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Drivers for optimum sizing of wind turbines for offshore wind farms

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The authors would like to thank the reviewers for examining the revised manuscript, for the acceptance of the manuscript by reviewer 1, and for the valuable additional feedback from reviewer 2. The reply to the comment made by reviewer 2 is marked in blue while the actual changes in the manuscript are marked in red.

Reviewer 2 comment

The authors have made an effort to address the technical concerns raised during the initial review. The manuscript has seen improvements based on the comments provided earlier. However, I am still contemplating the broader significance of this contribution to the research community. The study, as presented, seems to be an application of existing methodologies with a somewhat simplified representation of wind farm design. The analyses of the results could benefit from a deeper exploration of their significance. Recognizing the challenges of prolonging the review process, it would be enriching to observe distinct scientific values beyond minor improvements in LCoE and its associated sensitivity. Given the manuscript's simplified modeling approach, the current fidelity of the LCoE estimation might fall short in fully underscoring the study's merit. It would be beneficial if the authors could delve deeper into the advantages of the concurrent MDAO approach, particularly highlighting any unique optimal design outcomes that may not be evident through traditional methods.

The authors understand that the significance of the study may not have been fully clear to the reviewer and may have been interpreted differently. This paper does not intend to focus on LCoE improvements but rather provides a new way of looking at drivers of optimum turbine sizes, via gradients of key farm-level parameters. The models used capture the necessary trade-offs at a farm level and hence, the paper doesn't draw insights about the absolute values themselves but rather, the trends. There have been studies that have looked at the benefits of MDAO in offshore wind exploring the benefits of MDAO at a turbine level using aeroelastic simulations. However, a comprehensive study looking at turbine sizing in an offshore wind farm capturing the essential trade-offs is missing in the literature. The paper first establishes that there is a global optimum beyond which, upscaling might not be beneficial. The paper also shows how upscaling, in general, along a constant specific power, does not result in LCoE reductions. This contributes significantly to the ongoing debate about whether or not to upscale.
The findings of this study have also been used in providing feedback for the proposal of the North Seas Standard (`https://www.nwea.nl/the-north-seas-standard-enable-growth-with-wind-turbine-standardization/`). The standards propose a minimum tip clearance of 25 m and maximum tip height of 1000 ft (aviation limit), restricting the maximum rotor diameter to be around 280 m. The study shows how imposing this limit is not a threat to LCoE reductions that can be attributed to turbine sizing. The LCoE of all the designs in the 300-400 $\mathrm{W m^{-2}}$ range differ by less than 5% compared to the LCoE of the global optimum (see Fig. 1). This again implies that continuous upscaling in the direction of similar specific power will lead to LCoE improvements that may be less than improvements obtained by the benefits that standardization may have on manufacturing, installation and supply-chain optimization.

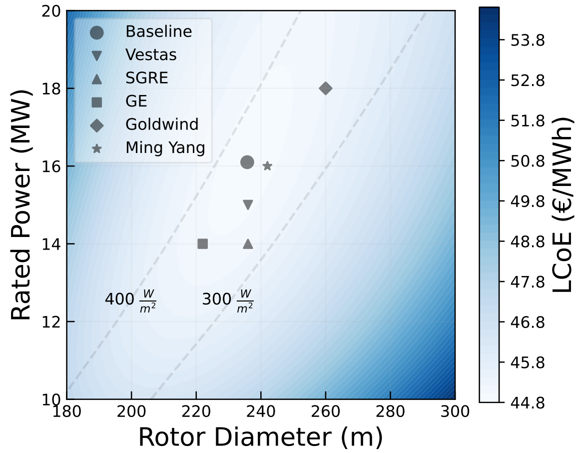

Figure 1: LCoE across the entire design space

How the global optimum shifts with any change in the technology (material) or farm design conditions, or policies, can simply be understood by looking at the impact on specific gradients. The paper discusses how certain parameters (like wind speed, fixed costs) affect the gradient in the direction of changing specific power while others (like farm power density) drive a change in the direction of constant specific power. The gradients are also useful in analyzing how a change in the policy (in the form of removal of farm power/area constraint) shifts the optimum.
In the literature, a comprehensive study discussing how several factors impact both the magnitude and direction of the global optimum, is missing. It is essential to capture the necessary trade-offs at a farm level, making the usage of MDAO, for a turbine sizing study, inevitable. Hence, the intent was not to focus on how an MDAO-driven approach performs better than a traditional sequential approach. However, we understand that the benefits of such an analysis need to be better explained and the modeling limitations might not fully underscore the merits of this work. Hence, we think it could be useful to explicitly clarify, in the manuscript, that the purpose of the paper is not to show how an MDAO-based approach is superior but rather, to use it as a means to perform a comprehensive system-level analysis. A general overview of the approach used in this study along with the purpose of MDAO in this research is discussed in a new section (2.1), now added at the beginning of the methodology chapter. The research question is also slightly tweaked since the 'How to size...' might also be construed as 'what method to use' putting an emphasis on the method, which was not the original intent. Following the suggestion, a new section (3.3) is added before the sensitivity section that explicitly focuses on the benefits of having these individual gradients and their usefulness in determining the drivers for the optimum turbine size. Finally, some benefits of the study are explicitly stated at the end of the conclusions.

