Reviewer comments

Thomas Duc

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1 Response to short comments 1 and 2

Dear authors,

Thanks for a nice paper, which I read with great interest ! I am listing some comments below, I hope some at least can be useful. Apologies if the comments are not perfectly neat and well written. Some may just be incorrect or irrelevant, I hope you won't mind if that is the case. Very interesting paper, much work has been put into this, well done.

All the best, Rémi Gandoin

Dear Rémi Gandoin, thank you very much for taking the time to review the article. We appreciate your input and your interest in our work! You can find detailed responses to your comments down below.

1. Introduction

"in some cases wake effects are still persistent at significant distances downstream": maybe quantify "significant"

A quantification of 10 to 15 D, which is taken from the publication of Sanderse, is now provided.

"maximize their own power production": this is true only for the constant TSR control region, right ?

Not exactly: this is true that the efficiency of a wind turbine is maximum in the region 2 of the power curve, but this is not the point of the sentence. This sentence essentially means that with current state-of-the-art control, for a given wind velocity, a wind turbine will try to extract as much power as it can from the wind by applying its power curve and will not consider what is happening downstream. In contrast, with coordinated control, the power of upstream wind turbine is purposely de-rated to increase the power of downstream turbines.

"Two different strategies are mainly considered": in this paper ? or in general in the literature ?

It is meant in general in the literature, e.g. see the paper from Knudsen. Some other strategies have also been studied, like tilt control or individual pitch control but they seem currently less feasible and much less popular in wind farm control research. In this paper, the focus is only on axial induction control.

"either the upwind turbines are curtailed": does this mean that the output power is set to a constant value, or that the power is just decreased compared to the original control settings ?

This means that output power is just decreased compared to the original control settings.

"small gains in power production are indeed possible": using the first or the second strategy, or both ?

Apparently from both strategies, but some latest results tends to indicate that the yaw offset (or wake steering) strategy have much better potential for increasing power production.

"high variability with incoming wind conditions": - does this mean that they can have positive and negative effect on park production ? or only positive effect but with some (how much ?) variability ? - what is meant by "wind conditions" (speed, direction, temporal/spatial scale) ?

"where wind conditions are fluctuating constantly and significantly": same as above

Depending on the wind conditions, they might have a positive or a negative impact on power production. The most critical parameter is wind direction but as underlined in this paper wind speed and turbulence intensity are also very important. See e.g. later on section 5 : for axial induction control, there is a very limited range of wind speed and direction for which the strategy is profitable. If the wind direction changes but the turbine does not react quickly enough and curtailment is still applied on the wind turbine, then there will be loss in aggregated power production because the up-stream curtailment will not create any (or sufficient) gain downstream.

"Very few full scale field tests have been realized to investigate this question": can you refer to these few, if there are publications available ?

These references are already listed in the following sentence of the paper.

"uncertainties remain high": can you specify whether you refer to accuracy and/or precision ?

The uncertainty here is related to both the accuracy and adequacy of the model (i.e. simplified steady-state model to be evaluated against dynamic conditions in the field) as well as the precision of the measurements (i.e. how 'trustworthy' the SCADA readings are and how the measurement period affects the overall assessment of the model performance). It is shown in the uncertainty quantification section that the gains expected are small with respect to the scatter of experimental data points. So it is required to have longer periods of measurements with higher precision where possible, to make sure that there is a positive impact in the production.

"La Sole du Moulin Vieux (SMV)": 7 x Senvion MM82/2050 ? maybe refer to Figure 1.

The wind farm is described in detail in section 2, we added a mention to this when presenting the outline of the paper at the end of the introduction.

"and was dedicated to axial induction control strategy": what does this mean (in a few words) ?

The upstream wind turbines are curtailed so that their axial induction is decreased. This leaves a more energetic flow downstream that can be beneficial for the turbines in the wake.

"high level of curtailment": see my question about defining curtailment above.

The upstream wind turbine was de-rated by 20%, see section 5.3.

"could be observed": how ?

This was done by the analysis of downstream active power data at the downstream turbine. This is now mentioned in the paper.

"combined power production": you mean the sum of all WTG production ?

Yes, in this case it there were only two wind turbines. We changed the "combined" into "aggregated" to make the sentence clearer.

"part of the lost power": can this be quantified ?

This is actually a bit difficult to quantify because it really depends on the wind speed and wind direction bins. In the revised version of the paper I added as reference my master thesis, in which more details can be found in section 6.1. if you are interested.

"the best settings": which parameters are changing ?

This was a bit misleading as in practice we do not have access to control parameters. This has been changed into "the optimal de-rating to be applied as a function...".

"as a function of wind speed and wind direction": measured by the nacelle anemometry ?

In general, any sensor able to measure the incoming wind speed and direction and send this information to the wind turbine controller could be used, but in our field tests only nacelle anemometry

is involved for the optimized control.

"Jensen model": reference ?

The reference to the Jensen model is now added in the introduction.

"local measurement of turbulence intensity": how ?

This is provided by the nacelle anemometer. This is now indicated on the revised version of the paper.

"The resulting wake deficit appears to be more consistent with observed data": can you quantify ?

Some figures are already provided in the abstract and will be discussed in more details in section 4.

"the original model": you mean the k-parameter value of 0.075 as in `http://orbit.dtu.dk/fedora/objects/orbit:66401/datastreams/file_f7da8eb2-e49c-4dc9-9ee5-72846f40ef34/content` ?

Yes, in the revised version it is now written "when using a constant value" to clarify this.

"Figure 1. Layout of SMV wind farm and location of wind measurement devices. Inter distances between the wind turbines are expressed in rotor diameters": please specify that D=82m.

The mention of the diameter is now added in the revised version.

Could we worth showing a bigger area, maybe {49.816789°;2.753916°} to {49.868842°;2.843664°};

As it would further elongate the paper, as was criticized by the other reviewers, the broader location map is skipped for now. Additionally, the added value of such figure would be limited and the readers could always refer to other sources (e.g. Google Earth) to see the details of the area of the wind farm if interested.

"red arrows indicate the main wind direction ": maybe add that these are °N. How wide are the wind-directional bins ? How is the wind direction defined ?

Reference for 0° in wind energy is conventionally absolute north, so would be redundant to mention in the article. Regarding bin width, they are defined later in section 4.

Section 2

"SCADA data": 10-minute ?

Both 10-minutes and 1-second data are studied, see later in the paper.

Section 3.1

"where U0 is the incoming wind speed at the upstream wind turbine, Uw the velocity in the wake and R the radius of the upstream rotor.2": ,and C_T the Thrust Coefficient corresponding to U0.

c_T ***is already defined above the equation.***

"its inaccuracy": which one ?

The inaccuracy of the Jensen model.

"local turbulence intensity": see my question above regarding how you measure this.

This is now corrected following the comment above.

Section 3.2

General comments: - you may also want to refer to Section 2.4 of (Lissaman, 1976): `https://drive.google.com/drive/folders/1tI2p3W1qRj2GsYkt6RI6VITJMpQh7PMc`.

This reference has been added to the revised version.

- if the wake expansion factor changes within the wind farm, could this be visible on high-resolution wake measurements reported in `http://iopscience.iop.org/article/10.1088/1742-6596/1037/7/072008/pdf` ?

It would be interesting to look at as a separate study, although it might be a bit difficult to see the change in wake expansion because of the superposition of the wakes emitted by the different upstream turbines.

If $k = 0.9 * TI_{WTG}$ then, based on Figure 7, the first wake "cone" should expand with an smaller angle than the one for the rows downstream, since the TI of the first WTG is smaller, have I understood correctly ?

Yes, exactly.

"This empirical constant is supposed to vary from one wind farm to another": reference ?

Well, this is actually seen later in the paper: we have a value of 0.075 for SMV wind farm, but 0.09 for Horns Rev (while generally values of 0.04 and 0.05 are used for offshore wind farms).

"or vice versa": why is that ?

This depends on how the model has been calibrated and the particular layout of the wind farm.

Section 3.3

"Four months of second-wise SCADA data": you mean 1-Hz ?

Yes, this has been clarified in the revised version.

"Figure 3": - could you use a function using "density scatter plots" in Matlab and plot the mean and median binned values as well?

In this graph we prefer to stay with the scatter plot in order to be consistent with the reference Göçmen and Giebel (2016) that we are using in the discussion.

- the plot NWS vs Met mast shows less scatter than the plot NWS vs LiDAR: could you also show Met mast vs LiDAR (there maybe 10-minute time offset) ?

The plot Met-mast vs Lidar is already there : it is the top left graph. The scatter is explained by the fact that sensors are not facing the same wake effects since measurement do not occur at the same location. The Met-mast is less affected than the windcube to wake effects because it is located further away from the farm.

Section 4.1

General comments: - have you considered using the M2 mast dataset measurements for Horns Rev 1?

First and foremost, during the period where the 1Hz SCADA from Horns Rev-I was available, M2 was already out of operation. Additionally, the idea was to focus only on SCADA data in order to make this study easily reproducible for any wind farms, as especially offshore a met mast is often not feasible/available. To be consistent, the met-mast data at SMV wind farm is only used to validate the TI measurement from SCADA, where the rest of the analysis is based on.

- have you considered a wider wind directional bin ? As I remember, Gaumond showed that using narrow bins, led to bias in the validation, since the model is "steady state" and will consider the turbines always aligned. A workaround is to run a model simulation every 0.5°and then weight the results using a gaussian distribution of the wind directions.

We considered using a larger bin width but finally decided to stay with that one to ensure a consistency with the results found later in the paper. Indeed in section 5.4.1., it is shown that axial induction control is only beneficial on a ±5°wind direction sector centered on full wake conditions. The objective in this section was essentially to compare the two calculation procedures in the same conditions, i.e. with the same bin width and no gaussian averaging. It is expected that any post processing that will improve the behavior of the original calculation procedure will also benefit to the new calculation procedure.

"modified Jensen model": maybe only semantics here, but it seems to me that you are only tuning the input k parameter and not changing the model.

Yes this is right. In the revised version we changed "modified" into "tuned".

"Region II": can you highlight this region in Figure 5 and Figure 2 ?

These regions are defined two paragraphs later, adding them also here might just overload the figure.

"Figure 6": - could you state that "TI" is the TI measured using the Nacelle Anemometer (and not the ambient TI) ?

This has been added in the figure caption.

- could you add a curve which uses $k_w = 0.4TI_{ambient}$, as suggested in the Sexbierum paper ?

We tried to add this particular curve but it did not fit well with the experimental data we had (the modeled wake deficit was too high). Thus we decided to remove it in order not to overload the figure with a curve that would not be used in the discussion. For your curiosity, I am just adding in this document the figure with this particular curve.

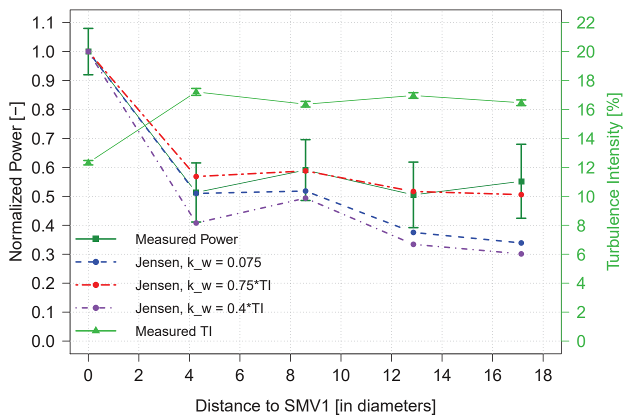

Figure 1: Comparison of the model performance at SMV wind farm. Variation of experimental and modeled normalized power and turbulence intensity (measured by the nacelle anemometer) along the row. Error bars indicates the 68% normalized confidence interval.

