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.

RC1

RC	**The presentation should be improved. Several abbreviations are used before being clearly defined. For example, “RV” and “AP” should be introduced with their full names when they first appear.**
AR	Both “RV” and “AP” are now fully introduced at the first time they are mentioned. Additionally, “MIL” was introduced twice. Once on page 4 and again on page 15. The latter introduction was deleted.
AC	-
	Page 4, line 100: 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… *Page 6, line 143:* …and a reference value (RV) describing the average expected electricity price achieved over the lifetime of the WF. *Page 15, line 395:* This subsection introduces the ~~mixed-integer linear (~~MIL~~)~~ operation optimization…

RC	**There is a cross-reference error on page 6, lines 148–149. The text contains the unresolved reference: “Fehler! Verweisquelle konnte nicht gefunden werden. (Lagarias et al. 1998).” This should be corrected.**
AR	The reference is now given correctly.
AC	Page 6, line 162
	…, which ~~that~~ is further described in Sect. 2.2.

RC	**The terminology should be made consistent. The manuscript uses both “HRES” and “HWF” to describe the co-located wind farm, electrolyzer, and battery system. This may confuse readers. In addition, this type of generation system is commonly referred to as a hybrid power plant (HPP). The authors are encouraged to check the definition of HPP used by IEA TCP Wind Task 50 and align the terminology accordingly.**
AR	According to IEA TCP Wind Task 50 the latest publication is the annual report from 2024. Figure 1 in this annual report shows a decision tree for determining the type of hybrid energy system being used, created by Work Package 1. According to this decision tree our described co-located wind farm, electrolyzer, and battery system is a grid-connected, unidirectional, multi-commodity hybrid power plant (HPP). Both abbreviation HRES and HWF are therefore replaced with HPP.
AC	-
	Page 2, line 49: One way to counter these problems are ~~hybrid renewable energy systems (HRES)~~ hybrid power plants (HPP)… (*In the following sentences HRES and HWF were replaced by HPP. In total it has been 36*

	replacements in the whole manuscript. For the sake of clarity, we have omitted a list of all these changes here.) *Page 3, line 95:* ~~Since all components will be placed close to an already existing WF we will further call the considered HPP a hybrid wind farm (HWF).~~

RC	**The operational strategy in Figure 2 should be clarified. The strategy appears to be rule-based, but the current figure is difficult to follow. The authors are encouraged to present the operational logic as a flowchart, which would make the decision process for power allocation among the wind farm, electrolyzer, BESS, and grid more transparent.**
AR	We appreciate the reviewer's suggestion regarding the presentation of the operational logic. As illustrated in Figure 2, the system's dispatch logic is governed by the interaction between wind farm power output and the battery energy storage systems state of charge, resulting in nine distinct operational states. Each state involves specific power allocation setpoints for the electrolyzer, the grid interface, and the battery energy storage system. Given the multi-variable nature of these transitions, mapping all nine configurations and their respective decision branches into a single flowchart would lead to an overly complex and potentially fragmented diagram. We believe that the current consolidated representation provides a more concise and readable overview of the interdependent power flows. To improve clarity, we have refined the caption of Figure 2 to ensure the decision logic is more intuitive for the reader.
AC	Page 12, Figure 2
	Figure 1: ~~**Overview of power flows for a timestep in the assumed operation strategy.**~~ **Figure 2: Power flows of HPP components for the determined operation strategy for a timestep depending on the relative WF power output (top row) and the BESS state of charge (left column).**

RC	**Battery degradation should be considered or discussed in more depth. The BESS is central to the conclusions: it reduces electrolyzer degradation and increases annual profit, while only slightly increasing LCOH. However, BESS degradation and replacement are neglected, although the manuscript acknowledges that cycling degradation could affect the optimal BESS capacity. The authors should either include battery degradation in the model or provide a more detailed discussion of how battery degradation may influence the main conclusions.**
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 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 $\max(OAP) = \max(\sum_{t=0}^{T}\left(SE(t)\cdot p_{\mathrm{elec}}(t) + SH(t)\cdot p_{\mathrm{hy}}(t) - WSC(t)\right) - DegC_{\mathrm{El}} - DegC_{\mathrm{BESS}}),$

