \psi_{o,n})] & \sin[n(\psi_2 + \psi_{o,n})] \\ \cos[n(\psi_3 + \psi_{o,n})] & \sin[n(\psi_3 + \psi_{o,n})] \end{bmatrix} \tag{4}$$

3. PROPOSED METHODOLOGY

This section describes the developed methodology: the simulation environment and the wind turbine model in which the method is tested; the control system scheme and its components; and the optimization procedure using GAs.

3.1 Wind turbine model and simulation environment

This work applies the proposed methodology to the 5–MW NREL turbine model that is based on the REpower 5 MW commercial model. This model has often been reported in the literature (Jonkman et al., 2009) and it is simulated with the assistance of MATLAB/Simulink and OpenFAST (Fatigue, Aerodynamics, Structures, and Turbulence) software. This software provides the 5–MW NREL turbine model and the wind profile. More details can be found in (Jonkman et al., 2009). In this study, the wind turbine is operated only in the full load region, where the blades suffer the most damage since the blade bending moments increase with the mean wind speed. The required turbulent wind field is generated using TurbSim. The wind signal is configured with a mean wind speed of 18 m/s, a Kaimal turbulence spectrum with 0.540 m/s of standard deviation, and a power-law vertical shear with an exponent of 0.2. The sampling frequency is set to 50 Hz. Since the FAST wind turbine model does not include pitch actuator dynamics, this is modeled with the first-order unity-gain transfer function: $\beta_a(s)/\beta(s)=1/(0.4s+1)$, which has a time constant of 0.4 s. This time constant has been chosen to show the problems of reducing the 2P load harmonic when pitch actuators with slow dynamics are used (Mulders and van Wingerden, 2019). The control scheme and the pitch actuator model are implemented with MATLAB/Simulink.

3.2 Control system

The control scheme proposed in this work is shown in Fig. 2. It consists of two controllers: a CPC and an IPC. The control actions of these controllers are added to generate the pitch signals for the pitch actuators. Since the wind turbine is assumed to operate in the full load region at its rated power, the generator torque T_g is fixed at its rated value of 43093.55 Nm. According to $P_g=T_{g\_rated}\omega_g$, the generated power can be maintained at its nominal value if the wind turbine speed is controlled at its rated value of 1173.7 rpm. The CPC maintains this speed at its nominal value and rejects the wind speed changes. The tuning procedure of the CPC is not considered in this work; we use a pre-designed gain-scheduling PI controller (Jonkman et al., 2009).

The IPC block reduces the periodic blade loads of several harmonics. The IPC scheme used in this work is shown in Fig. 3, which consists of two different MBC transformations for 1P and 2P harmonic reduction and incorporates the azimuth offset in the reverse transformations. This is a 1P+2P IPC scheme, where there are two feedback control structures connected in parallel: the top one for harmonic 1P and the bottom one for harmonic 2P. In the structure of each harmonic, the MBC transformation provides the tilt and yaw moments in the non-rotating frame from the measured OoP blade moments in the rotating frame. Two pure integral controllers are used in a decentralized control scheme to reduce these tilt and yaw moments and to provide the tilt and yaw pitch signals, respectively. The same integral gain is used in each pair of Integral controllers of the same *n*-P harmonics. Therefore, the proposed 1P+2P IPC scheme has only two integral gains to be tuned when there is no azimuth offset: k_{I1} and k_{I2}. These are decision variables in the optimization procedure. Then, the computed non-rotating tilt and yaw pitch signals for each harmonic are transformed with the reverse MBC transformation into three distinct blade pitch angles implementable in the rotating frames. The two IPC signals of blade *i* are added to compute the total IPC pitch signal β_{IPCi} for this blade. When the reverse MBC transformation is used with azimuth offset for each harmonic, the 1P+2P IPC scheme has two additional parameters to be optimized: $\psi_{o,1}$ and $\psi_{o,2}$. The azimuth offset is used to improve the decoupling of the tilt- and yaw-axes, which expects to achieve further reduction of the periodic blade loads compared to the IPC scheme without offset ($\psi_{o,1}=\psi_{o,2}=0º$). Finally, the total IPC signals are added to the CPC value to obtain the whole pitch angle of each blade.