- the TI value of 12% for the first WTG at HR1 seem large, for offshore conditions - see typical values in `https://pcwg.org/proceedings/2014-10-06/06-Turbulence-Intensity-measmntsoffshore-4-PC-verification-wind-res-assmt.pptx` - can you show a histogram of the corresponding wind speeds ?

There is a misunderstanding here: Figure 6 is about SMV onshore wind farm, so a value of 12% is very consistent.

- for (b): do you see a difference between nightime and daytime ?

We did not investigate this, it goes a bit beyond the scope of this paper (see the new added section 5.6) but it might be an interesting point to study in the future.

"was clearly overestimating the power deficit for the wind farm of Horns Rev-I, as it 10 gives narrower wake growth within the wind farm": it depends actually, see `http://www.eera-dtoc.eu/wpcontent/uploads/files/Nygaard_Systematic_quantification_of_wake_model_uncertainty_offshore2015presentation.pdf`. The stability conditions may well differ significantly between the different studies, for the same wind farm, since people use different datasets for model validation.

In the reference of Nygaard et al, the wind farms are anonymous so it is not possible to conclude anything about Horns Rev-I wind farm particularly. Still, the changes in stability even for the same

wind farm is simply a physical phenomena which shows again the importance of uncertainty quantification as the model performance assessment depends on the period of the input and validation dataset. A way to reduce those uncertainties might be to "dynamically" calibrate the Jensen model. One can find different wake expansion coefficients for different seasons, etc. However interesting the concept is, those analyses are beyond the scope of this paper.

"Figure 7": - the value of TI for the first WTG at HR1 is 8 %, is was 12% in Figure 6 - can you explain why this is ? - same as for Figure 6: could you state that "TI" is the TI measured using the Nacelle Anemometer (and not the ambient TI) ?

Both these comments are adressed above.

- same as for Figure 6: could you add a curve which uses $k_w = 0.4TI_{ambient}$, as suggested in the Sexbierum paper ?

Same as above, the modeled wake deficit using $k_w = 0.4TI_{ambient}$ ***did not really fit the experimental data we had. Here is the corresponding figure.***

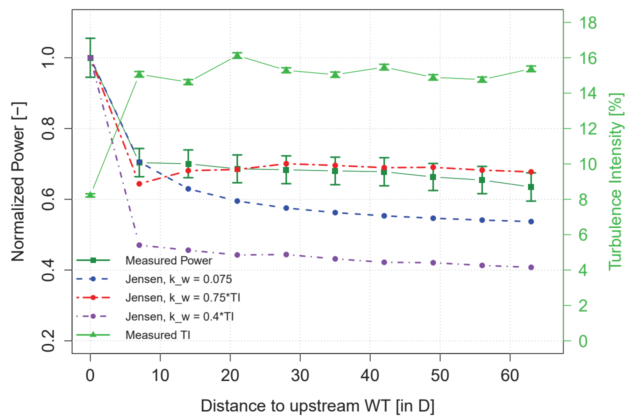

Figure 2: Comparison of the model performance at Horns Rev-I wind farm (row 5). Variation of experimental and modeled normalized power and turbulence intensity (measured by the nacelle anemometer) along the row. Error bars indicates the 68% normalized confidence interval.

Section 5.1

About eq. (5): once the WTG is curtailed, will this relationship hold ? See for instance Figure 1 of `http://iopscience.iop.org/article/10.1088/1742-6596/1037/3/032039/pdf` (I don't have the answer).

This equation is derived from analysis of guaranteed curtailment modes so it is expected (to our best knowledge) that it will hold.

Section 5.2

"The reason for this increase was related the presence of the motorway": could it be the large warehouse located at 330°, 2km upstream of the mast ?

It could be, but the motorway is closer, and seems also to explain the increase in SMV1 TI observed at 5°.

Could you make a plot on nighttime and on daytime ?

As already mentioned above, we did not investigate difference between day and night. In Figure 9 the point is essentially to show that nacelle anemometer TI is capturing wake effects for all wind turbines and outside of any wake effects it is consistent with ambient TI measured by the mast.

Section 5.3

"as the upstream wind turbine is down-regulated, the wake added TI emitted by this turbine is reduced": because it is a function of CT, and CT is reduced ?

Yes, exactly.

The TI_{added} is also a function of the downstream distance, see chap 3 of `http://orbit.dtu.dk/fedora/objects/orbit:79899/datastreams/file_269c3f19-0001-4e41-b754-b5b322a826cb/content`.

Yes, but in this case downstream distance remains constant as we are studying two wind turbines.

Table 1: could you also show the relative power values, for a given wind speed bin (for instance 7 m/s) ?

Here there are no wind speed bins involved but only a binning against wind direction.

Section 5.4.1

"It is observed that the maximum gain represents an increase of about 2.5% and is found at 7 m/s when SMV6 is curtailed by 12% (cP decreases from 0.46 to 0.405)":as I understand, in this situation, you reduce C_p by x%, and derive a new C_t using eq. (5). Then, you choose a value of k using eq. (7). Can you then also plot these new and old values of C_t and k, that are used the calculation, in Figure 12 ? Or provide a worked-out example ? It may help the reader understand what goes on in the calculation.

Yes these are the steps we are following. In order not to surcharge the plot, we added a small sentence telling how much c_T is reduced when c_P is decreased. We hope this will improve the clarity of the paper.

"very stable incoming wind conditions": you mean stable atmosphere ?

No I mean stable wind direction and wind speed, in order to stay in the window for which coordinated control is profitable. If wind direction is changing too frequently, the turbine might not react quick enough to these changes to apply the optimal control at each instant. To clarify, this point, we changed the word "stable" into "steady".

2 Response to anonymous referee 1

This manuscript deals with an ad-hoc tuning of the expansion parameter of the Jensen model as a function of the incoming turbulence intensity. The calibrated model is then used for the power optimization of a wind farm through a coordinated axial-induction control. The concept is not new, but the application to a real wind farm is very interesting.

I would add some comments specifying that the variability in wind direction, thus of wake interactions, and the daily cycle of the atmospheric stability, might lead to a more complicated tuning of the model for real applications, or at least for a real implementation.

First of all, thank you for your contributions and comments regarding the review of our work. Indeed, this is an important point. We reorganized a bit the paper to add a new section 5.6 in which we discuss shortly these issues related to practical implementation of the axial induction strategy in the field.

I found a recent paper with a very similar approach to this, Santhanagopalan et al. 2018 Renewable Energy, 116, 232-243. In that paper, the authors used a RANS model to perform axial-induction optimization of a turbine array for the different incoming wind turbulence. They used as objective function the maximization of the power capture with a penalization due to the fatigue loads derived by the wake-generated turbulence. It will be interesting to see how these results compare to those presented in this manuscript.

Thank you for indicating us this paper, which is very related to our study. We thus added this reference in the introduction and in the discussion about the tuning of the Jensen model. The in-depth comparison between the results from the two papers might indeed be an interesting study to realize in the future.

3 Response to anonymous referee 2

This paper proposes a method for tuning the Jensen wake model for a wind turbine based upon the locally measured turbulence intensity. The work is based upon field test data at the wind farm La Sole du Moulin Vieux (SMV) in France. The tuned Jensen wake model is then used to optimize the power settings of the wind turbines to maximize the wind farm power capture; this optimization is similar to other wind farm optimizations that have been reported in the literature. The study in this paper considers a single wake case where there is only one wind turbine in the wake of another turbine, and the study also considers a multiple wake case where there is a row of 5 wind turbines where each turbine subsequently wakes (either fully or partially) the following turbine. Finally, the uncertainty of the calibrated Jensen model is quantified, showing that more work remains to be done before the tuned Jensen model can provide guarantees of increases in wind farm power production.

Overall, the paper is reasonably written and there may be useful results to be published, though the conclusiveness of the proposed wind farm control approach is still unclear due to the uncertainty that remains in the tuned Jensen model. As such, I would recommend that a much shortened paper summarizing the tuned Jensen model results based on field data and the uncertainty quantification, and indicating that more studies are needed before the tuned Jensen model can be reliably used for coordinated wind farm control based upon axial induction control strategies. The challenges of axial induction control strategies have already been reported in (Annoni et al., 2016), among other papers.

Thank you very much for your time and effort in reviewing this paper - we believe that the clarity is improved in the revised version. We agree that axial induction control has been a fairly widely studied topic over the past years, but most of the work was focused on high fidelity simulations. To our knowledge, it has very rarely been applied to a real and operating wind farm using a wake model calibrated with actual SCADA data in the scope of the realization of field tests. The principle of this paper is also to propose methodologies that will help for the implementation of wind farm control in the field. Furthermore, we also think that the c_P / c_T estimation procedure and the uncertainty quantification of the model are also nice results to show and they are better integrated with the rest of the paper if they can be illustrated and put in perspective with optimization study cases in the farm.
Consequently we think that the section 5 adds value and perspective to the paper about wind farm optimization. In order to address your remarks and reservations, we added a section 5.6 in which we discussed in more detail the limitations of the model and the requirements for a practical implementation of axial induction control in the field.

Some more specific comments and suggestions:

1. Yellow is used for one of the curves in several of the figures. Because the yellow curves are very difficult to see, I would highly recommend replacing each yellow curve with another choice of colored curve, perhaps with a different shaped marker on the curve to distinguish it from other curves in the same figure.

Thank you for pointing out this issue, we updated the graphs to take into account you recommendations.

2. In Figure 9, the curves for both SMV1 and SMV7 are nearly identical in color. The curves for SMV3 and SMV4 are also very similar in color. I would recommend at least choosing different shaped markers (not all circles) to help distinguish these curves in the Figure.

Same as above, Figure 9 has been modified to change the colors of the indicated curves and set a different marker for all curves.

3. There are small grammatical mistakes or typos throughout the manuscript, and it is recommended that the authors more carefully proofread subsequent submissions.

We read again the manuscript and tried to correct all these small mistakes.

Local turbulence parameterization improves the Jensen wake model and its implementation for power optimization of an operating wind farm

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Abstract. In this paper, a new calculation procedure to improve the accuracy of the Jensen wake model for operating wind farms is proposed. In this procedure the wake decay constant is updated locally at each wind turbine based on the turbulence intensity measurement provided by the nacelle anemometer. This procedure was tested against experimental data at onshore wind farm La Sole du Moulin Vieux (SMV) in France and the offshore wind farm Horns Rev-I in Denmark. Results indicate that the wake deficit at each wind turbine is described more accurately than when using the original model, reducing the error from 15 - 20% to approximately 5%. Furthermore, this new model properly calibrated for the SMV wind farm is then used for coordinated control purposes. Assuming an axial induction control strategy, and following a model predictive approach, new power settings leading to an increased overall power production of the farm are derived. Power gains found are in the order of 2.5% for a two wind ~~turbine~~ turbines case with close spacing and 1 to 1.5% for a row of five wind turbines with a larger spacing. Finally, the uncertainty of the updated Jensen model is quantified considering the model inputs. When checked against the predicted power gain, the uncertainty of the model estimations is seen to be excessive, reaching approximately 4%, which indicates the difficulty of field observations for such a gain. Nevertheless, the optimized settings are to be implemented during a field test campaign at SMV wind farm in the scope of the national project SMARTEOLE.

