Information how to read the document

- RC: Referee Comment
    - Pages and lines in the author comments refer to the manuscript submitted before the revision process, as we did not want to change author comments here.
- AR: Authors Response
    - To avoid confusion, we have removed the line references in our responses that we mentioned in our author comments, as these referred to the unmarked revised manuscript, and we now include them in the author changes.
- AC: Authors Changes
    - Parts indicated in blue were added, parts indicated red and which are crossed out were deleted – all lines and page numbers refer to the lines in the marked-up manuscript for easy trackability.

RC3

General Comment:

RC	**This manuscript addresses the design and operation optimization of wind-to-hydrogen systems including degradation. While the research topic is interesting, the authors should more clearly articulate the specific advancements and unique scientific contributions that distinguish this study from prior studies to justify its publication as a full research paper. Furthermore, the use of a local search algorithm (Nelder-Mead) in a non-convex space is not well justified, and treating degradation as a passive evaluation step rather than an active driver within the optimization loops limits the robustness and novelty of the study. Additionally, since the BESS is used specifically to mitigate electrolyzer shut-downs, the resulting impact on BESS degradation and the subsequent economic bias should be carefully addressed. Finally, although the authors identify a 21% LCOH underestimation due to degradation and a very significant 104%-110% profit gaps between the heuristic and MILP operation, the study fails to integrate these findings into the actual design loop. Relying on a sub-optimal heuristic for system sizing despite such a significant performance gap remains a major methodological concern.**
AR	We sincerely thank the reviewer for the constructive feedback, which helped us significantly strengthen the methodological rigor and clarity of our study. In response, we have thoroughly updated both the manuscript and the underlying optimization framework. Specifically, the introduction has been restructured to clearly articulate the core novelty and unique scientific contributions of our methodology. To ensure a robust global search within the non-convex design space, we replaced the local Nelder-Mead algorithm with a stochastic Differential Evolution optimizer. Furthermore, while a fully nested design loop can be computationally prohibitive and numerically unstable, our sequential two-stage approach deliberately provides a conservative baseline via the determined operation strategy. In contrast the idealized MIL operation optimization describes the upper bound of potential operational profits. Regarding BESS degradation, we have integrated battery degradation by reducing the BESS design lifetime to conservative 10 years and embedding cycle-based wear directly into the MIL objective function. Each of these structural and algorithmic updates is addressed in further detail in the subsequent responses below.
AC	-
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Specific Comments:

RC	**The abstract is overly long and functions more as a summary of specific numerical results rather than a clear statement of the paper's core contributions. While the findings are interesting, the inclusion of multiple secondary analyses distracts from the main message. I recommend refocusing the abstract on the primary research gap, the novel aspects of the proposed methodology, and the most significant high-level findings. Furthermore, it is recommended to move detailed**

	comparisons and specific data points to the Results and Discussion sections to ensure the main contribution is clearly highlighted for the reader.
AR	We sincerely thank the reviewer for the critical assessment of the abstract and the suggestion to refocus its content. After careful consideration of this feedback, we have decided to retain the current structure and level of detail in the abstract. In the field of techno-economic modeling and system optimization, specific quantitative results, such as the exact magnitude of LCOH underestimations or profit deviations are often the most crucial information for the scientific readership. We strongly believe that high-level qualitative statements alone would not sufficiently convey the concrete scientific contributions and the exact impact of the operational trade-offs investigated in this study. Including these specific data points ensures that the exact economic potentials and performance gaps are immediately accessible without losing the reader in generalities. While we understand the reviewer's concern regarding the abstract's length and density, we feel that the current comprehensive format best serves the scientific community by providing immediate, quantifiable insights into our case study.
AC	-
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RC	**Line 65: The literature review frequently lists multiple references to support general statements without a critical synthesis. Since many of these studies are cited only once and not used for later comparison, I recommend streamlining the list or providing a more specific explanation of how they specifically relate to the current work.**
AR	We agree that long lists of references can diminish the clarity of the underlying research gaps. To address this, we have reorganized the literature review in Section 1. We unbundled the initial collective reference list by grouping the previous studies according to their specific methodological limitations (e.g., distinguishing between non-optimizing configurations like Schnuelle et al. and Fabianek & Madlener, versus sizing optimizations that omit balance-of-plant components like Grant et al. and Tezer). Additionally, we streamlined the citations throughout the section by removing redundant or secondary references.
AC	
	Page 3, line 63: Various studies investigate the design of different types of HPP. Early assessments, such as by Schnuelle et al. (2020) and Fabianek und Madlener (2024), evaluated given system configurations without optimizing the underlying component capacities. Other recent optimization approaches lack detail by focusing exclusively on the main components, thereby neglecting the significant influence of site-specific conditions or balance-of-plant sub-systems such as hydrogen storage, pipelines, and compressors (Grant et al. 2024; Tezer 2025). ~~Schnuelle et al. (2020), Hofrichter et al. (2023), Fabianek und Madlener (2024), Grant et al. (2024), and Tezer (2025) either evaluated given systems without optimizing the components design or they lack on detail by only focusing on the main components of their considered HPP, neglecting the influence of site-specific conditions or sub-systems such as hydrogen storage, pipelines, compressor or equipment for the electrolyzer power supply.~~ *Page3, line 81:* To model this operation behavior of the systems components within the design stage a predefined operation strategies can be utilized, meaning it is initially defined at what time electricity is fed into an electrolyzer, a battery, or if considered the electricity grid (Hofrichter et al. 2023; ~~Grant et al. 2024~~; ~~Tezer 2025~~). However, ~~this~~ fixe operation strategies can lead to a suboptimal design… *Page 3, line 85:* To overcome the issue of a predetermined operating strategy, two-stage optimization consisting of an outer design optimization and an inner operation optimization loop are utilized (Balderrama et al. 2019; Dolatabadi et al. 2019; ~~Zheng et al. 2022;~~ Shams et al. 2021).

