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An advanced farm flow estimator for the real-time evaluation of the potential wind power of a down-regulated wind farm

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Abstract. This work aims at verifying the predictions of OnWaRDS, an open-source wake modelling framework that captures the main features of the wake dynamics, including its meandering, in ancillary services scenarios. OnWaRDS brings together Lagrangian flow modeling and flow sensing and runs in parallel with a wind farm environment (here Large-Eddy simulations coupled to an Actuator Disk model (LES-AD)) in order to use the available rotor states to predict the flow field. The performances of OnWaRDS are first assessed when it runs synchronously with the LES-AD of a down-regulated wind farm and tends to mimic the LES-AD behavior. This *synchronous* mode implies a continuous feeding of the wake model with LES-AD rotor data. Then, OnWaRDS is used in a *predictive* mode, in order to predict an alternate reality for the wind farm. In this study, OnWaRDS aims at evaluating, in real-time, what the potential power production would be when the LES-AD is down-regulated to provide operating reserve capacity to the electricity network. Switching to a *predictive* mode implies that certain measurements at the wind turbine level can no longer be used, because the flow and the rotor behavior change between LES-AD and OnWaRDS. The second part of this study thus aims at verifying the predictions of OnWaRDS, and highlighting the impact of switching from a *synchronous* to a *predictive* mode in OnWaRDS.

1. Introduction

The sustainable integration of high volumes of wind-produced electricity in the power grid system implies that wind farms should not only provide energy but also flexibility to the grid, via, among others, the provision of ancillary services. Wind farms should then regulate their output to provide an increase or a decrease in production when called upon and be able to guarantee this offer a certain amount of time. In a de-rating scenario, this also implies knowing what the nominal production would be. Indeed, if the wind farm production is reduced in the context of a potential upward ancillary service (i.e. the wind farm must increase its power if the grid operator requests it), it is important to quantify the maximal power available, in order to ensure that the wind farm can increase its power by the amount required by the grid operator, and to control the wind farm accordingly.

In the literature, most of the control strategies investigated in the context of the provision of ancillary services rely on a model-based approach [1]. While those online models often rely on a simple formulation, efforts have been made to increase their accuracy, for example, by including time delay to account for the travel time of the wake disturbance [2]. However, results showed that the achieved power output still varied considerably with respect to the power set-point, even when tested in a simple wind farm environment [3].

This clearly indicates that predictions of fine wake dynamics, including meandering, should be taken into account in those control algorithms. Among the existing medium-fidelity approaches that meet this objective [4, 5, 6], we select OnWaRDS [6, 7], an open-source framework for operational wind farm flow prediction. This approach captures the wake meandering and accommodates data assimilation techniques in order to estimate relevant inflow features.

Our literature review shows that OnWaRDS performances have not been assessed when wind turbines are subjected to an important variation of induction, which can occur in ancillary services scenarios. Before deploying OnWaRDS in control algorithms, we want to verify its estimates in such scenarios. The first part of this paper subsequently presents a comparison of OnWaRDS against a Large-Eddy Simulation (LES) of a down-regulated wind farm.

We also note that all publications about OnWaRDS implied a continuous feeding of the wake model with wind turbine data. This mode, denoted *synchronous*, means that OnWaRDS models the wind farm flow state synchronously with the LES, and tends to mimic the actual wind farm behavior in the most accurate way. All the wind turbines of the farm can therefore be used as sensors. The present work aims at using OnWaRDS in a *predictive* mode for the first time, to estimate the power production in an alternate scenario for the wind farm. We will challenge OnWaRDS by predicting in real-time what the power production would be in standard operation, while the LES wind farm is down-regulated (to provide, e.g., operating reserve capacity to the electricity network). The estimation of the available power and the reserve capacity, is essential toward generating added value for the farm. Switching to a *predictive* mode implies that certain measurements at the wind turbine level can no longer be used, because the flow and the rotor behavior change between LES and OnWaRDS. The second part of this study thus aims at verifying the predictions of OnWaRDS, and highlighting the impact of switching from a *synchronous* to a *predictive* mode in OnWaRDS.

2. Methodology

2.1. Wind farm environment

The objectives of this study entail the availability of a realistic wind farm environment in which the wake model predictions are verified. To this end, we perform LES of the wind farm flow, with turbines modeled as Actuator Disks (AD); this virtual wind farm is denoted LES-AD [8]. The considered AD approach implies a non-uniform force repartition in both radial and tangential directions, and is supplemented with a tip-loss correction [9]. Information can be recovered from such an approach, notably in terms of blade root bending moments [8], which will be useful for feeding the wake model and its flow field estimators (see Section 2.2). This work considers the NREL-5MW wind turbine and its standard controller [10], as OnWaRDS has been intensively verified and constructed around this wind turbine [6]. The standard controller of the NREL-5MW has been improved in order to follow a power reference set-point, by adapting the blade pitch angle and the generator torque. The regulation algorithm is chosen in order to keep the same rotation speed as that of a standard controller.