	Page 16, line 414: $\mathrm{DegC_{BESS}}$ denotes the degradation costs of the BESS, defined as $\mathrm{DegC_{BESS}} = \mathrm{DegC_{BESS,specific}} \cdot \Delta t \cdot \sum_{t=0}^{T} (P_{\mathrm{BESS,c}}(t) + P_{\mathrm{BESS,d}}(t)),$ (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): $\mathrm{DegC_{BESS,specific}} = \frac{CAPEX_{\mathrm{BESS,specific}}}{n_{\mathrm{cycles}} \cdot 2 \cdot \mathrm{DoD} \cdot \eta_{\mathrm{BESS}}}.$ (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	**The design problem is nonlinear and likely non-convex, and the paper uses the Nelder–Mead algorithm after an exploratory design-space sweep. The authors should provide more information on the optimization bounds, initialization, stopping criteria, convergence tolerance, number of function evaluations, and whether multiple starting points were tested. In addition, terms such as “global optimum” should be avoided unless global optimality can be justified.**
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. Replacing the optimization algorithm led to minor variations in the results. Consequently, Figures 7 to 10, Table 2 and 3, and their descriptions have been revised. Additionally, we have included the requested technical details of the optimization setup and avoided the term “global optimum”. Although the results shifted slightly during the revision process, the fundamental findings remain unchanged.
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. 2.2 ~~(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:

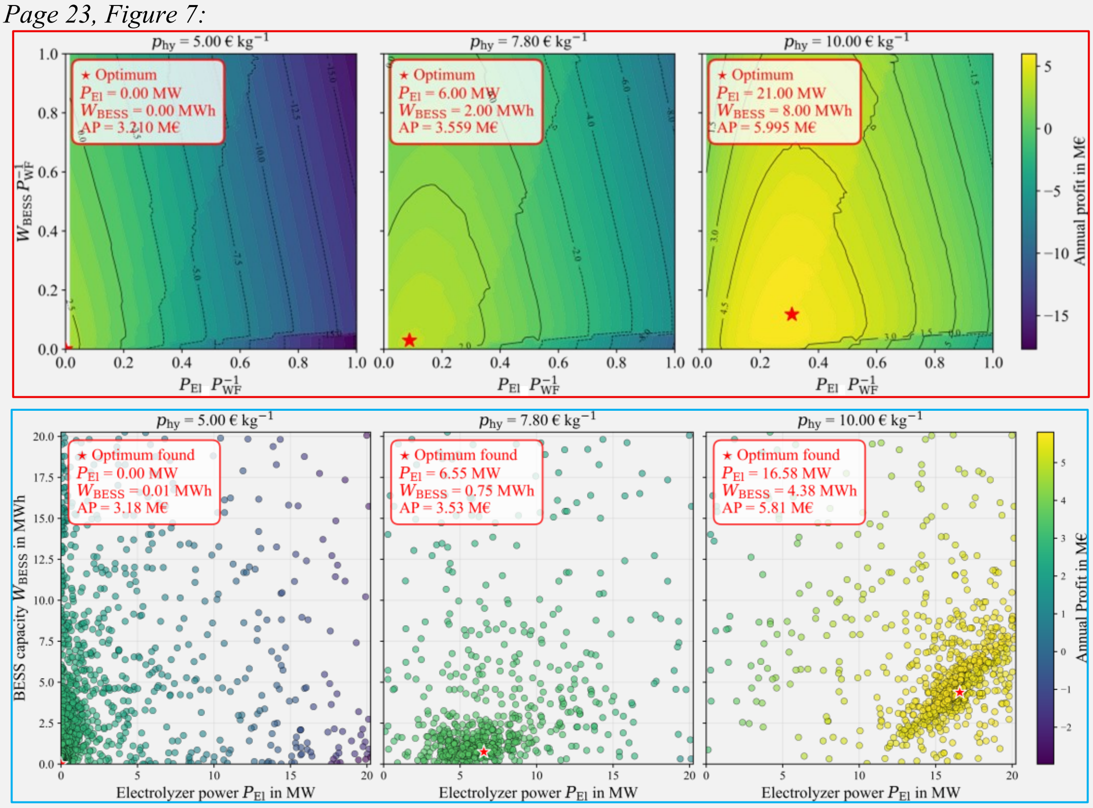


Figure 7: ~~Annual profit as function of electrolyzer rated power and rated BESS capacity over wind farm rated power for three different hydrogen prices.~~
Figure 7: Design space exploration of annual profit via differential evolution for three different hydrogen prices.