RC	**Line 105: The Introduction provides a comprehensive background. However, it fails to explicitly state the main contributions and the novelty of this work compared to existing literature. While several studies are discussed, the research gap is somewhat buried in the text. I recommend that the authors clearly highlight their specific contributions, for example, by supplementing (or even replacing) the research questions with a dedicated paragraph that ensures the reader understands what distinguishes this methodology from previous works.**
AR	Following the reviewers suggestion, we have completely restructured the end of the introduction by removing the bulleted research questions. This new section explicitly defines our core novelty. Subsequently, the paragraph integrates our primary research objectives directly into the running text.

	This revision significantly strengthens the introduction and ensures that the distinct advantages and novel aspects of our methodology are immediately apparent to the reader.
AC	Page 4, line 97:
	To address the gaps in the existing literature, the distinct novelty of this work lies in the introduction of a comparative, two-step evaluation framework that quantifies the performance gap between heuristic design assumptions and optimized system operation. ~~We assume an existing WF and first optimize the design of the electrolyzers rated power and the BESS capacity to achieve the maximum annual profit (AP).~~ First we establish a conservative baseline design. Following the approach of Hofrichter et al. (2023), ~~the design phase to optimize~~ the rated electrolyzer power and BESS capacity are sized to maximize the annual profit (AP) based on a fixed, rule-based ~~employs an~~ operation strategy that defines power flows for all design components. Crucially, this initial design phase is coupled with a detailed degradation evaluation. In a second step, a mixed-integer linear (MIL) operation optimization is applied to this designed system to determine an idealized upper bound for operational revenues. This idealized MIL operation, which includes linearized part-load efficiency of the electrolyzer, is then subjected to an identical degradation evaluation, yielding a more realistic operational annual profit (OAP). ~~This methodology entails assumptions regarding system operation that are evaluated by a subsequent mixed-integer linear (MIL) operation optimization for the optimized HPP design. This is done over a historical year by maximizing the operational annual profit (OAP) focussing explicitly on the operational revenues and costs. The MIL operation optimization includes a time constant and linearized part-load efficiency of the electrolyzer. This is a simplification that will be validated by a subsequent evaluation of the electrolyzer degradation and the linearized part-load efficiency to determine the more realistic OAP.~~ By contrasting these two approaches, we enable a direct comparison between the optimized, price-aware system operation and the conservative operation assumed during the initial design phase. Guided by this framework, this study investigates the optimized PEM electrolyzer rated power and BESS capacity for a given WF to maximize the annual profit under a fixed heuristic operating strategy. Furthermore, we evaluate how the integration of a BESS alongside dynamic operational constraints and degradation effects influences the LCOH. And finally, the study quantifies the exact extent to which the MIL operation optimization and the subsequent degradation evaluation can increase the OAP compared to the initial heuristic design phase. ~~Thus, this work provides guidance for decision makers in identifying an optimal HPP design and an optimized operation with electrolyzer degradation effects by answering the following research questions:~~ ~~-~~ ~~For a given WF, what is the optimum PEM electrolyzer rated power and BESS capacity for maximum annual profit taking site-specific costs, electrolyzer part-load efficiency, and degradation into account, while assuming a fixed operating strategy for the hybrid wind farm design components?~~ ~~-~~ ~~How does the integration of a BESS and the consideration of electrolyzer degradation and part-load efficiency influence the LCOH of the HPP?~~ - ~~To what extent can a MIL operation optimization and a subsequent degradation evaluation increase the operational annual profit compared to the design method?~~ To answer these questions, in Sect. 2 the methodology for the design optimization, the MIL operation optimization and the degradation evaluation with all underlying assumptions is described. Section 3 introduces a case study of which the methodology is applied and results are presented. In Sect. 4 results and limitations of the presented methodology are discussed and further research needs are indicated.

RC	**Line 120: The authors explicitly state that the methodology is an extension of the method by Reichartz et al. (2024b), with the primary contributions being a more detailed electrolyzer model and a shift in the objective function from LCOH to Annual Profit (AP). As currently presented, the work appears to be an incremental contribution that lacks the fundamental novelty required for a full research paper. Therefore, it is recommended that the authors elaborate further on the scientific novelty and the broader applicability of their findings beyond a specific model extension.**
AR	This comment aligns with the previous remark regarding the manuscript's core novelty. We have addressed this concern within the comprehensive restructuring of the introduction section detailed in our previous response.
AC	-
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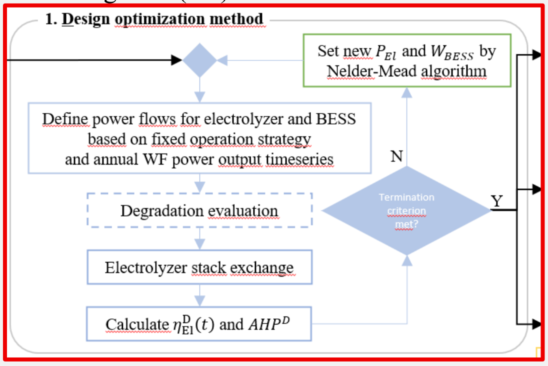
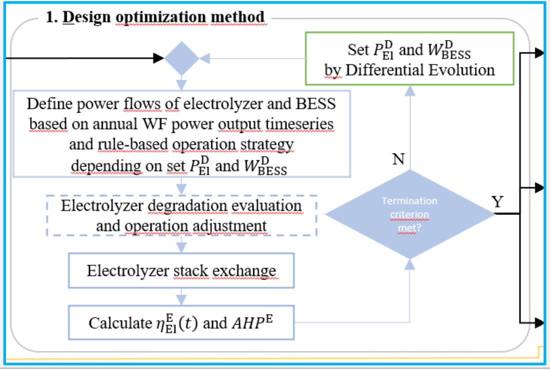
RC	**Figure 1: It is unclear why a two-stage approach was adopted (fixed-strategy design followed by MILP evaluation) rather than integrating the MILP model directly into the design phase. The**