We consider a wind farm arrangement of three lines of four wind turbines, separated by $7D$ in the streamwise direction and $4D$ in the spanwise direction (see Fig. 1); D is equal to 126 m, the diameter of the NREL-5WM [10]. The flow conditions are characterized by a hub velocity, $\overline{U}_h$, of about 8 m/s and a turbulence intensity (TI) of about 7%. Those conditions are ensured by an auxiliary atmospheric boundary layer simulation (without wind turbines) that runs concurrently with the main one. This concurrent simulation thereby allows inflow conditions to be directly transferred to the inlet of the main domain (see [8] for details).

The domain size is $32D\times8\mathrm{D}\times16\mathrm{D}$, with a grid of $N_x \times N_y \times N_z = 512 \times 128 \times 256$ (corresponding to a resolution of 16 points per D). The time step is imposed to 0.1 s and the total simulation time is equal to 3000 seconds.

We will use this wind farm environment in several control scenarios; those will be described in Section 2.3.

2.2. Wake model description

OnWaRDS brings together flow sensing and Lagrangian flow modeling. We here briefly describe the wake modeling framework, in order to better highlight the impact of switching from a *synchronous* to a *predictive* mode in OnWaRDS; we denote these two modes as SYNC and PRED, respectively. SYNCH mode means that OnWaRDS models the wind farm flow state synchronously with the LES-AD, and tends to mimic the actual wind farm behavior in the most accurate way. This mode thus means that all the wind turbines of the wind farm can be used as sensors. OnWaRDS uses information coming from the wind turbine state to reconstruct the flow field, and propagates this information downstream through the Lagrangian particles; when the particles reach another turbine, information is thus re-calibrated using measurements at this rotor level. When we switch to PRED mode, certain measurements at the wind turbine level can no longer be used, because either OnWaRDS aims at representing a different reality for the wind farm (case 1), or OnWaRDS estimates a forward time integration of the flow state (case 2). The first case, case 1, is the one presented in the paper: the "actual wind farm" (defined by LES-AD) is down-regulated, and, in parallel, OnWaRDS is used to predict what the wind farm production would be if it was not regulated.

The following description considers SYNC mode in particular; the differences with PRED mode will be highlighted and discussed in Section 3.2.

Flow sensing The first step consists in retrieving the characteristics of the inflow and wake from the wind turbine measurements and operating settings. To that end, the inflow velocity field, $\hat{\mathbf{u}}_{WT} = [\hat{u}_{WT}, \hat{w}_{WT}]$, is inferred from the machine response (i.e. the blade loads) it triggers using flow sensing techniques [11].

A $C_P - C_T$ Look-up table (LUT) is used along with a Kalman filter in order to provide estimates of the effective streamwise velocity, $\hat{u}_{WT}$. This LUT is generated using LES-AD under uniform wind conditions for different wind turbine operations and tabulates the power and thrust coefficients (C_P and C_T) of the NREL-5MW as a function the tip-speed ratio (TSR) and the blade pitch angle.

Regarding the transverse velocity estimation, $\hat{w}_{WT}$, which plays a key role in the dynamics of wake meandering, we use LES-AD measurements in a first approach. Specifically, it corresponds to the rotor averaged transverse velocity at the wind turbine location (see [12]). Alternatively, a Neural Network (NN) (*ie*: a Multi-layer Perceptron) could also be used in order to map the wind turbine loads to the associated $\hat{w}_{WT}$. As this NN-based estimator was shown to provide accurate results in previous works [6], switching to this estimation technique in future investigations should not affect the results and the discussion of Section 3.

Once both components of the inflow velocity field have been determined, they can be used to compute an estimate of the wind turbine thrust coefficient, $\hat{C}_{T,WT}$ (the thrust being obtained from the rotor measurements, so from LES-AD), and inflow turbulence intensity, $\hat{TI}_{WT}$. The infered rotor state, $[\hat{\mathbf{u}}_{WT}, \hat{C}_{T,WT}, \hat{TI}_{WT}]$, is then be fed to the flow model as an input.

Lagrangian flow modeling The flow model decomposes the farm flow field, $\mathbf{u}\,(\mathbf{x},t)$, into two coupled fields: the ambient velocity field, $\mathbf{u}_A\,(\mathbf{x},t)$, and the wake one, $\mathbf{\Delta u}\,(\mathbf{x},t)$:

$$\mathbf{u}\,(\mathbf{x},t) = \mathbf{u}_A\,(\mathbf{x},t) - \mathbf{\Delta u}\,(\mathbf{x},t) \tag{1}$$

The model discretizes each field as a series of information-carrying wake (W_i) and freestream (A_i) particles shed at successive time steps, t_i, and whose source condition is provided by the flow sensing data. .