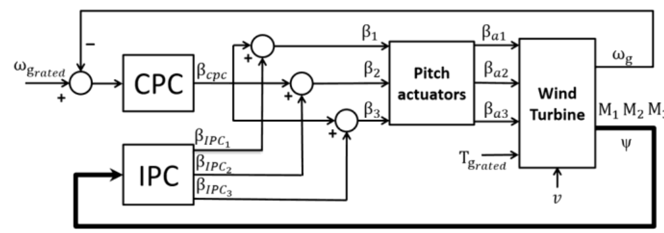


Fig. 2. IPC+CPC control system scheme for the full load region. The CPC provides the same pitch value for the blades to regulate the generator speed at its nominal value. The generator torque is kept at its rated value. The IPC provides the individual contribution for each blade to reduce the blade moments. Both contributions of CPC and IPC are summed to obtain the final pitch signals for the pitch actuators.

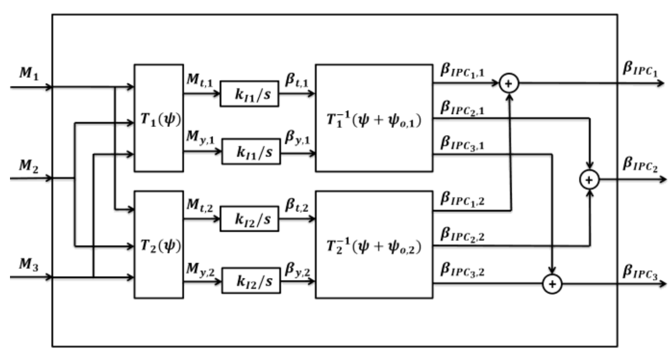


Fig. 3. 1P+2P IPC scheme with azimuth offset. The forward MBC transformations $T_n(\boldsymbol{\psi})$ convert the blade load harmonics of 1P and 2P rotational frequencies to a fixed reference frame. In this frame, a decentralized feedback loop for each harmonic is implemented with integral controllers to reduce the tilt- and yaw-axis loads. The control signals are transformed to the original frame with the reverse transformation with azimuth offset $\boldsymbol{T}_n^{-1}(\boldsymbol{\psi}+\psi_o)$. The 1P and 2P pitch contributions are summed to obtain the final IPC signals β_{IPCi}.

3.3 General theory of optimization using genetic algorithms

Genetic algorithms are stochastic global search optimization methods that simulate the phenomena of replication, crossover, and variation that occur in natural selection and inheritance. They are specially intended for optimization problems where the model to optimize is very complex, the cost functions need to be evaluated from simulation data and simulation-based approach is used. From a previous solution, the GA produces a new population through four layers: selection, crossover, mutation, and migration criteria (Andrade

Aimara et al., 2023). GA is based on the improvement of the first population, so the algorithm obtains the best result in each iteration. The population comprises individuals called chromosomes, each of which is encoded as an array of parameter values and represents a candidate solution. When a problem has N dimensions, each chromosome is encoded as an N-element array, where the i-th element is a particular value for the i-th parameter. Fig. 4a shows the steps of GA for the performed optimization. These steps are as follows:

1) Initial population: the first population values are generated randomly within the set parameter search range.

2) Fitness assignment: after the initialization, a fitness value is assigned to each individual in the population or chromosome. The fitness function is the cost function to be optimized. In a simulation-based approach, a simulation is performed for each individual to compute the corresponding fitness.