1 Introduction

Wind turbines are aggregated together in wind farms to take advantage of economies of scale and reduce overall costs (Pao and Johnson, 2009). However this creates wake interactions between the turbines which are responsible for an increase in mechanical loads and a decrease in power production. It is generally not possible to avoid completely these interactions due to constraints imposed on the development of wind farms and moreover in some cases wake effects are still persistent at significant distances downstream, up to 10 to 15 diameters (Sanderse, 2009).

To reduce these effects and improve wind farm efficiency and sustainability, wind farm coordinated control strategies are currently investigated. Contrary to the state-of-the-art control, in which all turbines maximize their own power production, coordinated control aims at controlling turbines at a wind farm scale to optimize its overall output. Two different strategies are mainly considered to achieve this goal: either the upwind turbines are curtailed to leave more kinetic energy downstream or they are yawed to deflect the wake away from the downwind turbines.

Results from simulations show that small gains in power production are indeed possible ~~(Bossanyi and Jorge, 2016; Gebraad et al., 2017)~~ (Bossanyi and Jorge, 2016; Gebraad et al., 2017; Santhanagopalan et al., 2018), however they also underline their high variability with incoming wind conditions (Knudsen et al., 2015). It is therefore not known to what extent these gains can be reproduced in an operating wind farm where wind conditions are fluctuating constantly and significantly. Very few full scale field tests have been realized to investigate this question. The concepts of "Heat and Flux" (Machielse et al., 2007) and "Controlling Wind" (Wagenaar et al., 2012) were studied some years ago at the Energy Center of the Netherlands (ECN) and more recently the National Renewable Energy Laboratory (NREL) provided in Fleming et al. (2017) a field test of their "yaw-based wake steering" method in an Envision offshore wind farm. They tend to confirm that gains can be achieved in practice, however in all cases uncertainties remain high and it is therefore difficult to give a definite conclusion.

Other full scale field tests are currently being held in France in the scope of the French national project SMARTEOLE. They are organized in an operating wind farm owned by ENGIE Green, La Sole du Moulin Vieux (SMV), in which different curtailment and yaw offset strategies are studied. The main objective of these tests is to investigate the relevance of these strategies on wind turbine power production and loads and determine whether they could prove beneficial when applied on commercial wind farms. A first experiment campaign was realized between December 2015 and April 2016 and was dedicated to axial induction control strategy. An intentionally high level of curtailment was applied on a wind turbine of the farm so that changes in its emitted wake could be observed from the analysis of downstream active power data. Even though no increase in ~~combined~~ aggregated power production was expected, a first analysis of wind turbine power production in the farm showed that part of the lost power at the upstream turbine could be retrieved downstream ~~(Ahmad et al., 2017)~~(Ahmad et al., 2017; Duc, 2017).

The goal of this paper is to use the knowledge gained during the first campaign to provide new optimized control commands that could be implemented in a second field campaign, and hopefully lead to an increase in ~~combined~~ the aggregated power production of the farm. As SMV is a commercial wind farm, these commands must be easily applicable without modifying the wind turbine control system, thus a model predictive approach is followed to determine the ~~best settings~~ optimal de-rating to be applied as a function of wind speed and direction. To limit computational costs and the complexity of the optimization process, fast and simple models are considered. Hence simplified engineering models are to be applied and the main issue when following this kind of approach is making sure that they are capturing accurately the wake deficit at each wind turbine. Consequently the data recorded during the first field test campaign is analyzed further and used to propose a ~~modification~~ new tuning of the widely used Jensen model (Jensen, 1983; Katic et al., 1986). In this new method the wake decay constant is expressed at each wind turbine based on the local measurement of turbulence intensity provided by the nacelle anemometer. The resulting wake deficit appears to be more consistent with the observed data at SMV wind farm than when using ~~the original model~~a constant value, and this calculation procedure is also validated considering experimental data from the Horns Rev-I offshore wind farm.

The rest of this paper is organized as follows. In Sect. 2, the wind farm and the experimental setup used during the first field test campaign ~~is~~ are shortly detailed. Section 3 describes the principle of the ~~modified~~ tuned Jensen model, and its performance

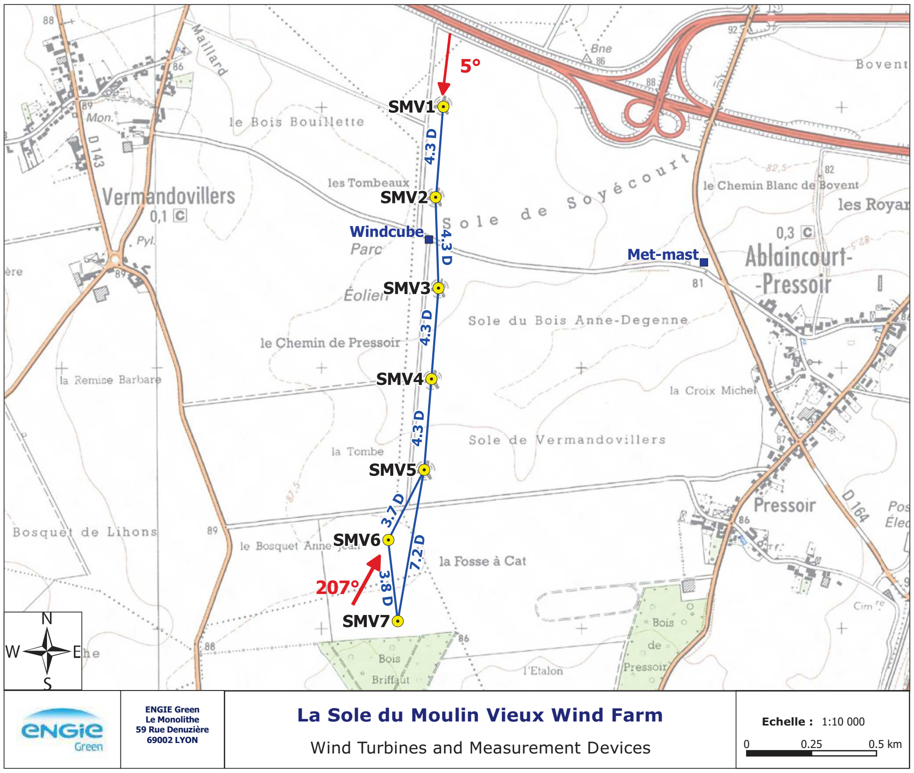

Figure 1. Layout of SMV wind farm and location of wind measurement devices. Inter distances between the wind turbines are expressed in rotor diameters (with D = 82m), while red arrows indicate the main wind direction angles used in this paper.

compared to the original model is assessed in Sect. 4. This ~~modified~~ tuned model is then used in Sect. 5 alongside with a simple c_T estimation procedure to predict in two study cases at SMV wind farm the optimized settings leading to an increase in overall wind farm production. Uncertainty of the model estimation is also quantified in this section and constraints related to field implementation are briefly discussed. Finally, Sect. 6 provides a summary of the paper and conclusions.

2 Experimental setup

La Sole du Moulin Vieux is a commercial wind farm owned by ENGIE Green and located at Ablaincourt-Pressoir in the region Hauts-de-France, approximately midway between Paris and Lille. Figure 1 shows the layout of the farm with the inter-distances between the turbines and the main direction angles used in this paper. It consists of 7 Senvion REpower MM82 2050 kW wind turbines 80 m hub height, that were commissioned in two steps: the first five turbines (SMV1 to SMV5) were put in service in 2009 while the two last ones (SMV6 and SMV7) were installed four years later in 2013. The site is not complex, with a very flat terrain composed mainly of grasslands, with the exception of a small wood located south of the farm.

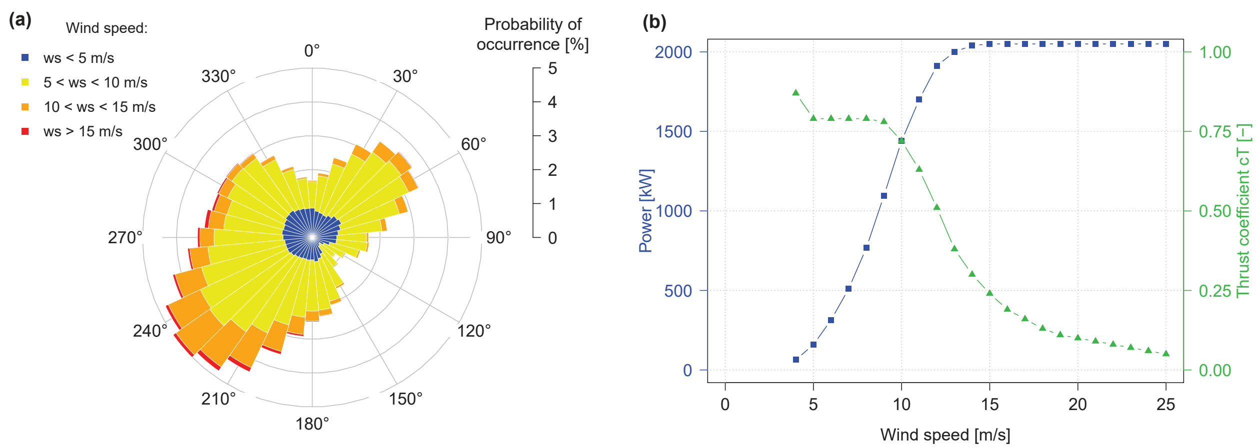

Figure 2. Long term wind rose observed at the site of SMV wind farm (a) and Senvion MM82 guaranteed power and thrust coefficient (c_T) curves (b).

It can be seen that wind turbines are more or less aligned on a North-South axis while prevailing wind direction is South-West, as seen on the long-term wind rose of Fig. 2(a). This particular wind farm was chosen for the field test campaigns of the SMARTEOLE project because of the proximity with ENGIE Green maintenance center (located 5 km away from the farm) and the wake event SMV6 - SMV5. Indeed, due to development constraints, these two turbines were installed very close from each other (only 305 m, i.e. 3.7 D) and aligned with prevailing wind directions. In this paper SCADA data from the seven turbines is analyzed along with data from a 80 m met-mast and a ground-based lidar (windcube V1). The location of these sensors is indicated on Fig. 1.

3 Modification of the Jensen model

3.1 Original model

The Jensen model as it was originally developed by Jensen (1983) and Katic et al. (1986) is introduced briefly here. In this model the wake grows linearly at a rate driven by a coefficient k_w called wake decay constant (WDC) or wake expansion coefficient. The wind speed deficit δ_w in the wake is assumed to be uniform, axis-symmetric and depends only on the down-stream distance x and the upstream wind turbine thrust coefficient c_T. It can be computed using mass conservation and can be expressed as:

$$\frac{U_w}{U_0} = 1 - \delta_w = 1 - \frac{1-\sqrt{1-c_T}}{(1+k_w x/R)^2}, \qquad (1)$$

where U_0 is the incoming wind speed at the upstream wind turbine, U_w the velocity in the wake and R the radius of the upstream rotor.

When summing the wakes from two or more upwind rotors, wind speed deficits are aggregated via quadratic sum. Therefore the wake deficit δ_n at the n-th wind turbine of a row is simply given by:

$$\delta_n = \sqrt{\sum_{i=1}^{n-1} \delta_i^2}, \tag{2}$$

where δ_i is the wind speed deficit due to wind turbine i.