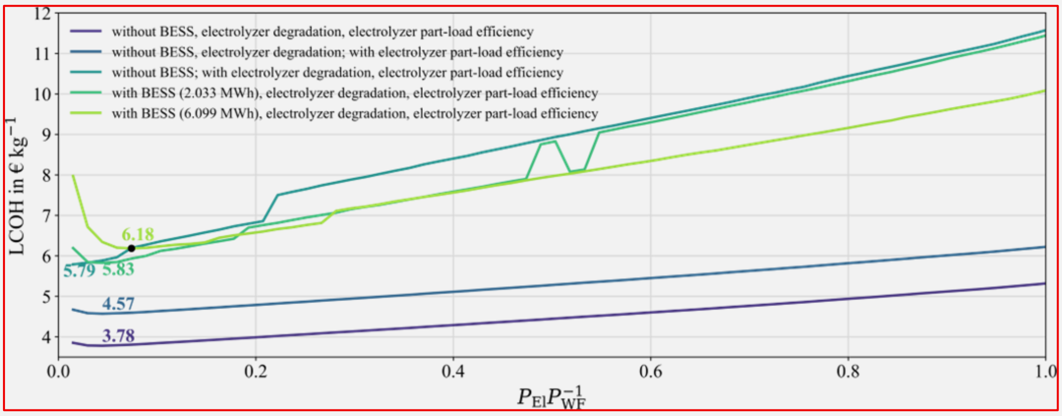
Figure 7 illustrates the strong dependence of the optimal ~~HWF~~HPP design on the assumed hydrogen price. The results indicate that the ~~global~~ optimum found shifts toward larger electrolyzer and BESS capacities as the hydrogen price increases. With a constant hydrogen price of 5.0 € kg^{-1}, the maximum AP occurs at neglectable electrolyzer and BESS sizes, because ~~for~~ the stand-alone WF remains the more profitable option. This AP without electrolyzer and BESS is calculated as the product of AEP and the difference between the RV and the LCOE amounting to 3.21 M€ a^{-1}. ~~A threshold price of 7.0 € kg^{-1} is~~

~~required for a configuration with 1 MW and 0 MWh to achieve a higher AP than the stand-alone WF. Below this hydrogen price level, the implementation of a HWF does not yield economic benefits under the given assumptions.~~ As seen in the middle and right panels of Fig. 7 the hydrogen price of 7.8 € kg^{-1}, results in an optimal configuration shift to 6.55 MW and ~~2~~0.75 MWh, while at 10 € kg^{-1} it further increases to ~~21~~16.58 MW and ~~8~~4.38 MWh. ~~The results indicate that variations in the electrolyzer rated power have more significant impact on the AP than variations in the BESS capacity.~~ The optimum identified in the central panel of Fig. 7with 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. 2.2 for the given use case of Sect. 3.1~~. ~~The optimized design variables, as well~~ Additional results as the mean AP, mean annual revenues, mean AHP, and TOTEX determined over the observation period, are detailed in Table 1.

Table 1: Design optimization results of the described use case over the entire observation period.

Output	Value	Unit
~~Optimized electrolyzer rated power~~	~~6.435~~	~~MW~~
~~Optimized BESS capacity~~	~~2.034~~	~~MWh~~
Mean AP	3.53 ~~3.57~~	M€ a^{-1}
Mean annual hydrogen profit	1.09~~1.12~~	M€ a^{-1}
Mean annual electricity profit	2.44~~2.45~~	M€ a^{-1}
Mean AHP	642~~626~~	t a^{-1}
Mean annual hydrogen revenue	5.01~~4.88~~	M€ a^{-1}
Mean annual electricity revenue	9.81~~9.84~~	M€ a^{-1}
LCOH	6.10~~6.01~~	€ $kg_{H_2}{}^{-1}$
TOTEX without WF	45.84~~44.20~~	M€
TOTEX electrolyzer	42.10~~40.00~~	M€
TOTEX pipeline system incl. water supply	1.59~~1.56~~	M€
TOTEX electricity supply	1.39~~1.37~~	M€
TOTEX BESS	0.76~~1.27~~	M€

