Response to Referee 2

The authors would like to thank the reviewer for taking the time and effort necessary to review the first version of the manuscript. We sincerely appreciate all valuable comments and suggestions, which helped us to improve the quality of the manuscript. Our responses to the reviewer's comments are described below in a point-to-point manner. Appropriated changes, suggested by the reviewers, have been introduced into the manuscript (they are highlighted in yellow in the revised version). When the line numbers are provided in this response, they refer to the revisions made in the new manuscript. Please note that the reviewer's comments are repeated in italics and our responses are provided in the bulleted sections of text.

General comment

The paper was clearly written and did a good job in exploring the topic. The paper claims 3 areas of contribution. I didn't find anything novel about the wind farm layout optimization, so I think those contributions are overstated. I see one contribution, the first one regarding the formulation of a new objective based on participation in reserve markets.

- We agree with the reviewer that the main contribution of the paper is the formulation of a new objective function for the wind farm layout optimization problem. The latter allows to take into account the participation of future wind farms to reserve markets during the design process. The test case shows interesting findings when we apply our objective function, but it is not a contribution per se.
- The section about the contributions of the paper has been modified and now focuses on the main contribution (P3L71-79)

To the best of the authors' knowledge, this is the first paper that presents a wind farm layout optimization that accounts for the participation to reserve markets in the revenue objective function. Therefore, the main contribution of this paper is the formulation of a new objective function for the wind farm layout optimization problem. The latter allows to take into account the participation to reserve markets during the design process. The new objective function aims at maximizing expected yearly revenues of a wind farm participating in both day-ahead and secondary upward reserve markets. It allows to compute the optimal offering in both markets, reserve allocation strategy, and subsequent expected revenues. The new objective function considers the uncertainty in forecasts of wind power, electricity prices and activated reserve volumes. The estimated penalties and balancing costs for failing to provide energy and reserve are also taken into account. The study is conducted for the Belgian system using existing market rules. However, although this system has some peculiarities, the main methodology could be applied in other systems with minor modifications.

Main concerns

Some of the results suggest that the sample sizes are too small (for example the best AEP design does not come from AEP optimization). Also, there is no real evidence to claim that one function "has better gradients" than the other from one data point (again just looks to be a small sample size problem for a problem that is well known to be multimodal).

- We agree with the reviewer that it is worth noticing that the best-performing AEP layout is not the one obtained by directly optimizing the AEP objective.
- Yet, as explained in the first version of the paper, this can be explained by the fact that gradient-based optimization may converge to better solutions when guided by more comprehensive objectives (e.g., JERM or DAEM), which offer smoother and more informative gradients. These richer objectives may implicitly regularize the search process, helping avoid poor local minima and yielding layouts that are not only robust in market performance but also superior in raw energy yield.
- The authors acknowledge the non-determinism of the optimization process, but do not believe that it is a problem of sample size. Indeed, the number of sampled timesteps for each SGD iteration is quite extensive, for many values of $K * T$. This is evidenced by the convergence of mean performance across independent runs and the low variance in key indicators such as AEP and revenues. To support this, we have verified that increasing the number of samples or optimization iterations consistently leads to the same observations.
- Overall, it should be noted that we do not make an indisputable claim regarding the better gradient, as we merely try to offer some plausible explanations for this.
- Indeed, if the AEP objective function has a poorly conditioned landscape (e.g., sharp ridges, flat regions), gradient descent might struggle to find high-quality optima.
- More comprehensive objectives (like DAEM or JERM, which combine multiple aspects such as price signals and reserve activation) may offer a better exploration of the solution space and produce better gradients, smoother curvature, and more informative updates, which can guide the optimization toward layouts that are superior across several criteria, including AEP.
- Optimizing a richer objective may act as a form of regularization, preventing overfitting to narrow aspects of performance (e.g., maximizing AEP in a single direction). This broader objective may lead to more balanced layouts, which incidentally perform better even on simpler metrics like AEP.
- However, to avoid confusing the reader, we removed our possible explanation of better gradients. We now state on P24L505-506 that this result (the best AEP design not coming from AEP optimization) is quite surprising and should be further investigated in future work.

The difference between AEP and JERM optimization was minimal (≈0.1%) between the best in each category. That type of difference is much smaller than the uncertainties in both the energy and cost metrics, which also makes it hard to make strong claims on improvements.

- The mean yearly expected profits for JERM optimizations is 71.8956 ± 0.105 M€, while it is 71.7638 ± 0.106 M€ for AEP optimizations. The mean absolute difference is 0.1318 M€, i.e., 0.18%, thus increased revenues of 2.6 M€ over the farm lifetime. We have added these results in a paragraph on P23L495-499.
- We agree that the scatterplot of Fig. 9 does not convey this information, and we have added a boxplot on P23 to show summarized results. We believe that while the improvement in expected profits is not as strong as when comparing the layout with optimized design, it is still higher than the uncertainties on cost metrics.
- However, for AEP, we do agree with the reviewer that the improvement in AEP is less noticeable, and it is smaller than the uncertainties in energy metrics. Therefore, we cannot straightforwardly claim that JERM optimizations give better AEPs than AEP optimizations. We added this observation in P23L499-501.

Minor comments

In the abstract it would be clearer to specifically state how much higher the profits are for the new methodology when compared to just optimizing with AEP ("Profits are also higher for the new methodology than when using the maximization of annual energy production, widely used in the literature, as objective function.")

- Indeed, this could improve clarity: we have added this information in the abstract of the revised version (P1L11).

Line 39: "This does not allow to capture the variation of day-ahead and reserve prices with wind speed and wind direction." maybe revise this sentence to "This does not capture the variation..."

- The sentence has been revised to what the reviewer suggested.

Line 73: "This allows to obtain rather accurate results in a reasonable computation time." Change to something like this - "This approach enables accurate results with reasonable computation time."

- The sentence has been revised to what the reviewer suggested.

Line 115: Q. How then can the power day ahead be predicted if the operator can't predict the day ahead wind forecast?

- This sentence states that the actual realization of wind is not know by the operator when making power bids. Therefore, the operator should first forecast wind speed (the day-ahead prediction of wind speed is widely studied in the literature) and wind direction, then obtain the corresponding wind power forecast by converting this wind information to power using a wind power model. In our paper, the latter is PyWake.
- We clarified this sentence in P5L134-136.

Line 270: "Prices for reserve capacity and reserve activation, as well as activated upward aFRR reserve volumes are were provided

- We have corrected this typo.

For the paragraph starting at line 415 it would be helpful to better quantify how much better the JERM optimization profit is than the AEP optimization over the range of AEPs.

- As explained in our response to the second main concern, the mean yearly expected profits for JERM optimizations is 71.8956 ± 0.105 M€, while it is 71.7638 ± 0.106 M€ for AEP optimizations. The mean absolute difference is 0.1318 M€, i.e., 0.18%, thus increased revenues of 2.6 M€ over the farm lifetime. We have added these results in a paragraph on P23L495-499.

Line 233 - bee too costly

- We have corrected this typo.

Different values of $K * T$ is said multiple times but is not very clear.

- The choice of K, the number of days, and T, the number of timesteps in a day, should be a trade-off between accuracy and computational time. Indeed, increasing values of K and T, i.e., increasing the number of samples for the computation of the total expected profit, allows to encompass more situations at each optimization step. However, this also has an impact on the computational burden.
- Therefore, we ran optimizations for $K * T$ ranging from 20 to 150. We have added this information in P13L315-316.
- It should be noted that we noticed that at some point, further increasing $K * T$ did not provide significant improvement in expected profits and AEP, notably with regard to the marked increase in computational time and resources.