	authors should justify this methodological choice, especially considering that the design heuristic already shows significant deviations from the theoretical MILP optimum.
AR	We thank the reviewer for raising this highly relevant methodological point. The decision to employ a sequential two-stage approach, using a rule-based heuristic for the design phase and a subsequent MILP for the operational assessment, rather than a fully nested "outer-inner-loop" optimization, was made deliberately to ensure both long-term robustness and computational viability. First, designing a system for a 25-year lifetime involves profound uncertainties regarding exact hourly spot market prices and volatile wind generation. To ensure the design is robust over the system's entire lifespan, we rely on a constant electricity reference value and a representative wind year (2024), which the anemos Wind- und Ertragsindex Report [https://www.windindustrie-in-deutschland.de/publikationen/fachartikel/anemos-wind-und-ertragsindex-report-2024] confirms as a highly representative 20-year average. A rule-based operation strategy can provide a conservative baseline operation for revenue estimations under these long-term average conditions. Second, embedding a fully functional MIL operation optimization model within every single iteration of the outer global search loop (here differential evolution) increases the computational effort extremely (Eltamaly & Almutairi, 2025 DOI: 10.3390/su17062744). Furthermore, it introduces severe risks regarding numerical stability. If the inner MIL solver experiences convergence issues or hits time limits in specific, sub-optimal regions of the design space, the resulting numerical noise in the objective function would disrupt the convergence behavior of the outer optimization algorithm. By keeping the steps sequential, the heuristic design establishes a reliable, conservative baseline, while the subsequent MIL operation optimization provides an idealized upper bound for operational revenues under actual variable day-ahead market price conditions. To clarify this vital methodological choice, we have explicitly added this justification as a new paragraph in section 2 below the description of Figure 1.
AC	Page 6, line 149:
	The separation of the design phase and the MIL operation optimization serves to ensure a conservative long-term design and computational stability. Sizing a system for a 25-year lifetime faces profound uncertainties regarding spot market prices and wind profiles. Therefore, the design phase utilizes the year 2024 that represents, according to anemos (2024), an average wind and electricity yield year over the past 20 years and a constant reference value as electricity price. Relying on a predefined rule-based operation strategy during the design phase provides a conservative estimation of the system's operational revenues. Embedding a fully functional MILP model within every single iteration of the outer global search loop would increase the computational effort (Eltamaly and Almutairi 2025) and introduce severe risks regarding numerical stability. If the inner solver experiences convergence issues in specific regions of the design space, the resulting numerical noise in the objective function would potentially disrupt the convergence behaviour of the outer optimization algorithm. Thus, the subsequent MIL operation optimization is applied exclusively to the finalized design to establish an idealized upper bound for revenues under actual volatile market conditions, allowing for a comparison against the conservative design assumptions.

RC	**Figure 1: The authors should clarify the functional role of the "Degradation evaluation" and "Electrolyzer stack exchange" blocks within the design loop. As presented in the flowchart, these steps appear as passive post-processing elements rather than active drivers of the optimization. Since the power flows are pre-defined by a "fixed operation strategy" before degradation is even assessed, it remains unclear how degradation dynamically influences the Nelder-Mead decision-making process for the sizing variables. The authors should address this apparent discrepancy between the "degradation-aware" objective and the sequential, non-integrated flow shown in Figure 1.**
AR	We thank the reviewer for pointing out this need for clarification regarding the feedback loop in Figure 1. First, we would like to note that the Nelder-Mead algorithm has been replaced by a Differential Evolution (DE) algorithm to better handle the highly non-linear and non-convex properties of the multi-dimensional design space. Within every single iteration of the outer DE algorithm, a specific set of design variables—namely the electrolyzer rated power ($P_{\mathrm{El}}^{\mathrm{D}}$) and the BESS capacity ($W_{\mathrm{BESS}}^{\mathrm{D}}$) is assigned. The resulting operational power flows, the dynamic stack degradation, and the subsequent timing of the stack exchange depend directly on these specified dimensions. Crucially, the degradation evaluation and stack exchange intervals directly dictate the efficiency losses ($\eta_{\mathrm{El}}^{\mathrm{D}}(t)$) and therefore the degradation costs and the annual

	hydrogen production (AHP^{D}). Because these degradation-induced technical and financial impacts are immediately factored into the calculation of the objective function, they directly alter the resulting Annual Profit (AP^{D}) of that specific candidate design. The outer DE algorithm utilizes the AP^{D} value to evaluate the fitness of the design vector and dynamically guides the decision-making process for the next generation of design variables. To highlight this active integration, we revised Figure 1 to explicitly include the dependencies on $P_{\mathrm{El}}^{\mathrm{D}}$ and $W_{\mathrm{BESS}}^{\mathrm{D}}$ within the power flow definition.
AC	Page 5, Figure 1
	Part of Figure 1 (old):  Part of Figure 1 (new): 