~~The optimized design variables obtained are an electrolyzer rated power of 6.435 MW and a BESS capacity of 2.034 MWh.~~ The AP of 3.53~~7~~ M€ a^{-1} of the ~~HWF~~HPP is composed of the annual electricity profit by a share of approximately two-third and the annual hydrogen profit by one-third. For the given hydrogen price, the AP of the ~~HWF~~HPP is about 10~~11~~ % above the AP of the stand-alone WF, demonstrating that the ~~HWF~~HPP can have a significant impact on the economics of the system installed at the given WF site. The annual electricity revenue accounts for 9.814 M€ a^{-1}, representing approximately two thirds of the total revenues, while hydrogen sales contribute the remaining one third with 5.01~~4.88~~ M€ a^{-1}, which is consistent with the relative contributions to the AP. The TOTEX without the existing WF respectively of the added hydrogen system amount to 45.84~~44.20~~ M€ over the entire observation period. The largest share of TOTEX is associated with the electrolyzer, driven primarily by variable electrolyzer OPEX in the form of electricity procurement costs, which account for about ~~64~~69 % of the electrolyzer TOTEX. The remaining costs are significantly lower. This cost distribution emphasizes that the profit optimization of the ~~HWF~~HPP depends primarily on the electricity procurement and secondary on the electrolyzer investment and replacement costs, rather than on the cost reduction of peripheral components.



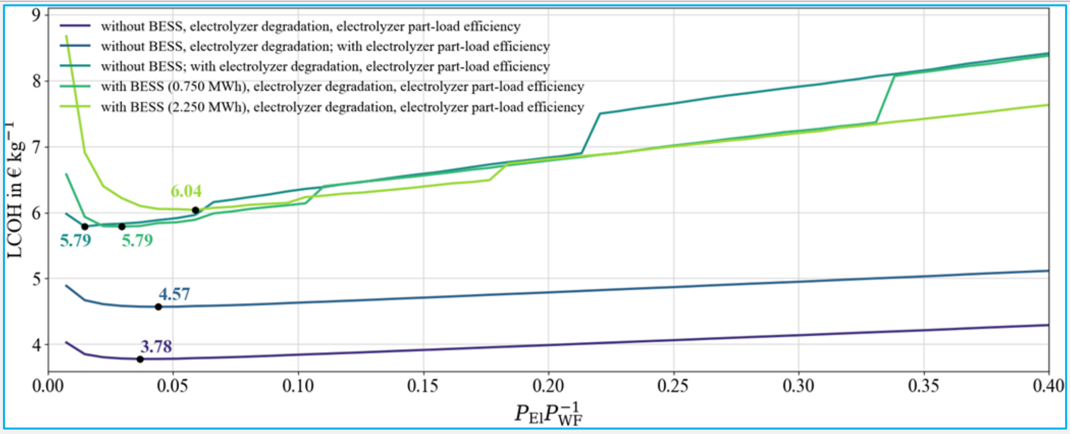


Figure 3: LCOH over the ratio of electrolyzer rated power to wind farm rated power for four different modeling approaches and two different BESS sizes.

A comparison of the minimum LCOH values of the model variants without BESS shows that neglecting electrolyzer degradation leads to an underestimation of the LCOH by approximately 21 %, while neglecting both degradation and partial-load efficiency results in an underestimation of about 35 %. These results highlight the critical importance of accurately representing both degradation effects and part-load efficiency in electrolyzer model~~l~~ing. By ~~A~~adding a BESS capacity of 0.750~~2.033~~ MWh, that was previously identified as optimum for the AP maximization for the given use case, ~~actually leads to an increase in~~ the LCOH ~~by less than one percent~~ remain at a constant level while ~~increasing~~ the AP increases by 7~~5~~ % in this scenario. While the incremental hydrogen yield is ~~in~~sufficient to offset the additional BESS-related TOTEX, resulting in constant ~~a marginal~~ LCOH ~~increase~~, the system benefits from enhanced operational flexibility. Consequently, the BESS effectively increases the AP by capturing higher market revenues ~~that outweigh the rise in levelized production costs~~. An increased BESS capacity shifts the LCOH minimum to higher electrolyzer capacities while ~~further~~ increasing LCOH. Ultimately, these findings underscore that the choice of the objective function is pivotal for the optimal sizing of both the electrolyzer and the BESS, as it fundamentally dictates whether the integration of a BESS is perceived as a profit benefit or a cost driver.