The research question is now formulated as:

What drives the sizing of wind turbines for minimum LCoE of offshore wind farms?

Added section in Chapter 2:

2.1 Overview and rationale of the approach

The problem of optimizing the turbine size for an offshore wind farm is complex, as changing the key specifications of the turbine impacts all elements in the farm. For instance, a change in the rated power of the turbine changes the current in the infield cables, and hence, cabling costs. If the farm power is given, changing the turbine rated power changes the number of turbines in the farm having a significant impact on O&M costs, installation costs, wake losses, etc. Similarly, any change in the rotor diameter affects the power and thrust curve of the turbine, impacting the support structure design, wake losses, etc. Hence, both key parameters of the turbine significantly affect both costs and AEP of the wind farm. For a turbine sizing problem, capturing the essential trade-offs at a wind farm level is paramount, making the use of an MDAO-based approach that includes all disciplines in the wind farm, inevitable.

The study does not focus on the development of an MDAO-based framework per se but rather uses the framework as an analysis block to evaluate the LCoE of the farm for a given turbine configuration. The framework will be used to perform analyses that provide insights into the fundamentals of optimal turbine sizing. Some studies that applied MDAO to a turbine-optimization problem for a wind farm, along with the missing dependencies, are discussed in Sec. 1. The requirements of the model-fidelity for each discipline of the wind farm depend on the purpose of the study. For a turbine-sizing study with turbine rated power (P) and rotor diameter (D) as the design variables, it is key that the models for any given discipline respond correctly to the change in the design variables, directly or indirectly. For instance, an increase in the rated power results in a decrease in the number of turbines (if the farm power is kept constant), and as a consequence, results in lower O&M and installation costs. It is essential for the O&M and BoS models to capture these trends reasonably well. However, a model that assumes O&M costs to be a function of the farm rated power or a function of the turbine rated power like in Ashuri et al. (2016), fails to capture the necessary trade-offs. Similarly, the turbine costs (including the support structure) change non-linearly w.r.t. changes in both the rotor diameter and rated power of the turbine. However, a model that scales the turbine costs linearly with the rated power, like in Shields et al. (2021), does not capture the variations in turbine costs because of changes in the rotor diameter. This would significantly impact the findings and conclusions. Hence, it is crucial that the models for all the disciplines in the wind farm capture the dependencies on the design variables. Having low-fidelity models that can capture the essential trade-offs allows the user to quickly evaluate hundreds of turbine designs. The purpose of the MDAO framework, in the context of this research, is not the accurate estimation of LCoE or the optimum design. The main purpose of the framework is to serve as an analysis block that captures the dependencies of various wind farm elements on the design variables and, hence, can be used in identifying the key drivers of turbine sizing. The drivers could be in the form of technology changes, farm conditions, or even policy-level changes, all of which could be identified and quantified with such a comprehensive framework. A summary of the key elements of the approach is given below.

- Model lowest necessary fidelity required for all wind farm disciplines
- Capture direct and indirect dependencies of each discipline on the design variables
- Capture interactions between different wind farm disciplines
- Analyze and visualize the response surface of the outputs
- Identify key drivers of turbine sizing by analyzing the sensitivity of the outputs to various inputs

In line with these considerations, the next sections first describe the MDAO framework and the optimization problem that is addressed with this. The subsequent descriptions of the models focus on the dependencies that are identified to be relevant for this study, rather than on comprehensive mathematical descriptions.

Added section in Chapter 3:

3.3 Significance of gradient components

The behaviour of individual contributions to the gradients at the optimum, in a typical wind farm, in terms of both magnitude and direction, is discussed in Sec. 3.2. The understanding of this behaviour is key in identifying drivers for turbine sizing in a typical wind farm. To understand how certain changes in technology, farm conditions, or specific tendering requirements affect the optimum, one could simply look at how the changes impact the individual gradients and their weightage.

For instance, a change in the fixed costs, like the costs of export cables or substation, changes only the weightage of the AEP gradient (see Eq. 17). This implies that if cables get more expensive, the optimum turbine shifts towards lower specific power turbines due to the stretching of the AEP gradient. Similarly, the removal of the export cable costs reduces the weightage of the AEP gradient, shifting the optimum towards higher specific power turbines. This situation applies, for instance, to the Netherlands, where the transmission system operator provides an offshore electrical connection. Sometimes, the effect on the gradient is more complex, such as for instance a change in blade material. Such a change alters both the magnitude and direction of the RNA cost gradient, resulting in a shift in the optimum along the direction of constant specific power.