3) Selection: the aim of this part is to choose the fittest individuals and let them pass their genes to the next generation. The roulette selection method is set in this work in such a way that chromosomes with low fittest values have a high fitness probability, and therefore, they have a higher chance to be selected. The fitness probability of i-th individual is defined as $P_i=\text{Dirlik}_i/\sum_{j=1}^{N}\text{Dirlik}_j$, and its cumulative fitness probability $q_i=\sum_{j=1}^{i}P_j$. Then, the selection is made on the basis of the position of the previous probability values in the roulette, expressed in a scale of cumulative fitness probabilities. To do this, a uniformly distributed pseudo-random number r is generated in the interval [0,1]. If $q_{k-1} \leq r \leq q_k$, then the k-th individual is selected as parent. The number r is generated so many times as to complete the necessary parents. The best chromosomes are always preserved (elitist selection).

4) Crossover: after sorting and discarding the chromosomes, the crossover operator recombines the chosen individuals, to create a fraction of the new population. For each pair of parents, mum and dad as defined in (5), a random gene crossing point is selected before mating, that is, a decision variable α is randomly chosen as crossing point. Subscripts m and d denote mum and dad, respectively. Then, the chosen parameters $p_{m,\alpha}$ and $p_{d,\alpha}$ are combined according to (6) to create new variables p_{new1} and p_{new2} that will manifest themselves in the offspring. The parameter γ is a random variable between 0 and 1. Finally, the crossover is completed by interchanging the other genes (parameters) to obtain the offspring, as shown in (7).

$$\begin{aligned}\mathbf{mum} &= [p_{m,1} \quad p_{m,2} \quad \cdots \quad p_{m,\alpha} \quad \cdots \quad p_{m,N}] \\ \mathbf{dad} &= [p_{d,1} \quad p_{d,2} \quad \cdots \quad p_{d,\alpha} \quad \cdots \quad p_{d,N}]\end{aligned} \tag{5}$$

$$\begin{aligned}p_{new1,\alpha} &= p_{m,\alpha} - \gamma(p_{m,\alpha} - p_{d,\alpha}) \\ p_{new2,\alpha} &= p_{d,\alpha} - \gamma(p_{m,\alpha} - p_{d,\alpha})\end{aligned} \tag{6}$$

$$\begin{aligned}\mathbf{offspring}_1 &= [p_{m,1} \quad p_{m,2} \quad \cdots \quad p_{new1,\alpha} \quad \cdots \quad p_{d,N}] \\ \mathbf{offspring}_2 &= [p_{d,1} \quad p_{d,2} \quad \cdots \quad p_{new2,\alpha} \quad \cdots \quad p_{m,N}]\end{aligned} \tag{7}$$

5) Mutation: it transfers a bit of randomness to the new individuals to maintain diversity in the population and avoid local optimum tracking, like crossover.

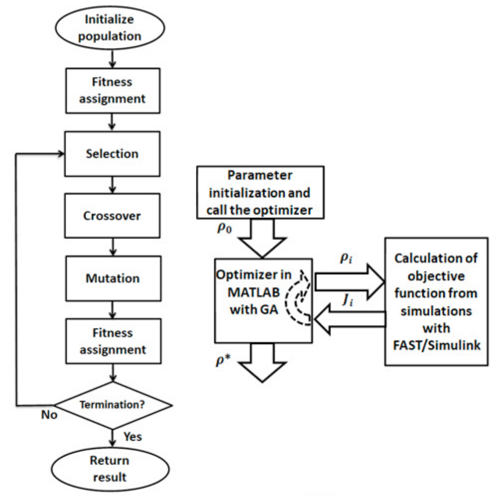


Fig. 4. (a) GA steps: initialization of population and calculation of the individual fitness according to the cost function; selection of the best candidates and rejecting others; creation of new population by mixing the selected individuals (crossover) and transferring randomness to the new individuals (mutation); and evaluation of the new population. The process iterates until a termination condition is reached. (b) Simulation-based optimization procedure: after parameter initialization, the optimizer using GA in MATLAB requires iterative simulations with FAST/Simulink to search the optimal solution that minimizes the Dirlik index.