As indicated earlier, the Jensen model is probably the most widely-used wake model for wind energy engineering applications, and that is mainly due to its simplicity and robustness. In particular, its very low computational cost makes it very suitable for optimization purposes as a high number of simulations can be run in a very short time. However, although this model gives fairly good estimation of the averaged power deficit in a wind farm (Göçmen et al., 2016), some studies underline its inaccuracy when it comes to looking at the individual power production of the wind turbines (Barthelmie et al., 2009; Gaumond et al., 2014). This is a crucial issue for power optimization using coordinated control, given that the production at the downstream turbines must be predicted as accurately as possible in order to choose the optimal settings of the upstream turbine.

There is therefore a need for improvement to be able to use this model for such purposes. Over the past years some new models have been derived from the main equation of the Jensen model. They aim at offering a better representation of the individual wake deficits by introducing new parameters and equations, while keeping a low computational cost. For example, in Bastankhah and Porté-Agel (2014) the equation of momentum conservation is included to the model and a Gaussian distribution is assumed for the velocity deficit profile. The multizone model developed by Gebraad et al. (2014) is also Jensen-based and considers three different areas in the wake, each with its own wake decay constant. Description of wind turbine wakes is indeed very much improved with these models, however they can be relatively difficult to calibrate as they consider up to ten parameters that need to be tuned properly (Annoni et al., 2018).

In this paper a very simple tuning of the original Jensen model is proposed based on the measure of local turbulence intensity (TI). The idea is to keep the simplicity of calibration and robustness of the model while improving its accuracy. As it will be discussed in the next section, and shown later in Sect. 4, taking turbulence intensity into account when tuning the model already improves significantly the performance of the model and offers a fairly good representation of the velocity deficit along a row of turbines, both onshore and offshore.

3.2 Tuning of the model

As can be seen in Eq. 1, there is only one parameter to be tuned in the Jensen model: the wake decay constant. This empirical constant is supposed to vary from one wind farm to another but generally the two recommended values of 0.075 and 0.05 are used for onshore and offshore wind farms, respectively (Mortensen et al., 2011). In some studies it is also expressed more specifically as a function of the particular conditions at the wind farm, using for example the roughness length and the atmospheric stability (Peña and Rathmann, 2014) or the ambient turbulence intensity (Peña et al., 2015; Thorgersen et al., 2011). ~~Recent~~ The link between wake growth and TI was pointed out by Lissaman (1976), but more recent studies, based on wind tunnel, Large Eddy Simulations (LES), Reynolds-Average Navier-Stokes (RANS) simulations and full scale turbine data, clearly ~~identifies~~ identify TI as one of the most influencing parameter on the wake growth and magnitude of the wake deficits ~~(Bastankhah and Porté-Agel, 2014; Mittelmeier et al., 2017; Annoni et al., 2018)~~ (Bastankhah and Porté-Agel, 2014; Mittelmeier et al., 2017; Santhanagopalan et al., 2018; Annoni et al., 2018).

It is known that TI varies significantly inside a wind farm, as the wake-added TI from upstream wind turbines is added to the ambient TI (Crespo et al., 1999; Vermeer et al., 2003; Göçmen and Giebel, 2016). Keeping the same wake decay constant for all wind turbines in the farm can therefore lead to errors in prediction of individual power production. The wake deficit is under-estimated at the first few downstream turbines and over-estimated further down the row (Gaumond et al., 2014) or vice versa (Göçmen et al., 2016). Consequently, it appears more accurate to assign a new wake decay constant for each wind turbine that would be directly linked to the local value of TI rather than considering an averaged value for the complete wind farm.

This strategy was followed in Niayifar and Porté-Agel (2016) and an expression between the wake decay constant and the local TI was proposed on the basis of LES data:

$$k_w = 0.3837\,(TI)_{mod} + 0.003678, \tag{3}$$

where $(TI)_{mod}$ is the modeled local TI obtained through the combination of ambient and wake added TI, the latter being estimated thanks to the empirical equation developed by Crespo et al. (1996). As in this present paper SCADA data is available, it was rather decided to use the direct measurement of turbulence intensity provided at each wind turbine rather than relying on such a generic expression. In the next section are presented several methods that can be used to estimate TI from SCADA. A direct proportionality is considered between k_w and the measured TI, $(TI)_{meas}$. This was done in order to keep the same simplicity as in the original Jensen model, i.e. to have only one parameter to calibrate, the constant c:

$$k_w = c\,(TI)_{meas}. \tag{4}$$

It should be noted that the tuning of the wake decay constant is based on TI only. Although TI is probably the most critical parameter, some studies underline the link between the variation of c_T and k_w (Bastankhah and Porté-Agel, 2014; Annoni et al., 2016). Accordingly in Sect. 4 the tuning of the Jensen model is evaluated in the constant c_T region, see Fig. 2, in order to isolate the local turbulence effects on the wake expansion. However, this is no longer true in Sect 5 where the model is used in an optimization process involving axial-induction control, whose purpose is precisely to change the c_T of upstream turbines.

3.3 Estimating TI from SCADA

There are several ways to assess the incoming wind speed from ordinary SCADA signals, all with their advantages and drawbacks. These different methods are presented in this section and they can all be used to derive a local estimation of TI which is a required input for the wake model presented above. Alternative methods using sensors that are usually not installed on wind turbines (e.g. lidars or spinner anemometers) are not developed here but could also fulfill the same purpose.

The first and most obvious way to obtain a wind speed measurement from SCADA is to consider the nacelle wind speed signal (NWS) emitted by the nacelle anemometers installed on the wind turbine. However, these sensors are located behind the rotor and are therefore exposed to a highly distorted flow (Zahle and Sørensen, 2011). They cannot be relied on to provide an

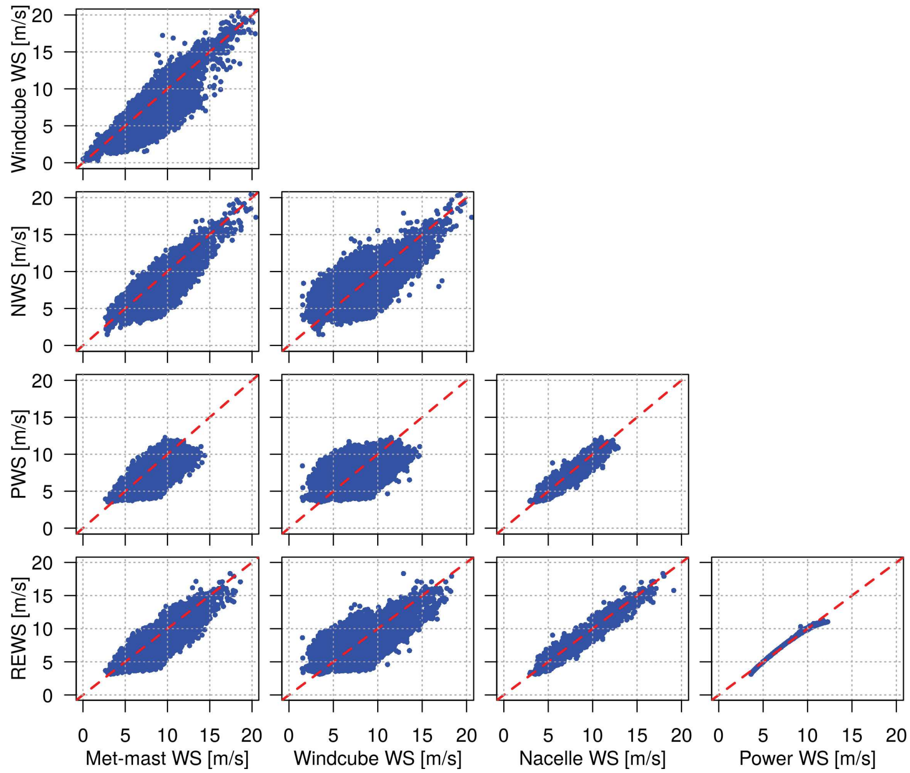

Figure 3. Comparison of wind speeds measurements at SMV5 (for Nacelle Wind Speed, Power Wind Speed and Rotor Effective Wind Speed) and at external sensors (met-mast and windcube). No sector filtering was applied to the data, explaining the scatter when comparing sensors at different locations.

accurate and instantaneous wind speed measurement, but when it comes to considering local TI they might be good enough as only 10-min average and standard deviation values will be involved.

Another wind speed measurement can easily be obtained from the active power production signal and the guaranteed power curve of the wind turbine (or a measured power curve). This new signal, labeled here as power curve wind speed (PWS), is generally more reliable than the NWS since the sensor is the wind turbine itself. Also, due to rotor inertia and the fact that the wind speed derived using this method is averaged over the whole rotor area, small fluctuations of the wind flow will be filtered out resulting in a much smoother signal. The main issue regarding this method is its limited applicability: it cannot be used above rated wind speed or during down-regulation, ~~therefore~~ and therefore is unsuitable for wind farm coordinated control purposes.

In order to solve this problem a third way was developed in the scope of the PossPOW project by Göçmen et al. (2014) to calculate the rotor effective wind speed (REWS) of a wind turbine in these particular situations~~by Göçmen et al. (2014)~~. In this method the REWS is calculated from three SCADA signals (active power, rotor speed and pitch angle) and a c_P model. It must be ensured that the chosen c_P model is fitting as best as possible to the real c_P curve. Alternatively a c_P look-up table can

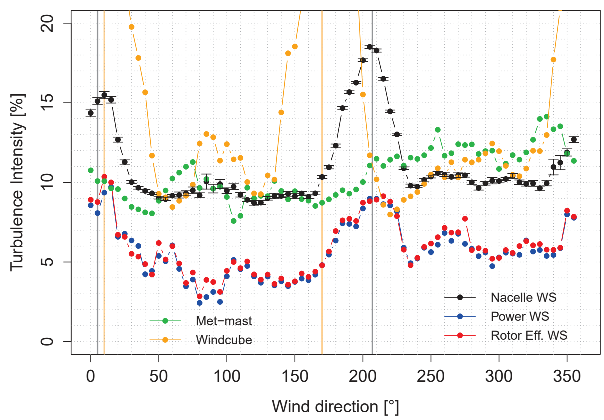

Figure 4. Comparison of TI measurements at SMV5 (for Nacelle Wind Speed, Power Wind Speed and Rotor Effective Wind Speed) and at external sensors (Met-mast and windcube), represented against wind direction. Error bars shows the 68% normalized confidence interval (represented for NWS but a same order of magnitude can be expected for other sensors in the same wind direction bin). Vertical lines indicate position of wakes for SMV5 sensors and windcube.

also be used, when available. In this paper the c_P model and the value of its parameters are the same as the one presented in Göçmen (2016), as they proved to offer a good performance for wind turbines in the same range (rated power of 2 MW with a diameter of about 80 m) as the ones studied here.