RC	**Line 145: The choice of the Nelder-Mead algorithm for the design optimization requires further justification. It is also important to address its ability to navigate a potentially non-convex design space to find a reliable optimum, given its nature as a local search method.**
AR	We agree that the Nelder-Mead algorithm, as a local derivative-free search method, may be susceptible to local optima in potentially non-convex design spaces. To address this we have replaced the previous optimization approach with a Differential Evolution (DE) algorithm. DE is a population-based, stochastic optimizer that is better suited for the non-linear characteristics of the wind-hydrogen-battery design space.
AC	
	Page 5, line 131: The electrolyzer input parameter vector $\overrightarrow{\boldsymbol{EL}}$ depends on the electrolyzer technology and defines the permissible ranges for the electrolyzer rated power $P_{\mathrm{El}}^{\mathrm{D}}$ and BESS capacity $W_{\mathrm{BESS}}^{\mathrm{D}}$ within the components size is allowed to vary. ~~consists of an initially set electrolyzer rated power P_{El} and BESS capacity W_{BESS}.~~ *Page 6, line 161:* Within the design optimization method the design parameters P_{El} and W_{BESS} are iteratively adjusted by the ~~Nelder-Mead~~ Differential Evolution (DE) algorithm (Storn and Price 1997), which ~~that~~ is further described in Sect. **Fehler! Verweisquelle konnte nicht gefunden werden.** ~~(Lagarias et al. 1998).~~ *Page 6, line 168:* Before the termination criterion for the ~~Nelder–Mead~~ DE optimization is verified… *Page 10, line 262:* It is solved using the ~~Nelder–Mead~~ DE algorithm~~, a derivative-free method commonly applied to NLPs (Scholz 2018)~~. Due to its stochastic search strategy, this population-based approach enables a robust

exploration of the complex design space while mitigating dependency on the initial starting point. Consequently, the best identified solution within the predefined termination criteria is reported as the optimal configuration. The search space for both the electrolyzer rated power and the BESS capacity is constrained between 0 % and 30 % of the wind farm rated power based on the boundary insights from Chatzistlyianos et al. (2025) and Reichartz et al. (2024). A random solver strategy was selected to maintain population diversity, utilizing a population factor of 15 and a crossover probability of recombination of 0.7 to balance vector mutation and target retention. To bypass local sub-optima and prevent population stagnation, dynamic scaling via dithering was applied with a mutation parameter of (0.5, 1). Computational execution was parallelized across all available CPU cores with the parameter workers set to minus one, which requires a synchronous population update scheme. Lastly, the optimization run was bounded by a maximum of 100 generations and a relative convergence tolerance of 0.001 to limit the computational overhead of the underlying hourly time-series optimization, while a fixed random seed of 1 ensures full numerical reproducibility of the optimization trajectories.

Page 23, line 546:
However, to identify ~~the region where the global optimum likely resides,~~ a near-optimal solution the design space is explored by varying the design variables P_{El} and W_{BESS} within the differential evolution optimization algorithm. ~~Therefore, the ratio of the electrolyzer rated power to the WF rated power is varied from 0.015 to 1.0 and the BESS capacity from 0.0 to 1.0 in 0.015 increments. Thus, an increment corresponds to a deviation of 1 MW respectively 1 MWh.~~

Page 23, Figure 7:

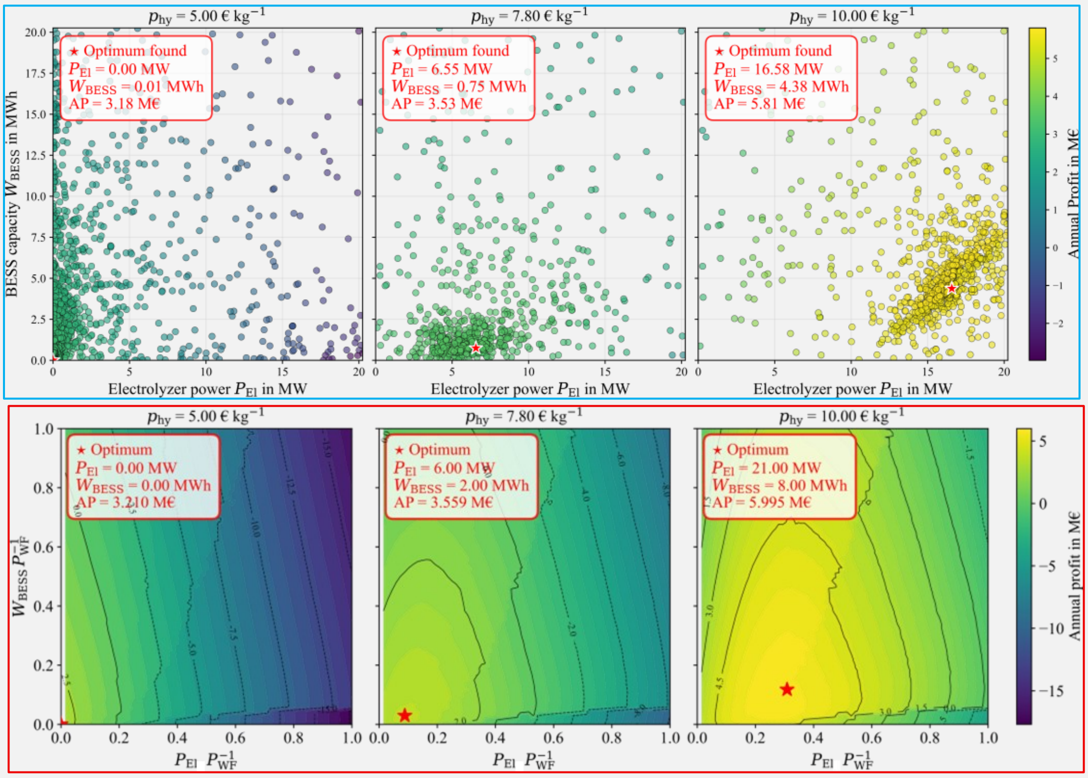


Figure 7: ~~Annual profit as function of electrolyzer rated power and rated BESS capacity over wind farm rated power for three different hydrogen prices.~~
Figure 7: Design space exploration of annual profit via differential evolution for three different hydrogen prices.

Page 24, line 557:
The optimum identified in the central panel of **Fehler! Verweisquelle konnte nicht gefunden werden.** with p_{hy} equals 7.8 € kg^{-1} serves as ~~the initial~~ configuration for the following observations. ~~design optimization method, which employs the Nelder-Mead algorithm described in Sect.~~ ~~**Fehler! Verweisquelle konnte nicht gefunden werden.**~~ ~~for the given use case of Sect.~~ ~~**Fehler! Verweisquelle konnte nicht gefunden werden.**~~.