A wake particle, W_i, shed at time t_i, is described by a position, $\mathbf{x}_{W_i}(t)$, an orientation, $\mathbf{n}_{W_i}(t)$ and a curvilinear coordinate along the wake centerline, $\xi_{W_i}(t)$. Three additional states allowing to characterize the wake speed deficit finally complete this wake particle description: namely the thrust coefficient, $C_{T,W_i}(t)$, the rotor-effective TI, TI_{W_i}(t), and the rotor-normal velocity component of the impinging flow, $u_{n,W_i}(t)$. Inserting the wake particle state into the speed deficit model proposed by Bastankhah and Porté-Agel [13] then yields:

$$\Delta u_{W_i}(\mathbf{x}) = u_{n,W_i}\left(1-\sqrt{1-\frac{C_{T,W_i}}{8(\sigma_{W_i}/D)^2}}\right)\times\exp\left(-\frac{1}{2(\sigma_{W_i}/D)^2}\left(\frac{r_{W_i}(\mathbf{x})}{D}\right)^2\right) \quad (2)$$

where $\sigma_{W_i}\left(\xi_{W_i},\hat{C}_{T,WT}\right)$ denotes the effective wake width while $r_{W_i}(\mathbf{x})$ is the radial position of the arbitrary point $\mathbf{x}$ with respect to the wake centerline. The particle speed deficit in the wind turbine frame is in turn obtained by projecting this simple analytic speed deficit model along the particle orientation vector, $\mathbf{n}_{W_i}$. Eq. 2 can finally be generalized to multiple overlaping wakes using the standard linear superposition strategy.

Likewise, the ambient flow field is represented by a series of ambient particles, A_i, shed at successive time steps t_i, and described by a position, $\mathbf{x}_{A_i}(t)$ and a characteristic advection velocity, $\mathbf{u}_{A_i}(t)$ whose state is determined by the measurements of the wind turbine it emanates from (computed using the Kalman filter and LUT, see above). By definition, the ambient flow field should not include any wake effects; therefore, the source state has to be adapted for waked turbines. The source state of ambient particles emanating from these turbines is then selected so that it mirrors the information shed by the freestream wind turbines located upstream of the rotors considered, based on the frozen turbulence assumption. The estimation of the effective upstream velocity provided through the rotor-as-sensor approach is thus not used for these wind turbines, except when there are fully out of the upstream wakes.

The wake and ambient fields can then be reconstructed using the passive scaler tracer assumption: the wake particles are advected downstream at their own characteristic velocity, thereby incrementally reconstructing the flow field.

For more details about the model, notably regarding the interpolation of the different fields from the discrete particle states and a complete definition of the ambient and wake advection velocities, we refer to the associated papers and thesis document that provide a comprehensive description of the model [6, 12].

2.3. Scenarios

We will first consider a case where all the wind turbines are controlled in a standard way; this case is denoted STD in the remaining to the paper. A second wind farm simulation is then performed where several power commands are required for the first row of turbines; this case is denoted REG. WT0, WT1 and WT2 (see Fig. 1) starts at 100% of their maximal power, $P_{max}(t)$, for those wind conditions. At t = 1512 seconds, they decrease their production to reach 80% of their $P_{max}(t)$. Then, at t = 2016 seconds, they decrease their power to attain 60% of $P_{max}(t)$. Finally, at t =2520 seconds, they increase their power to reach 70% of $P_{max}(t)$. While its sharp transitions reduce its level of realism/fidelity, this scenario should still be able to highlight the abilities of the wake model to capture sharp wake disturbances due to various power commands.

For both STD and REG cases, OnWaRDS will run in SYNC mode. Then, we will run OnWaRDS in PRED mode in parallel with the LES-AD of the down-regulated wind farm, in order to estimate, at each time step of the simulation, what the power production would be if there were no regulation.

3. Results

We first analyse the results obtained using OnWaRDS in SYNC mode for both STD and REG cases; the PRED mode of OnWaRDS is then discussed.

3.1. OnWaRDS in SYNC mode

Wind farm streamwise velocities In a first step, the LES-AD wind farm velocity field is compared to that predicted using OnWaRDS. Figure 1 shows the wake response of the wind farm for case REG, at several instants. We see that OnWaRDS predicts quite accurately the main features of the wake physics (wake centerline position, velocity deficit) and captures the wake disturbance resulting of the regulation control. For example, at $t = 1584$ seconds and at $t = 2014$ seconds, we see the effect of the power command on the wake at $x/D = 2.5D$ in both LES-AD and OnWaRDS simulations. Although OnWaRDS captures satisfactorily the main features of the wakes, the increasing levels of wake asymmetry and incoherence observed in LES-AD for turbines deep in the array are not reflected by the wake model. Wakes are pictured more coherent in OnWaRDS than what they really are. This reflects the limitations of the wake merging strategy: the turbulence mixing occurring at the interface of the adjacent wakes is not modeled and the wakes consequently cross each other without any real interactions. We note that the development of efficient wake merging models remains an open research topic to this day (e.g. Zong and Porté-Agel [15] or Lanzialo and Meyers [16]).