Four months of ~~second-wise~~ 1 Hz SCADA data were processed (1st December 2015 - 31st March 2016) for the wind turbine SMV5 to compute 10-minutes average wind speed and turbulence intensity using these three different methods. Figure 3 compares these wind speed values with measurements from reference sensors (met-mast and windcube). No sector filtering was applied to the data, consequently a significant scatter can be found when comparing two sensors at different locations due to wake effects. It can be observed that these results are very similar to the ones that were obtained at the Lillgrund offshore wind farm and were presented in Göçmen and Giebel (2016), showing a very nice correlation between the PWS and the REWS, and more scatter when considering the NWS. This is because the wind speeds calculated through the REWS or PWS methods contain a geometrical averaging of the wind flow over the whole surface of the rotor which smooths out wind speed fluctuations (Göçmen and Giebel, 2016). On the other hand NWS and met-mast are point-wise measurements and therefore are affected by every single variation of the wind speed.

In Fig. 4 the turbulence intensity calculated from all these signals is represented against wind direction (5° bins). It can be seen that outside any wake events, the TI obtained through the NWS signal is of same order of magnitude than the one measured by external sensors. On the contrary, TI obtained with either the PWS or the REWS signals is approximately twice as low. As previously mentioned, this is explained by the geometrical averaging provided by these two methods.

All wake events are clearly captured by any of the TI signals. At a particular location of a wake, the TI measured is about twice as high compared to the free-stream conditions, indicating that wake added TI is significant and can be measured reliably

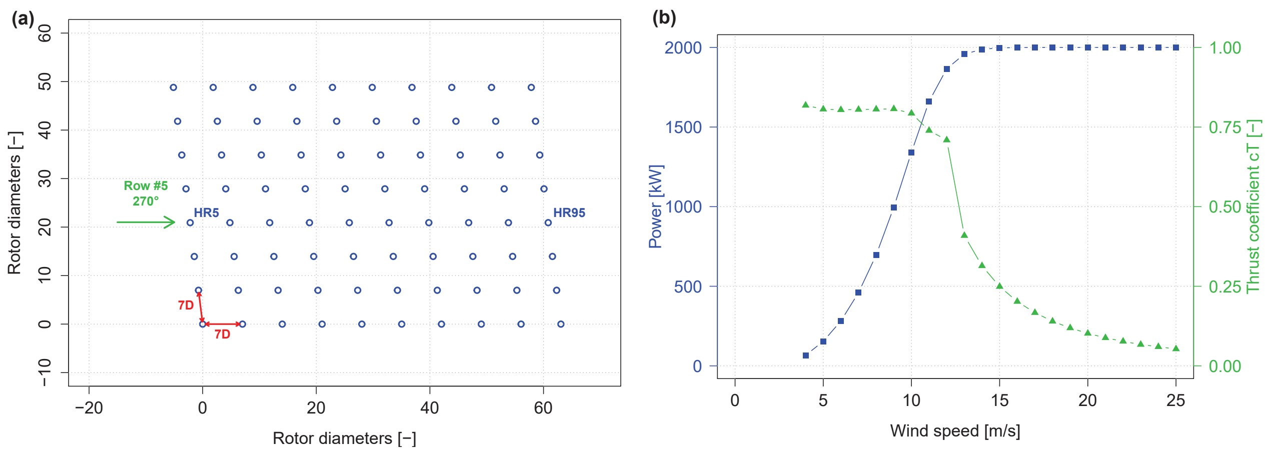

Figure 5. Layout of Horns Rev-I offshore wind farm with turbine spacing and wind direction angle used in ths study (a) and Vestas V80-2MW guaranteed power and thrust coefficient (c_T) curves (b).

with a SCADA signal. Consequently any of these TI signals could be used as input for the ~~modified~~ tuned wake model, it is simply needed to adjust accordingly the value of the constant c in Eq. 4. However, for the rest of this paper, only the NWS TI could be considered in practice given that the PWS signal cannot be used for down-regulation purposes, while the REWS method requires acquisition and processing of second-wise data, which were not available for some of the turbines in the wind farm.

4 Validation of the tuning strategy

4.1 Data filtering and processing

The performance of the ~~modified~~ tuned Jensen model is now assessed in this section and compared to the results obtained for the original model. Production data from two wind farms are considered: the onshore SMV wind farm and the offshore wind farm of Horns Rev-I (layout of the farm and power and c_T curves for the Vestas V80-2MW wind turbines are shown on Fig 5). In both case, the normalized power production along a row of turbines is analyzed. The data is filtered to keep only the 10-minutes periods when all wind turbines are in operation and the incoming wind direction is within a $\pm\,5°$ interval around the main orientation of the row. Another filtering is done based on the power production of the most upstream turbine in order to consider only the 10-min periods when wind turbines are all in the constant c_T region (the Region II of the power curve).

For each valid 10-min period, the power production deficit at each wind turbine is simulated for both the original and the tuned models. When considering the original Jensen model, the value of k_w is calibrated using the first wake event of the row. In the case of the tuned wake decay constant, the value of the constant c in Eq. 4 is adjusted roughly to limit the individual error of the model along the row. The value used for $(TI)_{meas}$ is the 10-min TI measurement from the NWS signal. The normalized simulated deficits are then averaged over all valid 10-min periods and compared with the normalized measured deficits. The averaged value of the NWS TI signal at each wind turbine is also drawn to show the variation of the measured TI along the row of turbine. Error bars indicate the 68% normalized confidence interval.

At SMV wind farm, the power production deficit is studied along the row SMV1 to SMV5. The wind direction sector considered is $5 \pm 5°$, and the valid power range for the most upwind wind turbine (SMV1) is fixed to 600 - 1100 kW to fulfill the constant c_T condition. The filtered data-set finally consists of 156 valid 10-min periods recorded between 15th June 2015 and 1st August 2016 (due to small occurrence of northerly winds, it was needed to consider a longer period than the actual field tests to gather enough valid data). The wake decay constant for the original Jensen model was kept as 0.075, the traditional value for onshore wind farm as it proved to show a good performance for the first wake event of the row SMV1 - SMV2.

At Horns Rev-I wind farm, the power production deficit is studied along the row number 5, from HR5 to HR95 (see layout of the farm on Fig. 5(a)). The wind direction sector considered is ~~270 ± 5~~$270 \pm 5°$, and the valid power range for the most upwind wind turbine (HR5) is fixed to 0 - 1200 kW to fulfill the constant c_T condition. The filtered data-set finally consists of 270 ~~10-minutes~~ 10-min periods recorded between 16th February 2005 and 25th January 2006. The value for the wake decay constant of the original Jensen was fixed to 0.09, which is much bigger than the value of 0.05 traditionally used for offshore wind farms but much more consistent with the measured deficits. It was already found on other studies (e.g. Niayifar and Porté-Agel (2016)) that using a wake decay constant of 0.05 was clearly overestimating the power deficit for the wind farm of Horns Rev-I, as it gives narrower wake growth within the wind farm.

4.2 Results

The evaluation of the original and the ~~calibrated~~ tuned Jensen model on SMV and ~~Hons Rev~~ Horns Rev-I wind farms are presented on Fig. 6 and 7, respectively. In both cases the normalized deficit is shown as a function of distance to the most upstream turbine, as well as the difference between the modeled and the observed ~~deficit~~ deficits at each wind turbine for different values of wake decay coefficient.

It can be seen that the graphs for the two wind farms have a very similar behavior with the tuned Jensen model performing better than the original model. Except for the first wind turbine, the wake deficit calculated with the original model is always overestimated and the error is getting more significant towards downstream: from approximately 10% at the third turbine of the row, it goes around 15 to 20% further downstream. On the contrary, with the tuned Jensen model the deficit is captured more accurately, especially at the wind turbines located at the middle of the row for which the error is kept between $\pm5\%$. These changes are consistent with the augmentation of turbulence intensity from the second wind turbine in the row. Increased TI provides a better mixing between the disturbed flow in the wake and the undisturbed free flow, which allows a earlier recovery, both in terms of time and space. This particularity is taken into account in the tuned Jensen model since the WDC is increased linearly with TI, while with the original Jensen keeping the same WDC all along the row leads to an overestimation of the deficit.

When analyzing the impact of the choice of the constant c linking TI with the k_w in the tuned Jensen model, two observations can be made. First, it can be seen that the optimal c obtained for each wind farm is different, 0.75 for SMV wind farm and 0.9 in the case of Horns Rev-I. This shows the sensitivity of the model to the local conditions and tends to indicate that a small

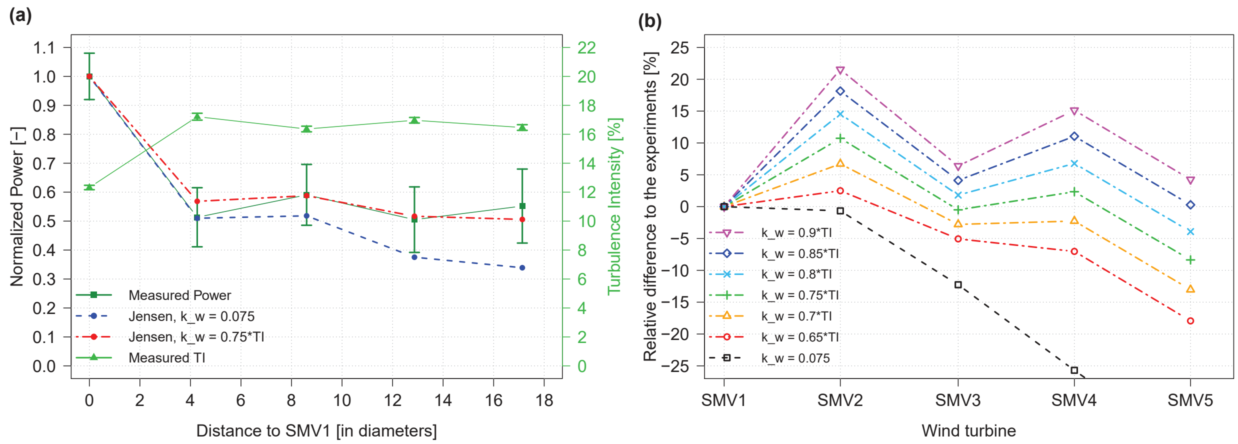

Figure 6. Comparison of the model performance at SMV wind farm. Variation of experimental and modeled normalized power and turbulence intensity (measured by the nacelle anemometer) along the row (a) and variation of the error of the model at each wind turbine for various values of wake decay constants k_w (b). Error bars indicates the 68% normalized confidence interval.

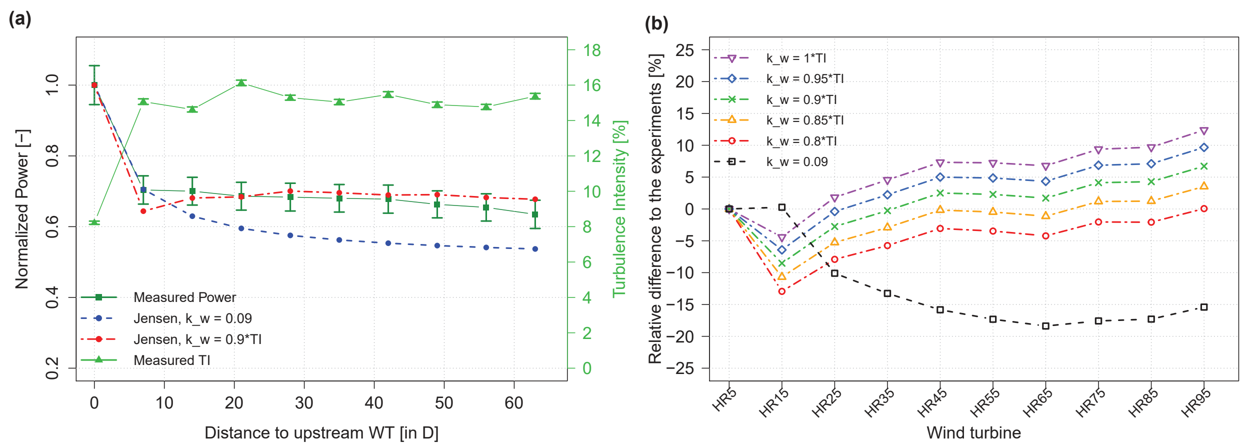

Figure 7. Comparison of the model performance at Horns Rev-I wind farm. Variation of experimental and modeled normalized power and turbulence intensity (measured by the nacelle anemometer) along the row (a) and variation of the error of the model at each wind turbine for various values of wake decay constants k_w (b). Error bars indicates the 68% normalized confidence interval.

calibration of the constant will still be needed for each wind farm to make sure that the wake deficit is correctly modeled. This site-dependency of the Jensen model was already present in its original form; indeed in this example it can be seen that the best WDC obtained for the offshore wind farm (0.09) is much higher than the recommended values (0.04 - 0.05) and than the one of the ~~offshore~~ onshore wind farm (0.075).