6) Generation of new individuals: after the offspring is mutated, it rejoins with other mutated offspring to reform a new population. The complete process of fitness assignment, selection, crossover, and mutation is repeated until a stopping criterion is met. The process will stop if the fitness of a given solution reaches the desired fitness, if the maximum number of generations is reached, or if the population stabilizes.

3.4 IPC tuning by optimization via genetic algorithms

The IPC block of Fig. 3 is tuned by using an optimization procedure that searches for minimizing blade fatigue loading through the OoP moment of the blades, that is, the moment on the y-axis of Fig. 1b. For fatigue assessment in wind turbines, the Damage-Equivalent Load is usually calculated in the time domain using cycle counting techniques. In the frequency domain, it can be approximated with Dirlik's method, which consists of a semi-empirical formula that determines stress ranges and fatigue damage from statistical moments on the structural response (Ragan and Manuel, 2007). Dirlik's method has already been proven to calculate fatigue damage values with good accuracy for various structures and wind turbines. In the proposed optimization, the Dirlik index for blade 1 OoP moment M_{y1} is the cost function J to be minimized, that is, the fitness function.

Two versions of the IPC are tuned for a subsequent comparison: IPC without azimuth offset, which has only the two integral gains k_{I1} and k_{I2} in the vector $\boldsymbol{\rho}$ of decision variables in the optimization problem; and IPC with azimuth offset, which also has the two offsets $\psi_{o,1}$ and $\psi_{o,2}$ as additional parameters to be optimized. The proposed objective function cannot be evaluated analytically since the Dirlik index is computed offline from the time series of simulation data. Furthermore, the dynamic model of the wind turbine in FAST is very complex. Therefore, the simulation-based approach shown in Fig. 4b is used in the optimization. First, the decision variables are initialized in vector $\boldsymbol{\rho}_0$. Then, the procedure enters an iterative loop for optimization, where the optimizer in MATLAB requires performing different simulations with FAST/Simulink to calculate the cost function **J** and search for the optimal solution $\boldsymbol{\rho}^*$. This optimization procedure becomes a nonlinear problem that requires intensive computational effort and time. To achieve better computational efficiency, the optimization is performed using genetic algorithms (GA).

In the proposed optimization, the chromosomes are comprised of $[k_{I1}\ k_{I2}]$ for the case of IPC without azimuth offset, and $[k_{I1}\ k_{I2}\ \psi_{o,1}\ \psi_{o,2}]$ for the IPC case with azimuth offset. The search range for integral gains is [0-0.05] rad·Nm^{-1}s^{-1} and the range for azimuth offsets is [0º-60º]. A population size is configured with 250 individuals. We use an elite count of 0.05 times the population size for reproduction, a crossover fraction of 0.8, and a mutation probability of 0.2 for offspring mutation. Table 1 shows the control parameters obtained for the two IPC versions after optimization. Table 2 shows the Dirlik indices of M_{y1} obtained from the optimal solutions. These indices are shown relative to the CPC without any IPC, which is considered as the baseline case, and therefore, it has a value of 100%. The IPC without azimuth offset achieves a reduction of 63.85% with respect to the CPC. The IPC with offset surpasses the previous one and achieves a reduction of 68.08%, which is a −11.7% with respect the value of the IPC without offset.