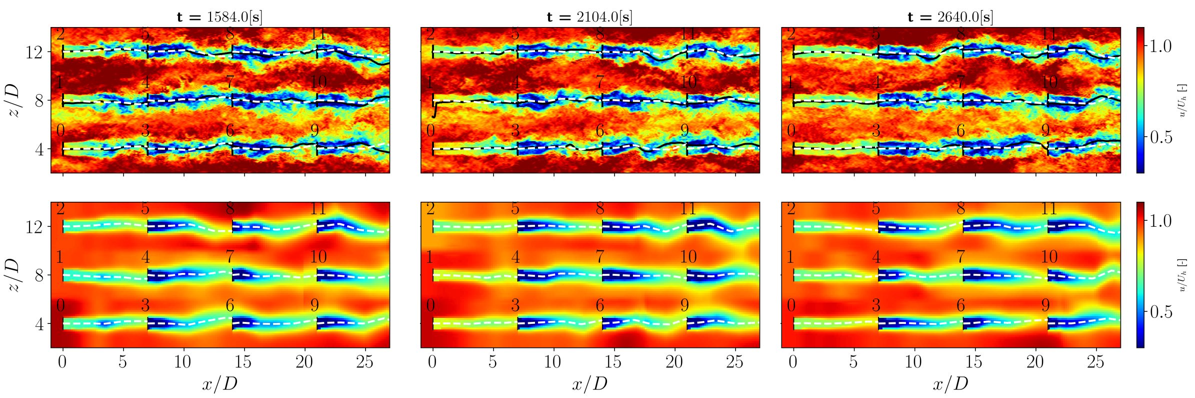

Figure 1. Horizontal planes at hub height of streamwise velocities at several instants, obtained using LES-AD (top) and OnWaRDS (bottom) in REG case. The wake centerline position is also shown (LES-AD : black lines; OnWaRDS : dashed white lines).

Rotor effective wind speeds and wake centerlines In order to analyse the results more qualitatively, Figs. 2 and 3 show the rotor effective wind speed at wind turbine location and the horizontal wake centerline position 5D downstream of each of the four machines of the first line (WT0, WT3, WT6 and WT9, see Fig. 1). The results are depicted for both STD and REG cases. In LES-AD, u_{WT} at WTi is computed based on data obtained using LES-AD performed without WTi and corresponds to the average over a rotor surface of the streamwise velocity at WTi location. The OnWaRDS results also present the rotor-averaged velocity at WTi location (again without the effect of WTi). For the first wind turbine, u_{WT} in OnWaRDS is computed

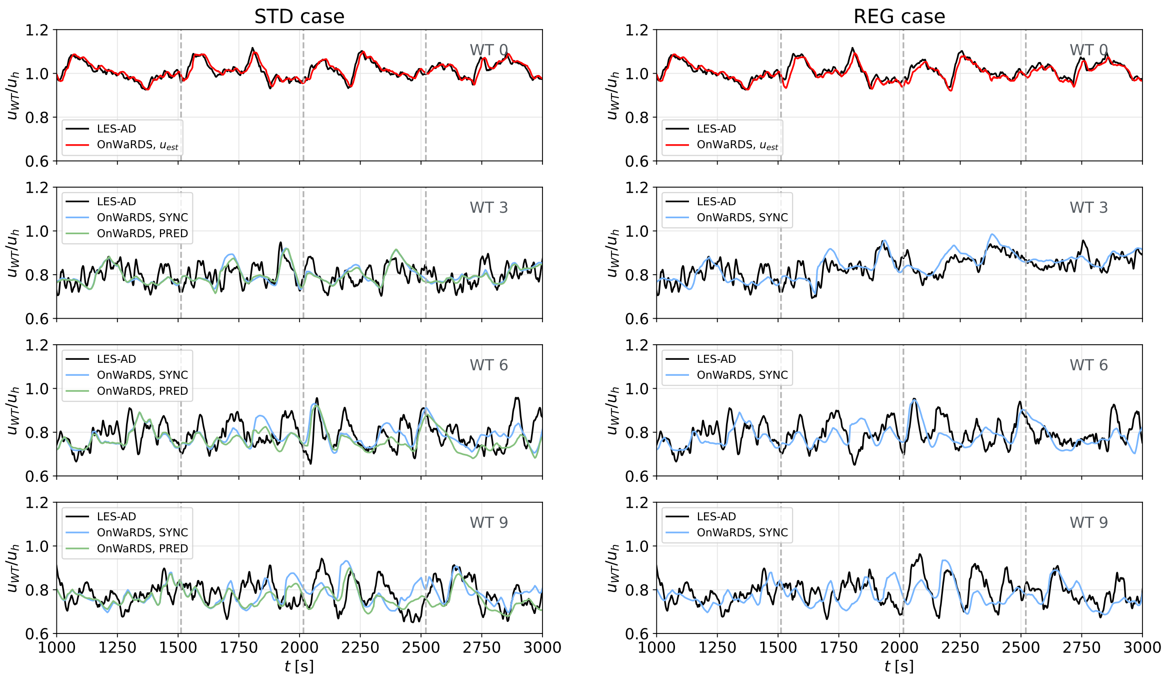

Figure 2. Rotor effective wind speed at wind turbine location for the first line for LES (black line) and OnWaRDS (blue line). OnWaRDS results are added for PRED mode in STD case (green line). For WT0, the rotor effective wind speed in OnWaRDS is computed using the estimator (red line).

as the effective upstream velocity estimated using the Kalman filter ($\hat{u}_{WT}$, see Section 2.2); this result will be useful for the discussion of Section 3.2.

Globally, we see that the effective upstream velocity computed using the Kalman filter gives an accurate value of the ambient flow field for WT0. At WT3 location, the low frequency oscillations and the mean value of u_{WT} are correctly estimated by OnWaRDS; the same observation can be made for the wake centerline prediction upstream of WT3 (see Fig. 3, top). OnWaRDS also captures the correct increase of velocity at WT3 location (see Fig. 2), when a wake perturbation resulting of a WT0 regulation command reaches WT3 (for e.g., around t = 1650 seconds).