The second observation is that the modeled wake deficit is varying regularly when c changes. This ensures that the calibration is as easy and robust as before, since it is simply needed to tune the value of c until the wake deficit is described as best

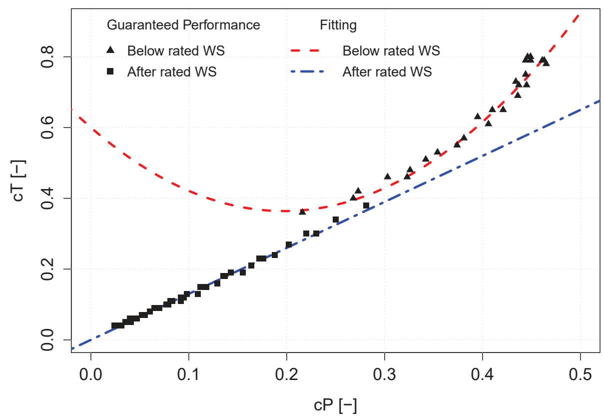

Figure 8. Correlation between c_P and c_T for a Senvion MM82 wind turbine, deduced from the analysis of guaranteed power curve modes for sound management.

as possible. Contrary to the original model, the accuracy is improved as taking into account the local TI allows a better representation of the individual wake deficit at each wind turbine.

Consequently, it can be concluded that this tuned Jensen model is providing an improvement compared with the original model, while keeping the simplicity of calibration and robustness of the original model. It can thus be used to define control instructions, as developed in the next section.

5 Optimization of wind farm power production

After having validated the performance of the tuned Jensen model, it is used in an optimization process to find the wind turbine settings maximizing their power performance. Only the axial induction strategy is developed here, due to its ease of application on a commercial wind turbine. Indeed, it simply requires to trigger a pre-implemented down-regulated power curve as a function of incoming wind conditions without modifying the control settings of the turbine. In practice only wind speed and direction can be used as input for triggering a curtailment mode, therefore power production is optimized for various wind speed and direction bins.

The hypotheses used during the optimization process are first presented, and then two study cases at SMV wind farm are analyzed. Finally, a study of the uncertainty of the model outputs is realized based on the data from Horns-Rev I, and the values obtained are compared with the predicted gains.

5.1 c_T estimation procedure

The principle of wind farm power optimization using an axial induction control strategy is to curtail the upstream wind turbines to gain more energy on downstream wind turbines. It is hoped that the decrease in the upstream c_T will be high enough to reduce sufficiently the wake deficit so that the increase in production downstream can compensate for the upstream c_P diminution. Consequently, it is a crucial issue to assess as accurately as possible how both c_P and c_T are being affected by the upstream down-regulation, in order to correctly estimate the overall production for various curtailment modes.

It is sometimes possible to use look-up tables to link c_P and c_T with operational parameters of the wind turbine, such as rotor speed and pitch angle. However for this work no look-up tables were available and therefore another method had to be developed. A workaround was finally found by the analysis of MM82 guaranteed curtailed power curves used for noise emission reductions. Indeed, when representing c_T against c_P, as in Fig. 8, two different behaviors are being observed: one below rated wind speed (parabolic relationship) and another after rated wind speed (linear dependency).

Thus an empirical relationship could be derived from this analysis, by fitting a second order polynomial to the first set of data points, and a first order polynomial for the second one. The final relationship between c_P and c_T used for the optimization process and valid for an MM82 wind turbine is represented on Eq. 5 below.

$$\begin{cases} c_T = 6.1\,c_P^2 - 2.4\,c_P + 0.6 & \text{if } 6 < V < 12.5 \text{ m/s and } c_P > 0.2 \\ c_T = 1.3\,c_P & \text{if } V > 12.5 \text{ m/s} \end{cases} \tag{5}$$

5.2 Turbulence intensity distribution

As developed in Sect. 3, knowing the turbulence intensity is of primary interest to assess properly the wake deficit. In Sect. 4, the TI was calculated in 10-min time scale resolution to compare the performance of the tuned wake model with the original one. Here, due to practical constraints, it is not possible to consider the real-time TI as input parameter for triggering a curtailment mode. Instead, it was decided to express the local TI as a function of wind speed and direction by calculating a TI distribution in the farm. Consequently a different WDC is chosen for each wind turbine and each wind speed and direction bin, so that local TI still has some influence in the optimization process.

This TI distribution was obtained by averaging the NWS signal of all wind turbines in the farm in 10° direction bins and 1 m/s wind speed bins. The dependency of incoming TI for each wind turbine is represented for a wind speed of 8 m/s on a turbulence intensity rose in Fig. 9, alongside with TI measured by the met-mast that can be used for comparison.

It can be seen that the TI measured by the wind turbines outside any wake events is around 9 - 10%, which is consistent with the met-mast measurements. Some particular terrain effects can nonetheless be observed. Between 160° and 220°, the TI measured by SMV7 is increasing up to 12 to 13%: this was attributed to the presence of a wood south of the farm and very close to SMV7 (please refer to the map of the wind farm on Fig.1). Likewise, an increase of 1 to 2% in the SMV1 TI is observed for wind direction between 340° and 20°. The reason for this increase was related the presence of the motorway at the north of the farm; indeed the met-mast curve shows also a similar increase in the sector [320°; 0°], corresponding to the direction of the motorway as seen by the met-mast location.

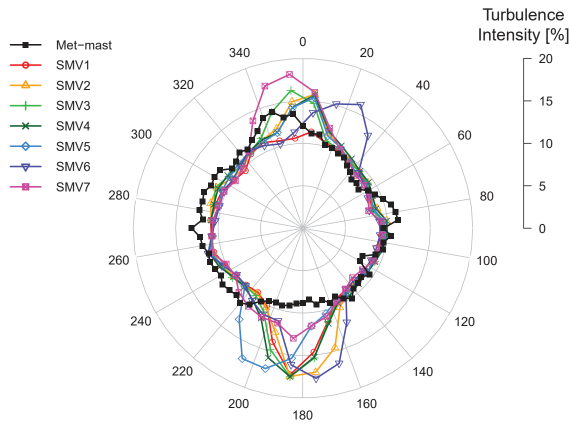

Figure 9. TI distribution at each wind turbine used during the optimization process. This rose is obtained for a wind speed of 8 m/s only, but similar roses were calculated for each wind speed bin. Ambient TI measured at the met-mast is also plotted for comparison.

5.3 Reduction of wake added TI

In order to describe as accurately as possible the variation of TI in the farm when optimizing the power production, the influence of the upstream curtailment on downstream wake added TI must be taken into account. Indeed, as the upstream wind turbine is down-regulated, the wake added TI emitted by this turbine is reduced. It is expected that this decrease will be more and more significant as the upwind curtailment increases. Therefore the TI distribution presented in the previous section, and calculated for normal operation conditions, is no longer valid: it must be reduced accordingly with the percentage of down-regulation applied on the upwind turbine. This is important especially when considering a row of three turbines (or more), since the deficit at the third turbine is calculated based on TI at the second turbine, which is itself dependent on the first turbine curtailment.

To study the impact of upstream down-regulation on downstream wake-added TI, data from the first field test campaign is considered. Between December 2015 and April 2016, SMV6 was occasionally curtailed of approximately 20% for south-western winds (in the direction of alignment SMV6-SMV5). Analyzing TI data provided by the nacelle anemometers, the wake added TI, TI_{wa}, can be computed with the following equation:

$$TI_{wa} = \sqrt{TI_{tot}^2 - TI_{amb}^2}, \tag{6}$$

where TI_{tot} is the total TI in the wake measured at SMV5, and TI_{amb} the ambient TI measured at SMV6.

Ambient and total TI were binned against wind direction (5° bin width) and wake added TI was deduced for each bin. Results are shown on Fig. 10, while numeric values are summarized on Tab. 1. Unfortunately, for the 20% curtailment case, only data on the right side of the wake could be exploited. However, it still provides a very interesting insight of TI reduction with down-regulation as it covers full wake situation (at 210°) to partial wake situations (220 - 225°).

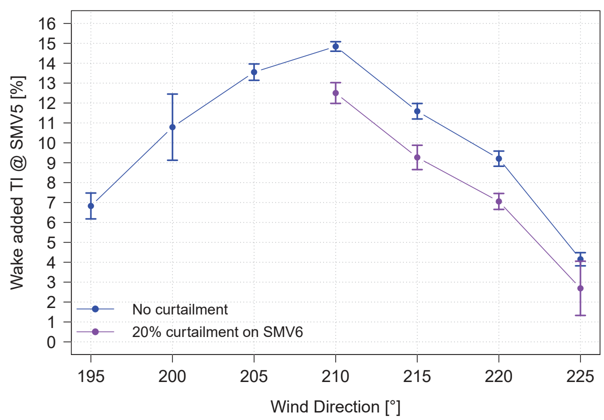

Figure 10. Variation of wake added TI as a function of wind direction, in normal operation and during SMV6 curtailment. Error bars indicate the 68% normalized confidence interval.

Table 1. Comparison of measured wake added TI at SMV5 wind turbine between no curtailment and 20% curtailment on SMV6, with their 68% normalized confidence interval.

Wind direction	No curtailment			20% curtailment on SMV6			Difference
[°]	TI_{amb} [%]	TI_{tot} [%]	TI_{wa} [%]	TI_{amb} [%]	TI_{tot} [%]	TI_{wa} [%]	ΔTI_{wa} [%]
195	15.31 ± 0.54	16.76 ± 0.37	6.83 ± 0.65	N/A	N/A	N/A	N/A
200	13.20 ± 1.43	17.05 ± 0.85	10.79 ± 1.66	N/A	N/A	N/A	N/A
205	12.20 ± 0.30	18.24 ± 0.28	13.55 ± 0.41	N/A	N/A	N/A	N/A
210	11.80 ± 0.16	18.96 ± 0.18	14.84 ± 0.24	12.73 ± 0.28	17.84 ± 0.44	12.50 ± 0.52	-2.34
215	11.90 ± 0.26	16.61 ± 0.29	11.59 ± 0.39	12.99 ± 0.30	15.96 ± 0.53	9.27 ± 0.61	-2.32
220	11.51 ± 0.23	14.74 ± 0.30	9.21 ± 0.38	12.78 ± 0.30	14.60 ± 0.27	7.06 ± 0.40	-2.15
225	9.56 ± 0.18	10.42 ± 0.28	4.15 ± 0.33	11.47 ± 0.85	11.78 ± 1.07	2.69 ± 1.07	-1.46

It can be observed that the upstream wind turbine curtailment provides a relatively significant decrease in downstream wake added TI, as it is reduced from 14.84% to 12.50% for a wind direction of 210°. As expected, as wind direction increases and we go from full wake situation to partial wake situation, reduction of wake added TI becomes smaller, from 2.34% to 1.46%. In this paper, to model the relationship between percentage reduction of wake added TI with percentage of upstream down-regulation, a linear dependency was assumed for a given wake condition:

$$(\%\Delta TI_{wa}) = \frac{\Delta TI_{wa}}{TI_{wa}} = p_{wake}(\%DR). \tag{7}$$

The value of the parameter p_{wake} linking ΔTI_{wa} with $\%DR$ is expected to be dependent on the relative wind direction between the turbines. Consequently, the parameter for full wake conditions, p_{fw} will differ with the one for partial wake conditions, p_{pw}.