Table 1. Optimized parameters of the IPC

IPC scheme	k_{I1} (rad·Nm^{-1}s^{-1})	k_{I2} (rad·Nm^{-1}s^{-1})	ψ_{o1} (deg)	ψ_{o2} (deg)
IPC (no ψ_o)	$1.25\cdot10^{-2}$	$7.45\cdot10^{-4}$	0	0
IPC with ψ_o	$1.91\cdot10^{-2}$	$3.58\cdot10^{-4}$	40.94	20.85

Table 2. Cost function and performance indexes

Control	DIRLIK(M_{y1}) (% relative to CPC)	TV_β (deg)	$IAE_{\omega g}$ (rpm)	STD_{My1} (kNm)
Baseline CPC	100	13.59	$2.44\cdot10^5$	1031
1P+2P IPC+CPC	36.15	585.56	$2.47\cdot10^5$	331.3
1P+2P IPC +CPC with ψ_o	31.92	520.46	$2.48\cdot10^5$	278.9

4. RESULTS

This section analyzes and compares the simulation results of the two proposed schemes tuned with the optimal parameters of Table 1. They are the CPC+IPC (no ψ_o) and the CPC+IPC with ψ_o. They are also compared with the CPC without IPC as the baseline controller. Fig. 5 shows the time responses of the wind turbine obtained for the wind profile depicted at the top in the figure. Below it, the figure shows the generator angular speed, the OoP bending moments of blade 1, and, at the bottom, the pitch angle for blade 1. Although data analysis is performed for a simulation time of 400 s, only a 100-s simulation is shown for clarity.

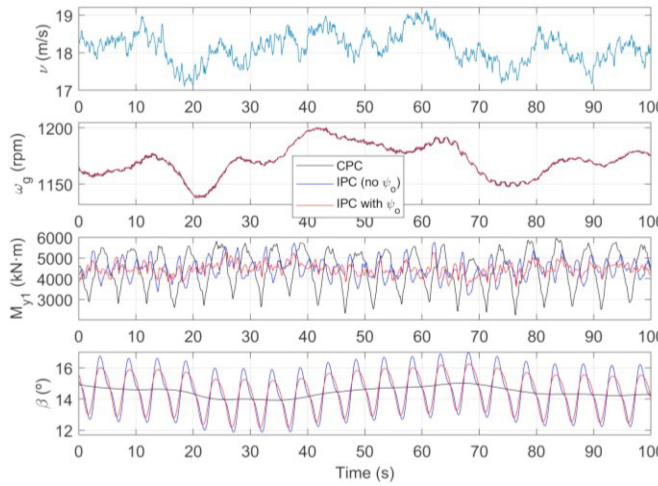


Fig 5. Comparison of the simulation time responses of the generator angular speed, the OoP blade moment M_{y1}, and the pitch signal β_1 for the wind speed depicted at the top. The generator speed is almost the same in the three cases. The CPC+IPC with ψ_o (red line) and CPC+IPC without with ψ_o (blue line) achieve a great OoP moment reduction compared to the CPC (black line). This reduction is accomplished at the expense of major pitch activity.

The responses of the generator speed ω_g achieved using the three methods are practically overlapped, which shows that the IPC strategies do not interfere with the CPC in regulating this speed. This is also demonstrated using the integral of the absolute error (IAE) of ω_g, which is calculated as $IAE_{\omega g}=\int_{t_0}^{t_s}\left|\omega_{g_{rated}}-\omega_g(t)\right|dt$. The obtained IAE values are listed in Table 2, and they have almost the same value for the three different control methodologies. The third plot of Fig. 5 shows how both IPC strategies considerably reduce the amplitude of the OoP moments compared with the CPC; in this case, the moment M_{y1} of blade 1 is illustrated as an example. This reduction is expected according to the minor Dirlik indexes achieved using the optimization tuning procedure. This mitigation is also evident in the lower standard deviations of this moment, which are shown in Table 2. This reduction is obtained at the expense of a higher pitch activity, as shown at the bottom of Fig. 5. The IPC schemes considerably increase the duty cycle of the pitch signal compared with the CPC. This major activity can be measured using the total variation (TV) of the pitch according to $TV_\beta=\sum_{k=1}^{n}|\beta(t_k)-\beta(t_{k-1})|$. The computed values are shown in Table 2. When both proposed IPC schemes are compared, it is important to remark that the proposed CPC+IPC with azimuth offset achieves smaller values of both Dirlik index and TV_β than those achieved by the CPC+IPC without offset. When azimuth offset is used, the TV_β is 11.12% smaller compared to the IPC without offset.