RC	**Line 150: The design phase relies on a fixed operation strategy, which prevents the optimizer (Nelder-Mead) from exploring active trade-offs between dynamic operation and stack longevity. The authors should justify why a heuristic was preferred over an integrated sizing-operation approach and clarify if this "fixed" logic might lead to a sub-optimal system design in the presence of degradation. Relying on a simplified fixed strategy for the design phase, while recognizing its limitations regarding the paper's core topic (degradation) raises concerns about the validity of the reported optimal configurations.**
AR	This comment aligns with the previous remark regarding the two-step approach shown in Figure 1. We have addressed this concern within the added paragraph in Section 2 detailed in our previous response.
AC	-
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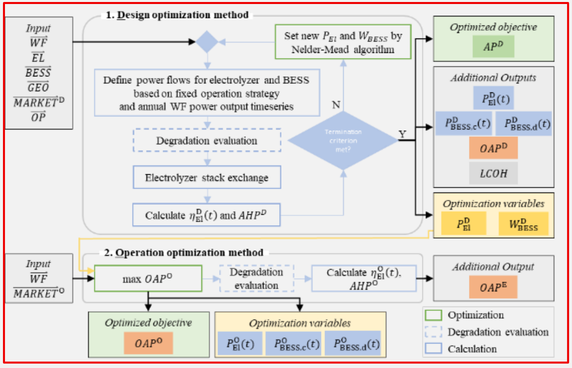
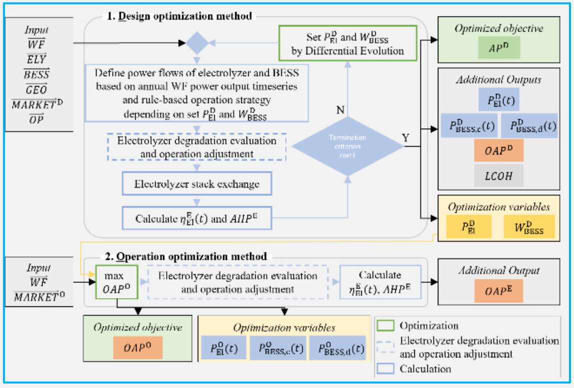
RC	**Line 160: The manuscript explicitly states that the operational MILP model "neglects the impact of degradation on the electrolyzers efficiency", creating a discrepancy with the design model. To ensure a fair assessment of the reported deviation, the authors should clarify how this omission biases the comparison. It is recommended to either align the MILP model assumptions with the design model or provide a thorough discussion on the limitations of using an "idealized" benchmark to validate a degradation-aware study.**
AR	We thank the reviewer for this insightful comment regarding the assumption handling in the MIL model. It is correct that the operational MIL model itself omits the direct degradation feedback on electrolyzer efficiency during the optimization loop. This simplification is a deliberate modeling trade-off to maintain mathematical linearity, avoid non-linear constraints, and guarantee global solver convergence. To mitigate this limitation and ensure a completely fair, unbiased comparison with the design stage, we implemented the consecutive postprocessing degradation evaluation in which the determined electrolyzer operation gets adjusted according to the efficiency losses due to degradation. The MIL optimization determines an idealized dispatch upper bound. Crucially, this resulting dispatch profile is afterwards subjected to the exact same degradation evaluation framework used in the design phase. During this post-processing step, the idealized operation is corrected so that the true degradation-dependent efficiency is calculated for each time step, which subsequently penalizes. This reduces both the actual annual hydrogen production (AHP) and the resulting operational annual profit (OAP). Because both the heuristic design method and the optimized operational method culminate in the identical degradation evaluation framework, the final performance metrics are fully aligned, methodologically consistent, and directly comparable. To make this sequence transparent, we have updated Figure 1 to explicitly highlight that the degradation evaluation dynamically corrects the previously optimized power flows. We have also refined the text after Figure 1 to clarify this modeling limitation and its subsequent correction.
AC	Page 5
	Figure 1 (old): 

Figure 1 (new):



Page 6, line 163:
Subsequently, the degradation of the electrolyzer is evaluated based on the previously determined operation according to the method detailed in Sect. **Fehler! Verweisquelle konnte nicht gefunden werden.**. This evaluation framework recalculates the actual degradation-affected efficiency for each time step and structurally corrects the initial operational results to account for real-world performance losses.

Page 7, line 174:
These optimized design variables serve as input for the operational optimization method described in Sect. **Fehler! Verweisquelle konnte nicht gefunden werden.**, where the OAP^{O} OAP is maximized through MIL optimization. ~~Since~~ To maintain mathematical linearity and ensure solver stability, this operation optimization step assumes a linearized part-load efficiency as calculated in Sect. **Fehler! Verweisquelle konnte nicht gefunden werden.** and ~~neglects~~ tracks the electrolyzers degradation as detailed in Sect. **Fehler! Verweisquelle konnte nicht gefunden werden.** even though the impact of degradation on the electrolyzers efficiency is neglected. To address this limitation and guarantee a fair comparison with the design method, the optimized dispatch profile is subsequently subjected to the identical post-optimization degradation evaluation described above. This post-optimization step applies the degradation-dependent efficiency corrections to the optimized power flows, thereby penalizing the idealized hydrogen gains to report the true, realistic AHP^{E} and OAP^{E}. ~~even though the degradation is calculated during the optimization as detailed in Sect. **Fehler! Verweisquelle konnte nicht gefunden werden.**, a further degradation evaluation is performed. This is followed by the determination of the actual electrolyzer efficiency per time step and the resulting hydrogen production. Finally, the objective function value, the operational performance parameters, and the actual OAP after the degradation evaluation are reported.~~