In this example, where a 20% down-regulation was applied, values of $p_{fw} \approx -0.788$ (from the bin 210°) and $p_{pw} \approx -1.001$ (from the bin 215°) could be computed.

In Sect. 5.4.2, dealing with power optimization in a multiple wake case, reduction of wake added TI with upstream curtailment is modeled with the following steps:

1. First, wake added TI at each wind turbine in normal operation ~~case~~ is calculated based on the TI distribution presented in Sect. 5.2 and ambient TI deduced from the most upstream wind turbine.

2. Second, as upstream wind turbines are being gradually curtailed in the optimization process, wake added TI is adjusted based on Eq. 7 above. To simplify the process, only down-regulation of the closest upstream turbine is considered for the reduction of wake added TI. A similar procedure was followed in Niayifar and Porté-Agel (2016) when modeling wake added TI.

3. Finally total expected TI at the wind turbine is calculated by inverting Eq. 6. This calculated TI can then be given as input into the local TI based ~~calibrated~~ wake model to compute the wake deficit at downstream turbines.

5.4 Study cases

5.4.1 Wind turbines SMV5 and SMV6 (Single Wake case)

The first case to be studied is the SMV6-SMV5 wake event. It is of particular interest because of the very short spacing between the two wind turbines and their alignment close to prevailing wind directions. For this study case a very simple optimization procedure is used: for each wind speed and relative wind direction, the c_P of SMV6 is gradually decreased up to 20% of its actual value (and the c_T adjusted consequently based on Eq. 5) and the power production of both wind turbines is computed using the ~~calibrated~~ tuned Jensen model. The optimized power curve for SMV6 is then deduced from all the c_P values giving the best combined production at each wind speed.

Results are presented on Fig. 11 for full wake conditions. In Fig. 11(a) power curves for both wind turbines are plotted while Fig. 11(b) shows the relative increase in combined power production which is obtained at each wind speed with the associated amount of curtailment which is applied to SMV6. It is observed that the maximum gain represents an increase of about 2.5% and is found at 7 m/s when SMV6 is curtailed by 12% (c_P decreases from 0.46 to 0.405, while in the same time c_T is reduced from 0.79 to 0.63 according to Eq. 5). More generally, it can be seen that the interest of coordinated control is limited to the wind speed range 5 - 11 m/s, i.e. when both c_P and c_T of the upstream turbine are high. In this range, a small decrease in c_P causes a high reduction of c_T, as illustrated on the parabolic c_P - c_T relationship of Fig. 8. As wind speed increases further, the upstream wind turbine naturally starts to pitch to limit power production to its nominal value and therefore axial induction control is no longer beneficial.

In Fig. 12 is studied the impact of a changing relative wind direction on the relevance of applying a coordinated control, showing the optimal gain that can be expected (a) and the optimal amount of curtailment required on SMV6 (b) as a function of the wind speed. It is seen that the wind direction sector on which gains can be observed is particularly narrow. As soon as the

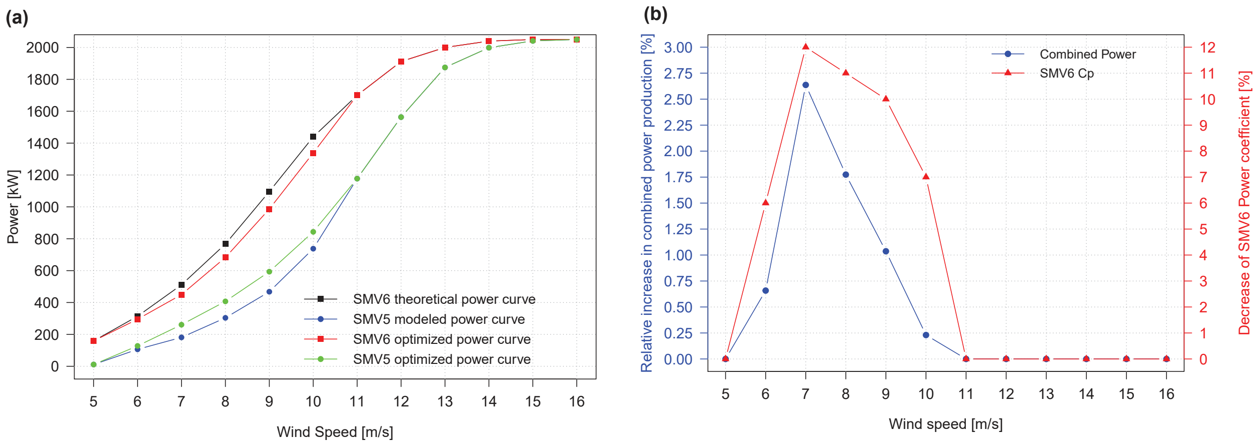

Figure 11. Optimization of power production of SMV6 and SMV5. Power curves in base and optimized case (a) and variation of power gain and optimal SMV6 c_P as a function of wind speed for the optimized case (b).

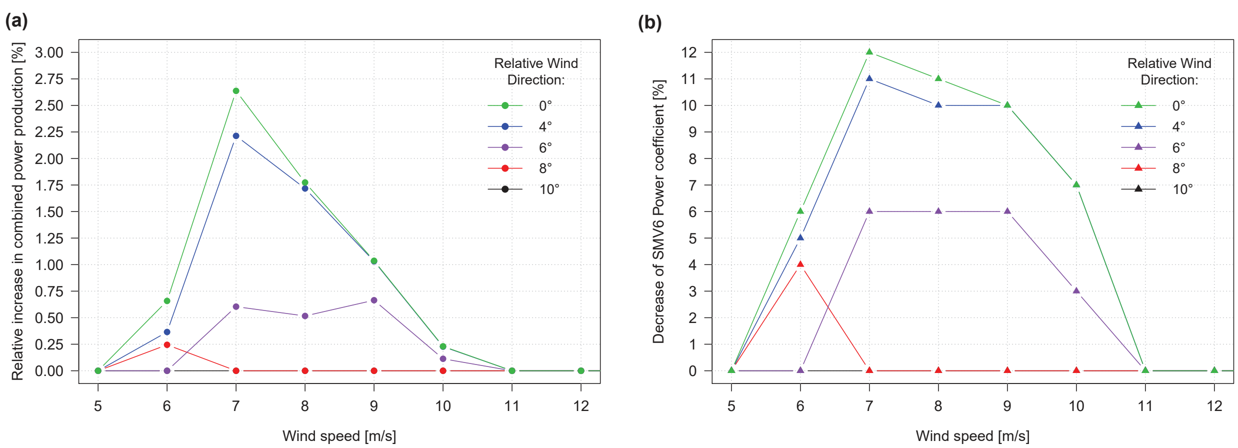

Figure 12. Influence of changing relative wind direction. Variation of power gain (a) and optimal SMV6 c_P (b) as a function of wind speed.

full wake condition is no longer respected, i.e. for relative wind direction above $\pm 5°$, the benefit of axial induction control drops almost instantly: when wind direction shifts from 4° to 6° at 7 m/s, gains are reduced from 2.25% to approximately 0.6%. This sensitivity confirms the very limited applicability of a curtailment strategy for power production optimization and the difficulty to implement it in a real case situation. As it is only beneficial on a 10° width wind direction sector centered around full wake conditions, very ~~stable~~ steady incoming wind conditions are required to make sure that gains in power production will actually be observed.

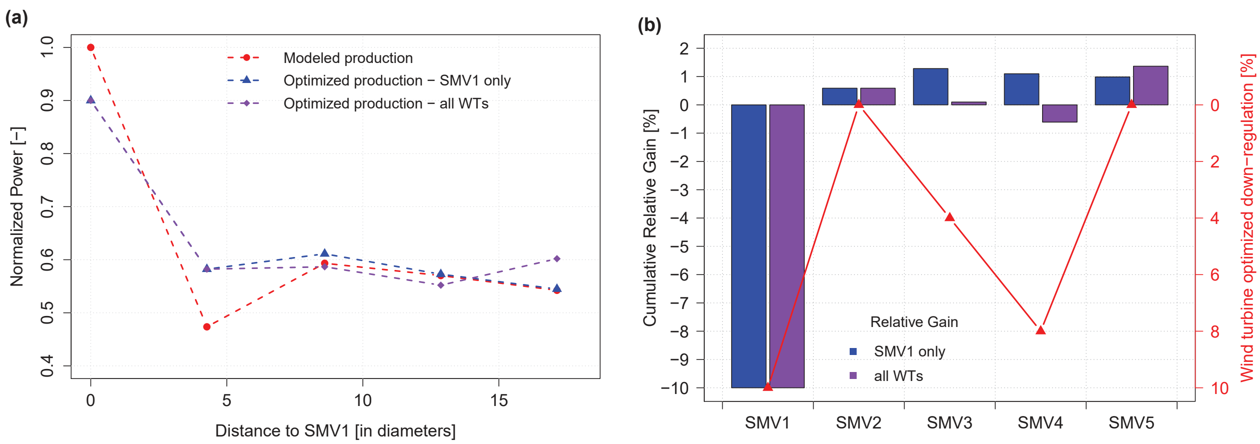

Figure 13. Variation of normalized power at each wind turbine (a), cumulative relative gain and optimized down-regulation settings (b) along the row, for full wake conditions (wind direction of 5° at 8 m/s).

5.4.2 Row SMV1 to SMV5 (Multiple Wake case)

The second case to be studied is the row SMV1 to SMV5. The power production along the row is now studied for full wake conditions and a wind speed of 8 m/s, for which the coordinated control is expected to give the highest possible gain. Two different control strategies are being investigated: in the first one only the most upstream turbine (SMV1) is being curtailed while in the second one each wind turbine is optimally curtailed so that total power along the row is maximized. In the first case, the optimum is reached thanks to the same method as in previous section, while for the second case the following procedure (adapted from Heer et al. (2014)) is used:

1. Start with no down-regulation applied on the wind turbines: $\%DR_i = 0\%$ for $i \in \{1-5\}$.

2. For wind turbine i, from upstream to downstream, find the value $\%DR_i$ maximizing power production along the row and considering that all other $\%DR_{j\neq i}$ remain constant.