For machines located further downstream, the predictions of the wake dynamics given by OnWaRDS slightly degrade, as already observed in previous studies [6, 12]. This reflects the effect of the increased flow complexity (less structured wake, wake merging, ...). These degraded performances deep inside the wind farm notably arise from the chosen wake merging strategy, a lack of adequate added turbulence model and the limitations of the frozen turbulence hypothesis, notably for the propagation of the ambient flow particles [12].

Powers and thrusts In order to estimate the power P and the thrust T predicted by OnWaRDS, which will be valuable for its future coupling with global control strategies, we consider the same LUT as that used for the effective wind speed estimator (see Section 2.2) and we couple them to the controllers of the NREL-5MW (see Section 2.1). The rotor speed and the blade pitch angle (required in LUT) are thus determined by the control schemes, while u_{WT} (used for the TSR in LUT) is given by the OnWaRDS results of Fig. 2. Figures 4 and 5 show the powers and thrusts for WT0, WT3, WT6 and WT9 for both STD and REG cases, and the

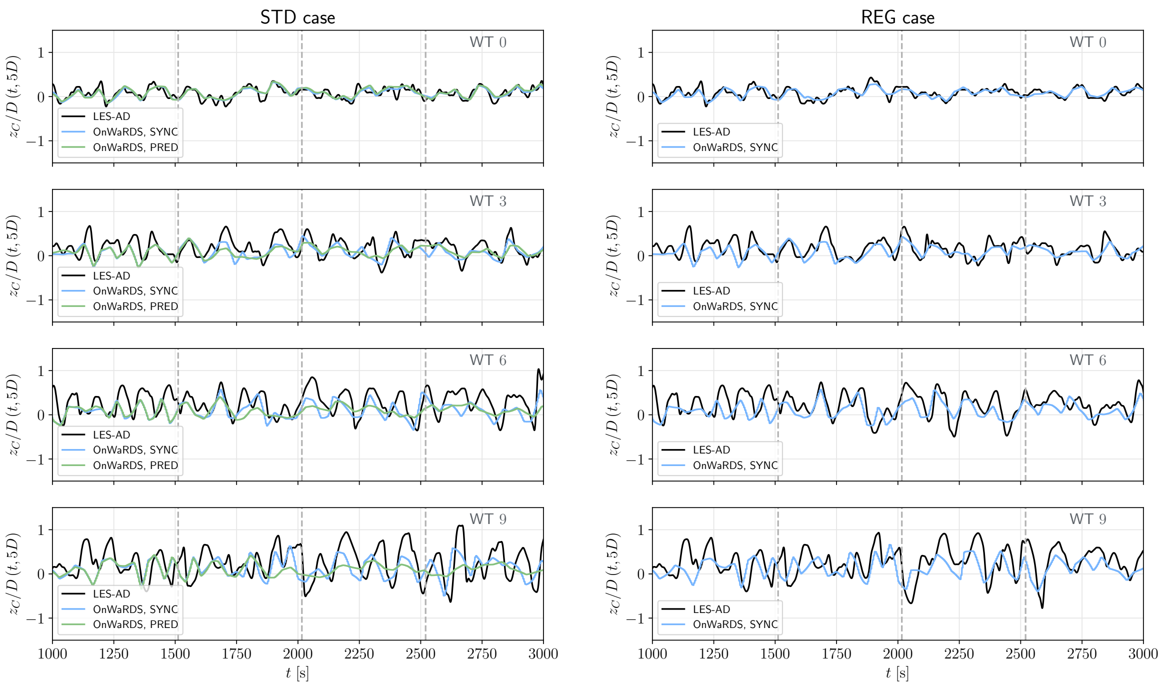

Figure 3. Wake centerline position 5D downstream of rotors for the first line for LES (black line) and OnWaRDS (blue line). OnWaRDS wake centerline position in PRED mode is added in STD case (green line).

total power and thrust of the line are reported on Figs. 4 and 5.

For WT0, as the computation of P and T is based on the same LUT as that used for estimating u_{WT}, the OnWaRDS results are very close to those obtained using LES-AD. For downstream machines, while the mean level of power and thrust seems to be correctly estimated, we observe more discrepancies in the signal oscillations, resulting of wake modeling errors already observed in Figs. 2 and 3.

In order to quantify the differences between LES-AD and OnWaRDS power and thrust histories, we report in Fig. 6 the relative error e between the time-averaged signals ($\overline{P}$, $\overline{T}$), and the Pearson correlation coefficient (ρ) between the histories. e verifies if the estimates of the model actually correspond to LES-AD data, while ρ assess how related are the temporal features of the two signals. The low errors and the high correlation coefficients for WT0 confirm the good agreement observed between LES-AD and OnWaRDS signals of Figs. 4 and 5. e_P and e_T increase for downstream machines but remains below 5% for $\overline{P}$ and $\overline{T}$ in both STD and REG cases. We also note that the correlation coefficient decreases for WT3, WT6 and WT9.