RC	**Line 270: The authors state that the BESS is operated specifically to minimize electrolyzer shut-downs and mitigate its degradation. However, BESS cycling significantly impacts battery lifetime and, consequently, the project's CAPEX and LCOH. It is recommended to explain how this issue is addressed, or otherwise provide a clear justification for this omission and acknowledge it as a limitation.**
AR	We agree that the BESS degradation is a central factor given its role in the system’s economic performance. To address this, we have significantly reduced the assumed BESS lifetime from 30 years to 10 years within the design method. This change ensures that BESS replacement is now more frequent which results in higher levelized cost of hydrogen (LCOH) and annual profits. Within the MIL operation optimization, we have introduced cycle-based degradation costs into the objective function. These costs are derived by linearizing the replacement costs over the expected total energy throughput. This ensures that the BESS is only dispatched when the economic benefit exceeds the costs of its own wear. We assume the replacement costs to be the initial investment costs (CAPEX) and that the BESS reaches its end of life after 8000 cycles. These updates on BESS degradation provide a more detailed economic assessment. While the system's optimal battery capacity decreases, the fundamental conclusion remains unchanged: the BESS remains a vital component for the economic viability of the plant, primarily due to its protective effect on the high-

value electrolyzer asset. Specifically, the MILP operation optimization reveals that the BESS undergoes only about one cycle per day, extending its expected service life to around 22 years. This demonstrates that the 10-year lifetime baseline assumed in the design method is highly conservative.

AC

Page 21, line 526:
For the BESS we assume a lifetime of 10 years (Lynus, 2026) ~~30 years (Ibáñez-Rioja et al. 2025)~~

Page 15, line 406:
Additionally, for the BESS, linear cycle-based degradation costs are added to t~~T~~he objective function ~~within the MIL optimization~~ that is defined as

$$\max(\mathrm{OAP}) = \max\left(\sum_{t=0}^{T}\left(SE(t)\cdot p_{\mathrm{elec}}(t) + SH(t)\cdot p_{\mathrm{hy}}(t) - WSC(t)\right) - DegC_{\mathrm{El}} - DegC_{\mathrm{BESS}}\right),$$

Page 16, line 414:
$\mathrm{DegC}_{\mathrm{BESS}}$ denotes the degradation costs of the BESS, defined as
$\mathrm{DegC}_{\mathrm{BESS}} = \mathrm{DegC}_{\mathrm{BESS,specific}} \cdot \Delta t \cdot \sum_{t=0}^{T}(P_{\mathrm{BESS,c}}(t) + P_{\mathrm{BESS,d}}(t))$,
(25) where $\mathrm{DegC}_{BESS,specific}$ represents the specific BESS degradation costs. These costs are calculated as a function of the maximum number of cycles until the end of life n_{cycles} , the depth of discharge DoD, and the roundtrip efficiency η_{BESS}, according to Eq. (26):

$$\mathrm{DegC}_{\mathrm{BESS,specific}} = \frac{CAPEX_{\mathrm{BESS,specific}}}{n_{\mathrm{cycles}}\cdot 2\cdot \mathrm{DoD}\cdot \eta_{\mathrm{BESS}}}. \tag{26}$$

The OAP monetizes electricity and hydrogen revenues while internalizing water supply and ~~electrolyzer~~ degradation costs of the electrolyzer and BESS, thereby incentivizing profit-maximizing operation that accounts for both immediate market returns and long-term capital preservation.

Page 17, line 443:
2.3.2 MIL electrolyzer degradation model

Page 21, line 526:
For the BESS we assume a lifetime of 10 years (Lynus, 2026) ~~30 years (Ibáñez-Rioja et al. 2025)~~

Tabel 1:

Lifetime T_{BESS}	10 years	-
Specific CAPEX $CAPEX_{\mathrm{BESS,specific}}$	560 € kWh^{-1}	Cole et al. (2025)

Page 27, line 627:
In contrast, the BESS undergoes approximately one cycle per day under the variable price operation optimization. Given a nominal cycle life of 8,000 cycles, this operational frequency corresponds to an expected service life of around 22 years. Consequently, the resulting BESS degradation costs are minor compared to both the OAP and the electrolyzer degradation costs, as seen in Fig. 9. Furthermore, this evaluation indicates that the baseline assumption of a 10-year lifetime utilized during the design optimization is highly conservative.

Page 29, line 697:
While the BESS effectively protects the electrolyzer stack from premature aging, the BESS itself is subject to wear-and-tear through cycling (Xu et al. 2018). BESS degradation, however, was only implicitly accounted for in the design method through a conservative assumption of a calendar life of 10 years. Cycle-induced BESS degradation was not explicitly modelled but could lead to an increase in ~~neglected in this study, likely leading to an underestimation of the~~ LCOH.

RC **Lines 364-367: The manuscript explicitly states that the optimization 'neglects the impact of degradation on the electrolyzers efficiency' to avoid non-linearities. This represents a significant methodological gap: if the optimizer is blind to efficiency losses, the operational decisions cannot be considered truly optimal regarding the stack's state of health. Given the paper's focus on detailed degradation modeling, this lack of integration should be addressed.**

AR We agree with the reviewer that because the MIL operational optimization neglects active degradation feedback within the optimization, the resulting dispatch strategy is optimal with respect to the linearized model constraints rather than the absolute, non-linear state of health of the stack. This is an already acknowledged limitation inherent to maintaining a solvable MIL formulation and avoiding severe mathematical non-linearities.