A technical driver behind this economic trade-off is the BESS ability to mitigate electrolyzer degradation. Specifically, the operation strategy assumed in Sect. 2.2.1 results in an annual electrolyzer degradation, calculated according to Sect. 2.2.2, for the in Sect. 3.1 presented HPP system of 0.1294~~0.1138~~ V a^{-1}. This TAD corresponds to degradation costs of 0.5900~~0.586~~ M€ a^{-1}, when converted according to Eq. (24). If the BESS is removed, the TAD increases to 0.1577 V a^{-1}, increasing the degradation cost by 0.1290~~0.226~~ M€ a^{-1}. The electrolyzer degradation with and without BESS divides into the different operation modes according to Table 2.

Table 2: Share of the total annual electrolyzer degradation depending on the electrolyzer operation modes with and without BESS.

Operation mode	With BESS (0.75 MWh): TAD = 0.1294~~0.1138~~ V a^{-1}		Without BESS: TAD = 0.1577 V a^{-1}	
	AD in V a^{-1}	AD share of TAD in %	AD in V a^{-1}	AD share of TAD in %
rated	0.0145	11.18~~12.74~~	0.0145	9.17~~9.20~~
partl	0.0012~~0.0019~~	0.96~~1.66~~	0.0009~~0.0008~~	0.56~~0.54~~
off	0.0021~~0.0015~~	1.61~~1.35~~	0.0026~~0.0025~~	1.63~~1.61~~
fluct	0.0675~~0.0665~~	52.19~~58.43~~	0.0666~~0.0668~~	42.21~~42.38~~
stop	0.0441~~0.0294~~	34.06~~25.82~~	0.0732~~0.0730~~	46.43~~46.28~~

The fluctuating operation mode is the dominant driver of electrolyzer degradation in the system with BESS. However, removing the BESS leads to a significant increase in the TAD by more than a fifth~~third~~. This is primarily driven by the degradation from start-stop cycles, which increases by about 60 % ~~more than doubles from 0.0294 V a^{-1} to 0.0730 V a^{-1}~~. Furthermore, the AP of the System without BESS decreases to 3.4 M€, representing a 3.7~~4.7~~ % reduction compared to the configuration featuring a 0.75~~2.034~~ MWh BESS. These findings underline the effectiveness of the BESS within the implemented operation strategy by buffering volatile WF power. The battery prevents frequent shutdowns and ensures a more continuous hydrogen production, thereby substantially mitigating cycle-induced degradation of the electrolyzer. While the BESS integration entails additional CAPEX, these costs are offset over the system's operational period by reduced electrolyzer degradation costs and increased hydrogen revenues, even when limited to a buffering operation strategy.