Such an approach is useful since it shows how drivers that alter mainly the weightage of the gradients (like changes in fixed costs, wind resource, etc.) shift the optimum in the direction of changing specific power, where the impact on LCoE is also significant (see Fig. 7a). On the other hand, drivers that alter both the direction and magnitude of the gradients (like some technological changes) shift the optimum in the direction of constant specific power, where the impact on LCoE is insignificant (see Fig. 7a). Since the framework uses low-fidelity models, the absolute values of LCoE and optimum designs should not be taken at face value. However, the values match reasonably well with those observed for recently announced turbines and wind farms, adding confidence to the veracity of the results. The analysis of gradient components shows how the framework captures the essential dependencies and how it can be useful in identifying key drivers.

Models that don't include these dependencies might lead to misleading conclusions. This can also be explained by analyzing the gradients. For instance, a model wherein the turbine costs are expressed purely as a function of rated power would assume that the costs increase linearly with the rating. In that case, an increase in the turbine rating from 10 MW to 20 MW would double the costs of an individual turbine while the number of turbines in the farm is reduced to half (due to the farm power constraint). Hence, the total costs of the turbines in the farm remain constant across the entire design space, resulting in the gradients for the RNA costs being zero. As a consequence of this model assumption, the total cost gradient would significantly decrease in magnitude and would now be skewed more in the direction of the rated power. The net resultant of the total cost gradient and the AEP gradient would then significantly push the optimum toward larger ratings and rotors. Practitioners and scientists who focus on LCoE accuracy and fidelity of specific models may overlook the effect that misrepresentation of dependencies may have on gradients in an optimization problem. The insights from this paper may help them make model developments that best match the needs for usage in an MDAO framework.

Added at the end of Chapter 5 (Conclusions):

The study provides a simplified approach that can be applied to a complex turbine sizing problem in order to generate meaningful insights. The findings of this study help the scientific community to focus future research on the most important aspects and goals. They provide insight into how various model improvements impact both the performance and the optimum turbine size. For instance, consider an improvement in the RNA model leading to an increase in the magnitude of its gradient and a higher dependency on rated power. The consequence of this improvement would be a large shift in the optimum along the constant specific power line, towards larger ratings and rotor diameters, without a significant change in the LCoE for the new optimum. Similar insights can be drawn w.r.t. other model improvements, based on the gradients presented in this study. The findings also show how constraints influence turbine sizing, guiding future studies w.r.t. the optimization problem formulation. The research serves as a stepping stone for the sizing of future reference turbines. However, the marginal change in LCoE for a wide range of designs shows the limited benefit of continuous upscaling. These limited benefits have to be balanced against the technical challenges and risks posed by further upscaling.

The purpose of the study and the approach is also clearly stated in the abstract now:

Large-scale exploitation of offshore wind energy is deemed essential to provide its expected share to electricity needs of the future. To achieve the same, turbine and farm-level optimizations play a significant role. Over the past few years, the growth in the size of turbines has massively contributed to the reduction in costs. However, growing turbine sizes come with challenges in rotor design, turbine installation, supply chain, etc. It is, therefore, important to understand how to size wind turbines when minimizing the Levelized Cost of Electricity (LCoE) of an offshore wind farm. Hence, this study looks at how the rated power and rotor diameter of a turbine affect various turbine and farm-level metrics

and uses this information in order to identify the key design drivers and how their impact changes with setup. A Multi-disciplinary Design Optimization and Analysis (MDAO) framework is used to perform the analysis. The framework uses low-fidelity models that capture the core dependencies of the outputs on the design variables while also including the trade-offs between various disciplines of the offshore wind farm. The framework is used, not to estimate the LCoE or the optimum turbine size accurately, but to provide insights into various design drivers and trends. A baseline case, for a typical setup in the North Sea, is defined where LCoE is minimized for a given farm power and area constraint with the IEA 15 MW reference turbine as a starting point. It is found that the global optimum design, for this baseline case, is a turbine with a rated power of 16 MW and a rotor diameter of 236 m. This is already close to the state-of-the-art designs observed in the industry and close enough to the starting design to justify the applied scaling. A sensitivity study is also performed that identifies the design drivers and quantifies the impact of model uncertainties, technology/cost developments, varying farm design conditions, and different farm constraints on the optimum turbine design. To give an example, certain scenarios, like a change in the wind regime or the removal of farm power constraint, result in a significant shift in the scale of the optimum design and/or the specific power of the optimum design. Redesigning the turbine for these scenarios is found to result in an LCoE benefit of the order of 1-2% over the already optimized baseline. The work presented shows how a simplified approach can be applied to a complex turbine sizing problem, that can also be extended to metrics beyond LCoE. It also gives insights to designers, project developers, and policy makers as to how their decision may impact the optimum turbine scale.