	However, we would like to emphasize that this optimization step is not intended to be the final word on performance, but rather to establish an idealized operational benchmark under volatile market conditions. To prevent an unrealistic or biased comparison with the design method, we report both the idealized MIL results and the post-processed degradation evaluated results. As detailed in our previous response and illustrated in the revised Figure 1, the optimized dispatch profile is subsequently subjected to the identical post-optimization degradation evaluation a used in the design method. This step calculates the exact non-linear efficiency drop and degradation costs based on the previous operational choices. Therefore, while the optimizer itself does not see the efficiency losses during execution, the reported performance metrics (AHP^{E} and OAP^{E}) are fully corrected for the stack's actual state of health. This sequence ensures a fair comparison between the two operating philosophies. This modeling choice, its limitations, and the subsequent corrective evaluation are already discussed in the manuscript and further clarified via the revisions detailed in our previous response.
AC	-
	-

RC	**Lines 505-510: The authors state that identifying a global optimum is "considerably more challenging" due to the non-convex nature of the problem. However, this is a weak justification in the context of current research. Established methodologies, such as convex optimization or metaheuristic global search algorithms, are well-known for addressing these complexities. It is recommended to improve the justification of relying on a local search method like Nelder-Mead, without even a multi-start validation or a discussion on why a convex reformulation was not explored.**
AR	We agree that the Nelder-Mead algorithm, as a local derivative-free search method, may be susceptible to local optima in potentially non-convex design spaces. To address this, we have replaced the previous optimization approach with a differential evolution (DE) algorithm. DE is a population-based, stochastic optimizer that is better suited for the non-linear characteristics of the wind-hydrogen-battery design space.
AC	
	Page 6, line 161: Within the design optimization method the design parameters P_{El} and W_{BESS} are iteratively adjusted by the ~~Nelder-Mead~~ differential evolution (DE) algorithm (Storn and Price 1997), which ~~that~~ is further described in Sect. **Fehler! Verweisquelle konnte nicht gefunden werden.** ~~(Lagarias et al. 1998).~~ *Page 6, line 168:* Before the termination criterion for the ~~Nelder–Mead~~ DE optimization is verified… *Page 10, line 262:* It is solved using the ~~Nelder–Mead~~ DE algorithm~~, a derivative-free method commonly applied to NLPs (Scholz 2018)~~. Due to its stochastic search strategy, this population-based approach enables a robust exploration of the complex design space while mitigating dependency on the initial starting point. Consequently, the best identified solution within the predefined termination criteria is reported as the optimal configuration. The search space for both the electrolyzer rated power and the BESS capacity is constrained between 0 % and 30 % of the wind farm rated power based on the boundary insights from Chatzistlyianos et al. (2025) and Reichartz et al. (2024). A random solver strategy was selected to maintain population diversity, utilizing a population factor of 15 and a crossover probability of recombination of 0.7 to balance vector mutation and target retention. To bypass local sub-optima and prevent population stagnation, dynamic scaling via dithering was applied with a mutation parameter of (0.5, 1). Computational execution was parallelized across all available CPU cores with the parameter workers set to minus one, which requires a synchronous population update scheme. Lastly, the optimization run was bounded by a maximum of 100 generations and a relative convergence tolerance of 0.001 to limit the computational overhead of the underlying hourly time-series optimization, while a fixed random seed of 1 ensures full numerical reproducibility of the optimization trajectories. *Page 23, line 546:* However, to identify ~~the region where the global optimum likely resides,~~ a near-optimal solution the design space is explored by varying the design variables P_{El} and W_{BESS} within the differential evolution optimization algorithm. ~~Therefore, the ratio of the electrolyzer rated power to the WF rated power is~~

~~varied from 0.015 to 1.0 and the BESS capacity from 0.0 to 1.0 in 0.015 increments. Thus, an increment corresponds to a deviation of 1 MW respectively 1 MWh.~~

Page 23, Figure 7:

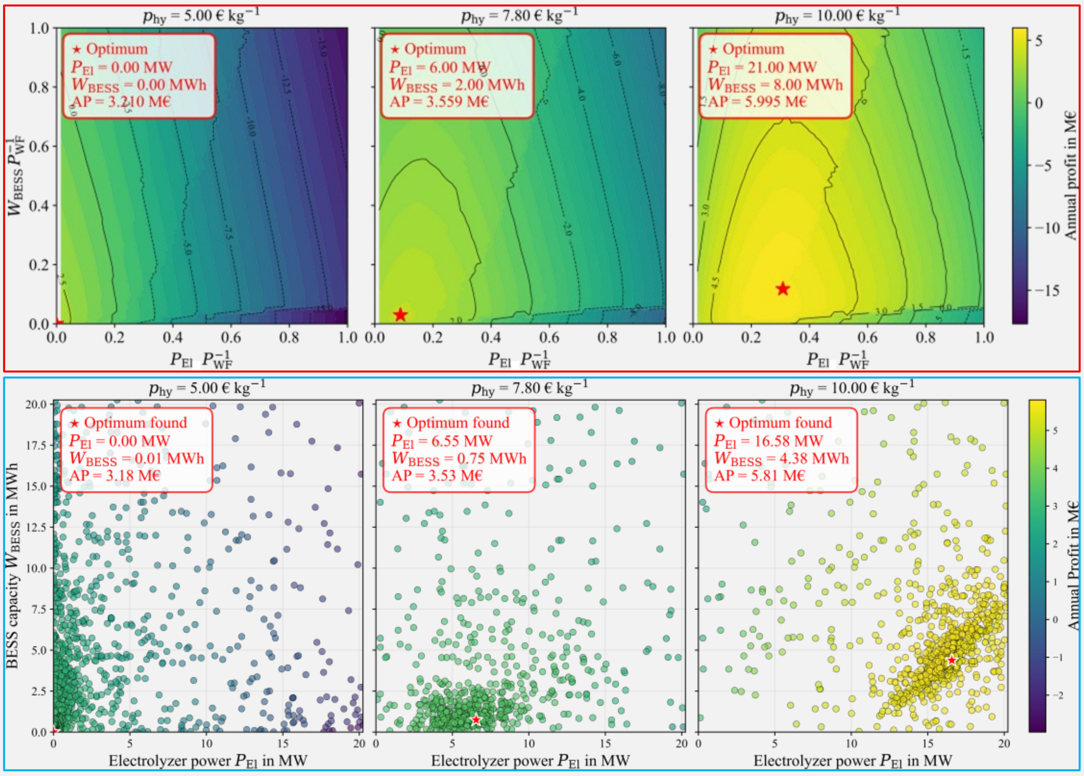


Figure 7: ~~Annual profit as function of electrolyzer rated power and rated BESS capacity over wind farm rated power for three different hydrogen prices.~~
Figure 7: Design space exploration of annual profit via differential evolution for three different hydrogen prices.