If we consider the total power and thrust of the line (see Figs. 4 and 5, bottom), we see that the predictions of OnWaRDS fall within a 7.5% error band[1] most of the times (see grey zones on Figs. 4 and 5) and e that remains below 4% for P and T for all the cases (see Fig. 6). The value of ρ is about 0.6 and even reaches 0.75 for T in REG case. The accuracy of the results for the line is related to the fact that the WT0 production, which is captured very well by OnWaRDS, contributes to a large part of the total line power and thrust.

[1] In the actual qualification procedure in Belgium the unit should be able to follow a predefined power set point within an error margin of 7.5% [17]

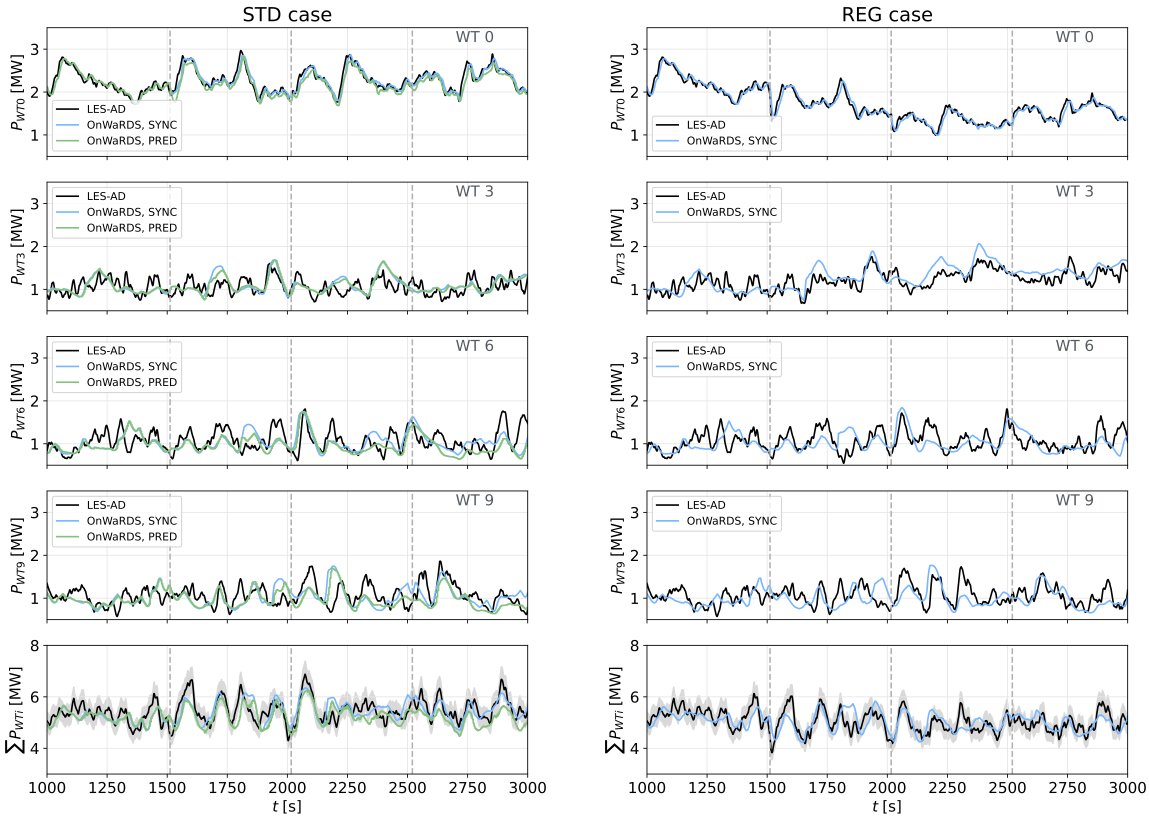

Figure 4. Power for the first line of rotors for LES-AD (black line) and OnWaRDS in SYNC mode (blue line). OnWaRDS results in PRED mode are added in STD case (green line).

3.2. OnWaRDS in PRED mode

As mentioned in Section 2.3, we also test OnWaRDS in PRED mode. In this configuration, OnWaRDS runs in parallel to the LES-AD of the down-regulated wind farm (REG case), in order to predict, in real time, what the wind farm production would be if it operated in standard conditions (i.e. no regulation). We first discuss the inputs that are used in OnWaRDS in this particular case. We then compare OnWaRDS results with the actual LES-AD in STD case to verify the predictions of OnWaRDS (see green line in Figs. 2 to 6).