Next, a frequency domain analysis and comparison of the OoP blade bending moments is performed showing the results for blade 1. Fig. 6 shows the Fourier spectra of the OoP blade load moment M_{y1} and the pitch signal. In comparison to the CPC, both IPC schemes practically remove the great 1P-component of the blade moment around the frequency of 0.2 Hz, as shown at the top in Fig. 6. However, the IPC proposals show different performance with respect to the 2P-component around 0.4 Hz.

The CPC+IPC with offset successfully removes this 2P-component compared to the CPC, whereas the CPC+IPC without azimuth offset increases it significantly. With respect to the pitch signal, the CPC does not show neither 1P- nor 2P-peak values. Both CPC+IPC schemes have an important peak value related to the 1P-component that is the main responsible for the major pitch activity of the schemes with IPC. The CPC+IPC without azimuth offset also has a pitch peak value related to the 2P-component whereas this peak is significantly smaller using the CPC+IPC with azimuth offset.

To sum up, from the previous qualitative and quantitative analysis, we can state the following advantages of the IPC with an azimuth offset over the IPC without it when both schemes are optimally tuned to minimize the Dirlik index of OoP blade moments: (1) a greater reduction of the Dirlik index by a 11.7%, (2) a reduction of the 2P-component of the OoP moments, and (3) a lower pitch total variation value of 11.12%.

5. CONCLUSIONS

In this work, the tuning of two 1P+2P IPC schemes with and without azimuth offset are tuned by optimization with GAs to reduce the OoP blade moments. They are combined with a pre-defined CPC, which is not modified. A qualitative and quantitative comparison is performed from the simulation results. This comparison demonstrates that IPC does not affect the performance of the CPC in regulating the generated power and considerably improves the reduction of OoP blade moments compared to not using IPC, at the expense of a higher pitch signal activity. The comparison between both proposed IPC schemes proves that the optimal solution of IPC without azimuth offset produces worse results than the optimal solution of IPC with offset. This last one achieves a higher moment reduction in both 1P and 2P components with a minor pitch actuator effort. Here, the resulting improvements when both schemes are optimally tuned are around 11% in the Dirlik index of OoP blades and the total variation of the pitch signal.

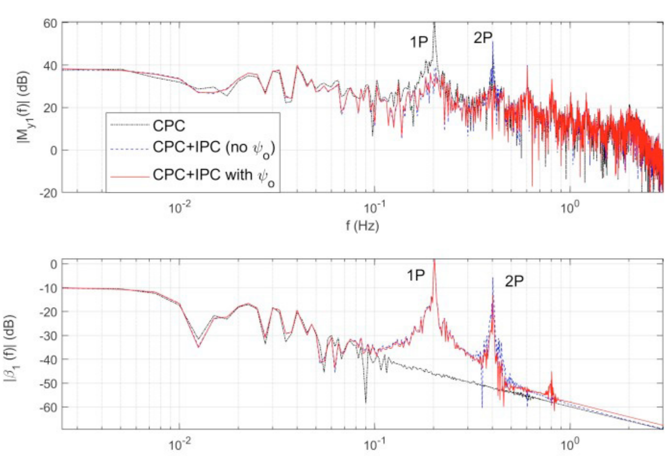


Fig. 6. Comparison of the Fourier spectra of the OoP blade moment and the pitch signal for blade 1. Both IPC reduce the peak values of the moment 1P- and 2P- that arises with CPC (black line); however, they attain it at expense of peak values in the pitch spectrum. The IPC with ψ_o (red line) achieves a greater reduction of the 2P component of the moment and the pitch compared to the IPC without ψ_o (blue line).

Further work is needed to analyze how these improvements vary with the wind speeds and turbulence and address the trade-off between different conflicting objectives, such as pitch signal effort and load reduction.

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