Page 24, line 557:
The optimum identified in the central panel of **Fehler! Verweisquelle konnte nicht gefunden werden.** with p_{hy} equals 7.8 € kg^{-1} serves as~~ the initial ~~configuration for the following observations.~~ design optimization method, which employs the Nelder-Mead algorithm described in Sect. **Fehler! Verweisquelle konnte nicht gefunden werden.** for the given use case of Sect. **Fehler! Verweisquelle konnte nicht gefunden werden.**.~~

RC **Lines 555-565: The finding that neglecting degradation leads to a 21% underestimation of the LCOH is highly significant and underscores the importance of the topic. However, there is a fundamental disconnect in the study's contribution: while these impacts are quantified, they are not actively integrated into the optimization process. Both the design and MILP stages remain "blind" to degradation effects during the decision-making loops. Consequently, the manuscript succeeds in quantifying the error of ignoring degradation but falls short of providing a methodology that actually optimizes life-cycle performance by accounting for these dynamics within the optimization itself.**

AR We thank the reviewer for highlighting the significance of our LCOH findings. However, we respectfully disagree with the assessment that the design phase remains "blind" to degradation effects during its decision-making loop. As detailed in our previous response regarding Figure 1, the degradation evaluation is a core, active driver inside the iterative design loop. Consequently, the design algorithm actively navigates the design space to find the exact capacity configuration that maximizes life-cycle performance under the determined degradation dynamics. Because this active integration is already a fundamental mathematical property of the design methodology as described in Section 2, no further modifications were made to this discussion section.

AC	-
	-

RC	**Lines 685-705: The authors report 104%-110% profit differences when switching from the heuristic strategy to MILP optimization. Despite this, the system sizing remains based on the heuristic approach. This demonstrates that the fixed operation strategy is unable to capture the real conditions of these systems, including variable market prices and degradation, leading to a design optimized for a sub-optimal operational logic. The authors should clarify how a design based on a "blind" heuristic can be considered robust given these identified performance gaps.**
AR	The identified profit gap between the heuristic operation within the design method and the MILP operation optimization is indeed substantial, and highlighting this exact discrepancy is one of the primary core contributions of this study. The reviewer is entirely correct that sizing the system based on a fixed, rule-based strategy yields a design tailored to a sub-optimal operational logic. However, this choice was a deliberate methodological step within our proposed two-step framework to establish a conservative design and to keep computational stability. By contrasting this conservative design with the idealized upper bound of the MILP operation, our work serves as a diagnostic framework to precisely quantify what is lost by using simplified design heuristics. These significant performance gaps do not undermine the methodology, but rather provide a mathematical justification for future research in developing more sophisticated, yet computationally stable, operational logic directly within long-term sizing loops. To avoid any misleading interpretations regarding the nature of the heuristic design, we have followed the reviewers advice and revised the manuscript to remove the term "robust" where it implied a globally optimal configuration. The text now frames this configuration as a conservative design baseline.
AC	
	Page 2, line 36: Furthermore, it demonstrates that a rigorous consideration of the operational strategy is necessary for a ~~robust and~~ reliable system assessment to account for volatile external factors. *Page 4, line 99:* First we establish a conservative baseline design. *Page 4, line 106:* By contrasting these two approaches, we enable a direct comparison between the optimized, price-aware system operation and the conservative operation assumed during the initial design phase. *Page 6, line 149:* The separation of the design phase and the MIL operation optimization serves to ensure a conservative long-term design and computational stability. Sizing a system for a 25-year lifetime faces profound uncertainties regarding spot market prices and wind profiles. Therefore, the design phase utilizes the year 2024 that represents, according to anemos (2024), an average wind and electricity yield year over the past 20-year and a constant reference value as electricity price. Relying on a predefined rule-based operation strategy during the design phase provides a conservative estimation of the system's operational revenues. Embedding a fully functional MILP model within every single iteration of the outer global search loop would increase the computational effort (Eltamaly und Almutairi 2025) and introduce severe risks regarding numerical stability. If the inner solver experiences convergence issues in specific regions of the design space, the resulting numerical noise in the objective function would potentially disrupt the convergence behaviour of the outer optimization algorithm. Thus, the subsequent MIL operation optimization is applied exclusively to the finalized design to establish an idealized upper bound for revenues under actual volatile market conditions, allowing for a comparison against the conservative design assumptions. *Page 30, line 730:* To derive reliable investment decisions, a hybrid wind farm design must demonstrate robustness against external factors. Therefore, the integration of adaptive operational optimization directly into the sizing process can ensure that the system responds to market volatility or volatile wind power generation,

	providing a ~~robust~~ basis for identifying the optimal HPP design even under uncertain external conditions.

Technical corrections:

RC	**125 Typo in "Bevor starting"**
AR	The typo has been corrected.
AC	Page 5, line 128
	~~Bevor~~ Before starting the design optimization

RC	**Line 148: Broken cross-reference ('Fehler!...'). A thorough proofreading of the full manuscript is recommended.**
AR	The reference is now given correctly.
AC	Page 6, lines 162
	…, which ~~that~~ is further described in Sect. **Fehler! Verweisquelle konnte nicht gefunden werden.**.