Similarly to SYNCH mode, the ambient flow field (upstream and transverse wind speeds, TI) can be recovered for the first row of machines. The measurements of flapwise root bending moments, rotor speed, blade pitch angles, and generator torque are used to estimate the upstream velocity and the turbulence intensity. Indeed, the operational mode of the turbine does not affect the performances of the estimator, as highlighted in Fig. 2 for $\hat{u}_{WT}$; the same observation is made for the estimation of the ambient TI (not shown here). The transverse wind speed is recovered from measurements at the nacelle level and is used as input in OnWaRDs. As the first row of turbine is down-regulated from t = 1512 seconds in LES-AD, we can no longer use the thrust measurements to feed the model. So, the wind turbine model (again, LUT) coupled to the controllers is used to estimate the thrust in standard operation (i.e. no power regulation), with $\hat{u}_{WT}$ as inflow velocity. As expected, when compared to LES-AD data in STD case, the thrust (and power) predictions given by LUT for WT0 are very accurate, as shown in Figs. 4,

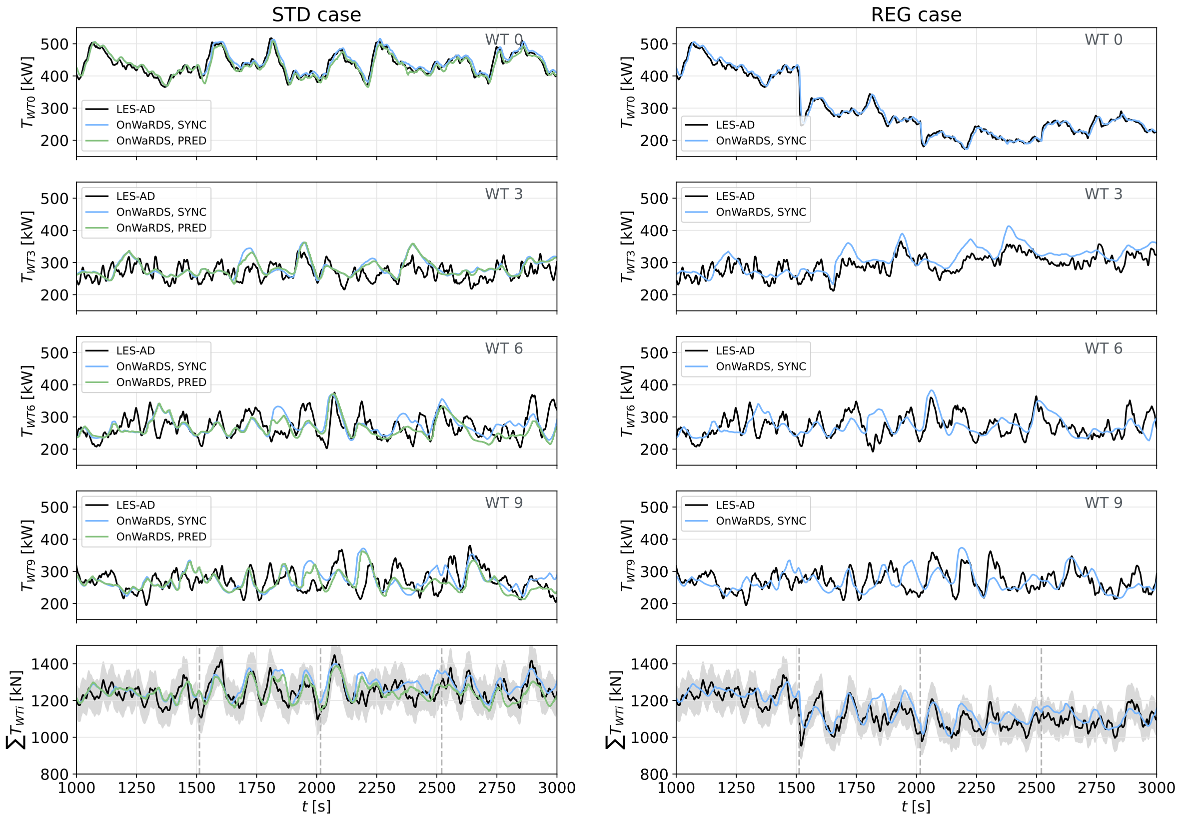

Figure 5. Thrust for the first line of rotors for LES-AD (black line) and OnWaRDS in SYNC mode (blue line). OnWaRDS results in PRED mode are added in STD case (green line).

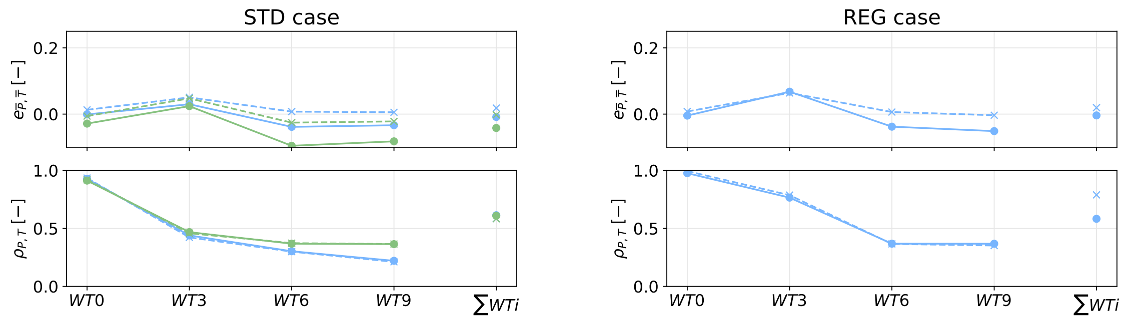

Figure 6. Relative error e and Pearson correlation coefficient ρ, between LES-AD and OnWaRDS in SYNC mode for the first line (blue line), for P (continuous line) and T (dashed-line). OnWaRDS results in PRED mode are added in STD case (green line).