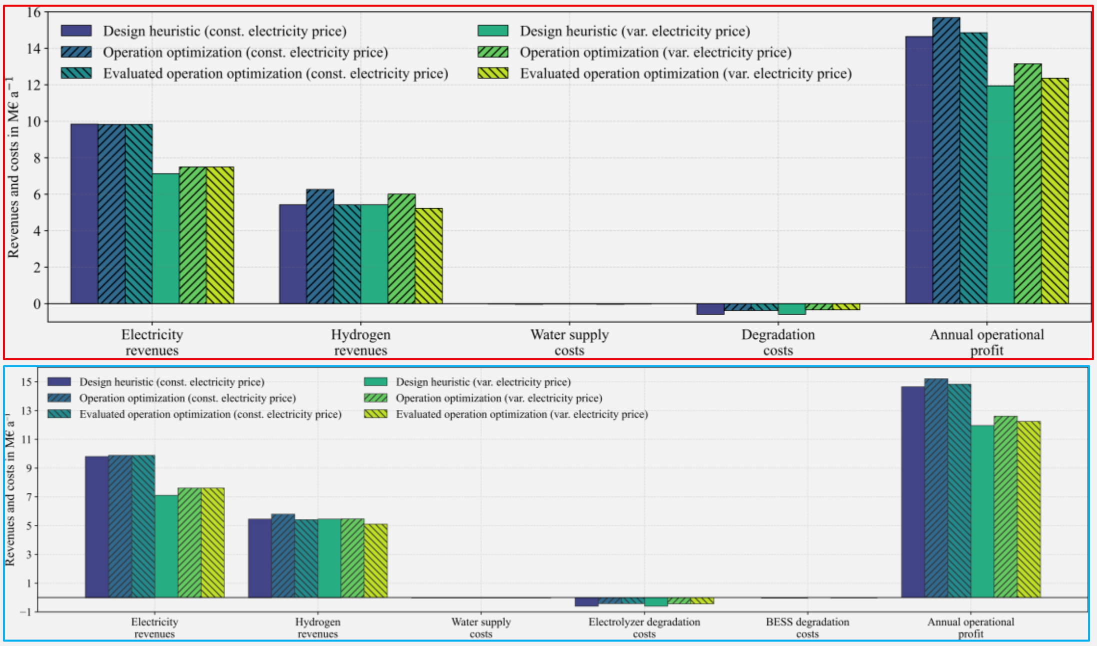


Figure 4: Comparison of the annual operational profit and its shares of the design optimization, the MIL operation optimization, and its degradation evaluation for constant and variable electricity prices.

Figure 4 shows that the assumed constant electricity price in the design optimization leads to a systematic overestimation of electricity revenues and, consequently, of the OAP by 23 % when compared to variable electricity price conditions of 2024. This highlights the limitations of design-stage economic assumptions when applied to real-world market environments with pronounced price volatility. In addition, the electrolyzer degradation costs associated with the operating strategy assumed during the design optimization amount to 0.59 M€ $a^{-1}$and can be reduced by about 38~~44~~ % through the proposed operational optimiz~~s~~ation under variable price conditions. This reduction underlines the strong influence of operational control on component ageing and long-term economic performance. 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.

Neglecting degradation-induced efficiency losses and using a piecewise linearized efficiency of the electrolyzer within the operation optimization leads to an overestimation of hydrogen revenues by 7~~15~~ % under variable electricity price conditions, relative to the revenues obtained from the subsequent degradation evaluation. Initially, the MIL operation optimization suggests a significant economic potential, with a projected OAP approximately 5~~10~~ % higher than that of the design heuristic. Despite the subsequent revenue correction due to degradation effects and efficiency linearization, the evaluated OAP remains above the value calculated in the design phase, reaching 102~~104~~ % under variable electricity prices and 101 % under constant electricity prices. This demonstrates that MIL operational optimization, even when neglecting degradation-related efficiency losses, can slightly enhance economic performance relative to the simplified operation assumptions in the design optimization. However, the gap between the initial 5~~10~~ % projection and the evaluated 1 % to 2~~4~~ % gain highlights the ~~clear~~ potential for further improvements through a more comprehensive representation of degradation effects within the economically optimum operation of the HPP.

To analyse the impact of the assumed hydrogen price on the optimal ~~HWF~~HPP operation and to evaluate the discrepancies between the system components operation of the design optimization and the MIL operation optimization, Figure presents different annual load duration curves. The figure illustrates the electrolyzer power input for varying hydrogen price scenarios alongside the WF power output. Additionally, the day-ahead electricity market price of 2024 is included and plotted in descending order.