3. Repeat step 2 until all $\%DR_i$ stay constant.

Reduction of wake added TI was considered as developed in Sect. 5.3. A value $p_{fw} \approx -0.788$ was used for all wake events in the row except for SMV2 $\rightarrow$ SMV3 which corresponds to a partial wake event (the alignment of these two turbines is found for a wind direction of -2°). A value of $p_{pw} \approx -1.001$ (deduced from wind direction bin 215° in Tab. 1) was used instead.

Figure 13 shows the result of the process, with the normalized power production along the row (a), and the cumulative relative gain and ~~percentage~~ the percentage of down-regulation at each wind turbine for the second strategy (b) (for the first strategy, same amount of curtailment is applied on SMV1 while all other wind turbines are not curtailed). The cumulative relative gain allows following the change of power provided by the optimization as we move downstream, it is defined at wind turbine i as:

$$\%RG_i = 100\frac{\sum_{j=1}^{i} P_j^{opti} - \sum_{j=1}^{i} P_j^{base}}{\sum_{j=1}^{i} P_j^{base}} \tag{8}$$

Consequently the cumulative relative gain at wind turbine SMV5 represents the total gain obtained thanks to the optimization process.

It can be seen from the figures that both strategies lead to an overall increase in power production, with the same amount of curtailment imposed on the most upstream turbine (10% down-regulation). As seen on the cumulative relative gain which is positive at the second turbine, the increase in power at SMV2 is enough to compensate for SMV1 down-regulation. However, for the first strategy, as downstream wind turbines are not curtailed, most of the energy released by SMV1 is captured by SMV2 and SMV3 only. The most downstream turbines SMV4 and SMV5 are only very slightly benefiting from the down-regulation and total relative increase is limited to approximately 1%.

On the contrary, when following the second strategy, the energy made available by SMV1 down-regulation is more equitably shared between all downstream turbines. Indeed, SMV3 and SMV4 are also being curtailed so that high gains can be obtained for SMV5 (as SMV2 is not perfectly aligned with the rest of the row, it is not beneficial to curtail this turbine). As a consequence the cumulative relative gain is decreased at SMV3 and SMV4, but when considering also SMV5 the total relative increase in power production is higher than in the first case, reaching almost 1.5%. This confirms the idea that best gains are obtained when each wind turbine is controlled individually to maximize the overall wind farm output, and not their own power production.

5.5 Uncertainty quantification of the calibrated Jensen model

In order to put the optimized wind farm performance into perspective, it is essential to estimate the uncertainty of the model outputs. Since the calibration of the model is based on the operational turbine data, the uncertainty quantification (UQ) is established through the input uncertainty assessment, and its propagation. The uncertainty is defined as the half width of the 68% confidence interval, which corresponds to a distance of a single standard deviation.

In general terms, the uncertainties attached to the SCADA signals are indicated in the IEC standards (IEC et al., 2013), where the main focus is the annual energy production estimates. With the same focus, Gaumond et al. (2012) investigated the wind direction uncertainty in particular, which is the most ambivalent input signal to the ~~modified~~ tuned Jensen model. Within 10-min intervals, the study showed the uncertainty to be at the levels of 5° for Horns Rev-I wind farm. However, since in this study the analysis is based on high frequency data (second-wise data), the documented value of 3° uniform uncertainty in the yaw position signal (IEC et al., 2013) is considered for now. For the wind speed input, the dependency of the uncertainty to the operational range, i.e. region II and III, is shown in Göçmen and Giebel (2018) for effective wind speed, and in IEC et al. (2013) for nacelle wind speed. Here, we consider the conservative estimate of 0.3 m/s with Gaussian distribution. The uncertainty in wind speed is propagated through the estimation of TI (see Sect. 3.3), estimation of k_w (see Eq. 4), estimation of c_T, and finally the estimation of wake deficit through Eq. 1. The resulting uncertainty distributions of the calibrated Jensen model is shown in Fig. 14. The uncertainty is propagated in a continuous time series of 18-hours from Horns Rev-I wind farm, using a Monte Carlo analysis with 1000 realizations per second. The indicators in the boxplots follow Tukey's descriptive

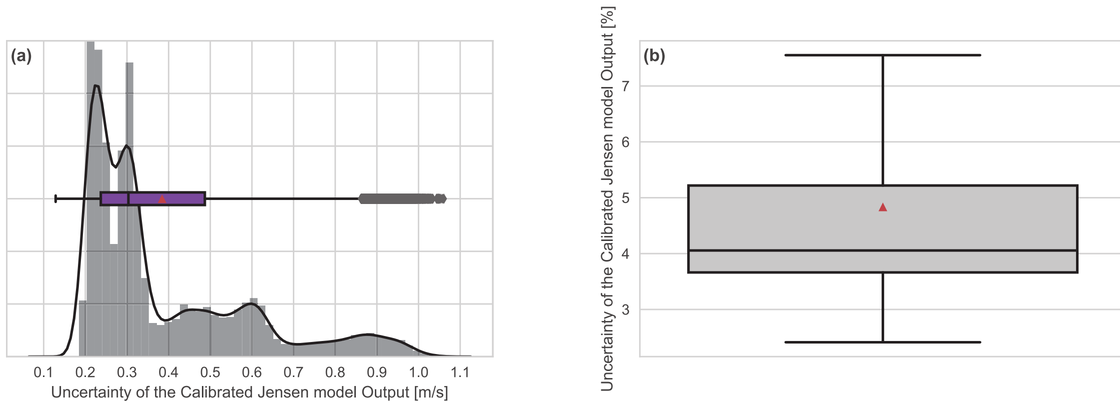

Figure 14. Distribution of the uncertainty in the estimated wake velocity by calibrated Jensen model, (a) the histogram and the boxplot of the distribution in units [m/s], (b) the boxplot of the percentage uncertainty distribution. The median, the boxes, the whiskers and the outliers are according to the Tukey's descriptive statistics (Tukey (1962)). The red triangles indicate the mean.

statistics (Tukey, 1962) where the boundaries of the whiskers are the lowest and the highest datum within the 1.5 inter-quartile range, IQR, corresponding to $\pm 2.7\sigma$ from the mean.

Figure 14 shows that the uncertainty of the calibrated model output is not normally distributed. This is mainly due to the fact that along the propagation process, different sources and distributions of uncertainties are convoluted. It is also seen that there are many outliers in the distribution, which occur near the rated wind speed, i.e. around the operational transition between Region II and III. Along that transition region, the assessment of the c_T is highly sensitive to the wind speed (see Fig. 5(b)), causing the propagation of the uncertainty to diverge. Since for the optimization scenarios discussed above the considered wind speed is lower, it is concluded that the conservative estimate of the model uncertainty can be stated as 0.3 m/s or, more generally, 4%. ~~Compared to the lower gains the developed control strategies show in the~~

5.6 Towards field implementation

As already mentioned in the introduction of this paper, the optimized control strategies developed in these case studies are to be tested in a new field test campaign of the SMARTEOLE project. Through the comparison of the gains expected via these strategies in Sect. 5.4 and the uncertainty quantification of the previous section, it is very important to note that the ~~modified~~ tuned Jensen model risks not to provide the reported power increase in the field tests. In other words, the uncertainty of the model outputs and control inputs needs to be fully analyzed in order to assess the true performance of the wind farm control approaches. Additionally, in order to see the full benefit of wind farm control schemes, more "accurate" sensors / data, more intelligent methods to analyze the data and different perspectives on how to include the physical complexity of the wind farm flow into the wake models are also needed.

Furthermore, the tuning of the model in the optimization process was focused to wind speed and direction only, as in practice these are the only two input variables that can easily be used for triggering the axial induction control for a wind farm operator having a limited access to the turbine control parameters. In reality, because of the highly fluctuating wind conditions (changes in wind speed, wind direction, turbulence intensity and atmospheric stability...), a more complicated tuning would be required in order to decrease the risk of implementing innovative control strategies. Ideally, it would be better suitable to tune the WDC every 10 minutes (or at even shorter time periods) based on the latest measurement of wind speed, direction and local TI and then calculate in real time the optimized settings to be applied at each wind turbine. Since it would enable to include more dynamics and complexity of the local flow (both in terms of time and space), model adequacy would further improve and the resulting uncertainty would be reduced. However, this kind of scenario would also require a much larger access to the wind turbine control parameters and goes beyond the scope of this present study.

Finally, it must also be mentioned that while the axial induction strategy seems to propose a limited benefit in terms of increased combined production compared to other strategies such as wake steering, its impact on wind turbine loads should be much more profitable. Indeed, thanks to the application of a curtailment on the upstream wind turbine, reduction in thrust and in the tower loads can be expected. Downstream, a decrease in the fatigue loading of the turbines can be predicted due to the reduction in the wake added TI, as illustrated on Fig. 10 above. These results are interesting and highly relevant since load reduction can be related to ~~increase~~ an increased lifetime, and therefore a decrease in overall cost of energy.

6 Conclusions

Field tests are currently being held on a commercial wind farm in France, La Sole du Moulin Vieux, in the scope of a national project. The objectives of these tests are to study the potential of wind farm coordinated control ~~strategy~~ strategies for power optimization and loads reduction. In this paper data from the first campaign was analyzed in detail to propose a ~~modification~~ new tuning of the widely used Jensen model. This modification, based on the local measurement of turbulence intensity given by the nacelle anemometer, proved to be enough to improve the accuracy of the model and describe more precisely the individual wake deficit at each wind turbine. The simplicity of calibration and robustness of the original model is kept since there is still only one parameter to calibrate. This new tuning strategy was validated with data from SMV wind farm but also with data from a row of ~~turbine~~ turbines at Horns Rev-I offshore wind farm.

Using this methodology, power production was optimized in two study cases at SMV wind farm. An axial induction strategy was considered with a model predictive approach, and a c_T estimation procedure was developed in order to assess as accurately as possible the combined evolution of c_P and c_T during down-regulation of the wind turbines. Results from the optimization process show that a gain of 1 to 2% in ~~combined~~ aggregated power production can be expected for full wake conditions and wind speed between 7 - 9 m/s. As wind direction changes or wind speed increases further, gains in power production obtained through the upstream wind turbine down-regulation quickly drop to zero, underlining the limited applicability of an axial induction strategy for power production optimization. Moreover, these gains have to be taken cautiously since some studies have already underlined discrepancies between model predictions and actual power productions of wind turbines, especially when variation of the wake decay constant due to changes in c_T was not taken into account (Annoni et al., 2016). These results are in line with the performed uncertainty assessment of the ~~modified~~ tuned Jensen model, where the uncertainty is shown to be more than the predicted power increase. This also indicates the importance of an extensive uncertainty quantification on the ~~(simplified , control-oriented)~~ simplified flow models to correctly evaluate the resulting wind farm control strategies.

However, even if the model is not as accurate as it could be, it is hoped that it is still good enough to give indications about optimal settings where gains would possibly be found. Based on the results derived in this paper, a new field campaign was realized between December 2017 and February 2018 during which a curtailment mode was applied to wind turbine SMV6. Data is currently being processed to determine whether augmentation in combined power production could be achieved. Furthermore data from strain gauges installed in the blades still have to be analyzed to study the impact of axial induction control on wind turbine fatigue loads. Given the quantified uncertainty, even though no gains in power production are obtained, a reduction in loads can be expected.

Future work about wind farm coordinated control realized in the scope of the SMARTEOLE project will also include the analysis of the potential of the wake steering strategy, and the study of the dynamics involved when a wind turbine is curtailed or yawed.

Competing interests. The authors declare that they have no conflict of interest.

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