5 and 6 (see green lines in each Figure, for WT0, STD case).

Further downstream, the flow varies between the LES-AD, which is regulated, and OnWaRDS that aims at modeling the wind farm in a standard operation: this decreases the number of measurements that can be used to feed OnWaRDS. As mentioned in Section 2.2, the waked turbines mirror the information shed by the freestream wind turbines for the estimation of the ambient upstream velocity (which is by definition without wake effects); we still use this principle in PRED mode. For the rotor turbulence intensity, we use $\hat{TI}_{WT}$ computed by the estimator at WTi level in REG case. This value remains close to that estimated by OnWaRDS in SYNC mode in STD case (see example for WT9 in Fig. 7) and is thus a good first approximation for this study.

For the evaluation of the transverse wind speed for downstream machines, we use the measurements at WT0, which propagate downstream [12]. We thus expect that the estimation degrades for downstream turbines, compared to those of OnWaRDS in SYNC mode, for which information of transverse velocity is updated at each WTi (see Section 2.2). This is translated in the wake meandering estimates, which use the transverse velocity : although OnWaRDS correctly captures the peaks and troughs, it underestimates the amplitude of the wake center oscillations, mainly for WT6 and WT9.

Again, the thrust of LES-AD can not longer be used to feed OnWaRDS, and LUT coupled to the controllers is used to predict the thrust in standard operations. In order to estimate the effective upstream wind speed, required by LUT, we use the rotor-averaged wind speed u_{WT} predicted by OnWaRDS (reported in green line for STD case in Fig. 2). The power of WT3, WT6 and WT9 is computed using the same approach.

Globally, for the two first machines in the line (WT0 and WT3), the results of OnWaRDS in PRED and SYNC modes are very close to each other (see Figs. 2 to 6). For downstream machines, the discrepancies increase, as the modeling errors and approximations accumulate. However, OnWaRDS in PRED mode still gives a quite good approximation of what the power and thrust of the line would be in standard operation : the errors remain below 5% for both P and T and the Pearson correlation coefficient is quite close to that obtained using OnWaRDS in SYNC mode, with a value of 0.6.

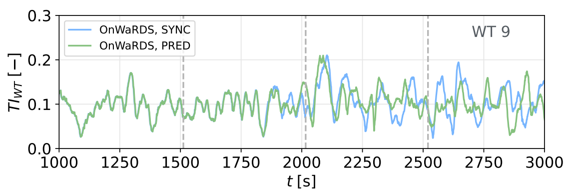

Figure 7. Temporal evolution of TI_{WT} for WT9 for OnWaRDS in SYNC mode for STD case (blue lines) and in PRED (green lines) mode.

3.3. Conclusions and perspectives

In this work, we verify OnWaRDS predictions against data obtained using Large-eddy Simulations coupled to an Actuator Disk model (LES-AD) in ancillary services scenarios. We also tested for the first time OnWaRDS in a predictive mode in order to model another reality for the wind farm. In this study, we used OnWaRDS to predict in real-time what the power production would be in standard operation, while the LES-AD wind farm is down-regulated (to provide, e.g., operating reserve capacity to the electricity network). To this end, we also identifies the main changes between OnWaRDS used in a synchronous (SYNC) mode (i.e. the wake model is fed by LES-AD rotor data during all the simulation) and in a predictive (PRED) mode (where the information collected by downstream machines is not relevant anymore).

Globally, OnWaRDS gives good predictions in terms of flow dynamics and captures the wake disturbances due to sharp changes in rotor induction. The accuracy of the OnWaRDS estimates decrease for machines located deep in the array, due to modeling errors and approximations that accumulate (mainly for PRED mode) and to the complexity of the flow that increases inside the wind farm. Eventually, OnWaRDS captures the power and the thrust well in both SYNC and PRED modes. These first results are thus promising, and OnWaRDS already performs well at predicting the flow field and the production. The predictions could be improved by performing data assimilation at the level of several machines, by considering another wake merging strategy and/or by accounting for added turbulence; it would also be valuable to consider a larger wind turbine and verify the OnWaRDS predictions for such a machine.

The impact of the power production discrepancies observed between OnWaRDS predictions and LES-AD data are difficult to quantify at this stage. When OnWaRDS will be deployed in global control strategies (through Model Predictive Control (MPC) approaches), it could be highlighted by observing deviations between the required and the actual power production and/or by quantifying deviations between the actual and promised power reserve capacity.

Coupling OnWaRDS to a MPC strategy is an ongoing work; the MPC strategy that was initially considered was an adjoint-based model predictive control. However, this requires important modifications and a “re-design” of OnWaRDS, as this was not initially written for such a control approach. We will thus consider another type of MPC strategies based on gradient-free optimization; those should clearly benefit from the computational affordability of the wake model. We are also investigating the time horizon for OnWaRDS predictions, depending on the control objectives. OnWaRDS is initially intended to generate predictions over short time intervals, in order to exploit its online modeling and maintain an accurate wake response; we are thus testing several intervals of time for predictions, in order to determine the optimal one.

3.4. Acknowledgments
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