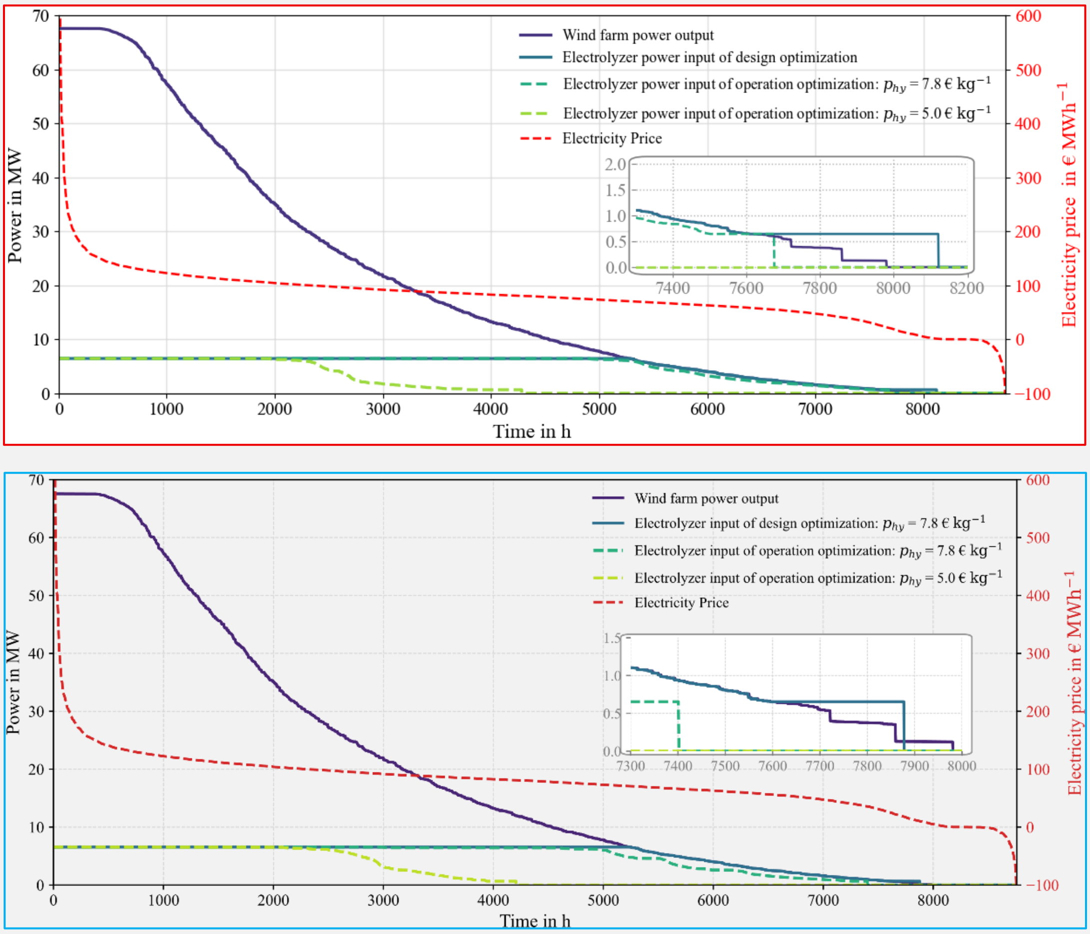


Figure 10: Sorted load duration curves of the WF power output, the electrolyzer power input of the design optimization, and for the MIL operation optimization for two different hydrogen price scenarios, and the sorted electricity price over one year.

The comparative analysis of the sorted load duration curves, as illustrated in Figure, reveals that the operational characteristics of the design heuristic and the operational optimization differ ~~only~~ marginally at a hydrogen price of 7.8 € kg^{-1}. Specifically, the design heuristic (~~dark~~ solid blue line) accounts for 6,375 ~~6,418~~ full load hours (FLH) per year, while the operational optimization (dashed teal ~~solid~~ line) reaches 5,892 ~~6,213~~ FLH. This high degree of similarity is primarily attributed to the fact that the assumed hydrogen price is significantly higher than the average electricity day-ahead market price of 79.6 € MWh^{-1}. Under these conditions, the marginal revenue from hydrogen production mostly exceeds the opportunity costs of direct electricity sales, incentivizing the system to maximize hydrogen output regardless of the specific operation approach. ~~Even~~ However, when reducing the hydrogen price to 5.0 € kg^{-1} (dashed light green line), the optimized electrolyzer operation shifts to 3,157 ~~2,858~~ FLH~~, the economic performance of the design heuristic alters.~~ Despite the design operation strategy's price-independent nature and the resulting inability to account for fluctuating market signals, the evaluated OAP ~~annual operational profit~~ achieved through MIL optimization exceeds that of the static design ~~optimization~~ operation under variable electricity price conditions by more than ~~only 4.5~~ 9 % at the lower hydrogen price scenario. This suggests that ~~while~~ the heuristic remains active during periods where market electricity prices exceed the marginal revenue of hydrogen production, resulting in ~~the~~ associated economic losses ~~are largely mitigated by the overall system design~~ compared to the price-dependent MIL operation optimization. ~~Although the operation optimization selectively decreases the input power of the electrolyzer during high-price electricity periods, the marginal profit gain remains limited.~~ It must be noted, however, that the ~~high accuracy of~~ results of the operation optimization ~~heuristic~~ compared to ~~within~~ the design optimization observed here are ~~is~~ specific to the investigated use case.

Page 29, line 684:

In this context, the design optimization identified a ~~global optimum~~ near-optimal solution for the electrolyzer rated power and BESS capacity of the investigated use case.

	Page 30, line 720: Alternatively, nonlinear optimization could directly integrate degradation effects into the decision-making process, although this significantly increases computational effort ~~and may hinder the identification of a global optimum~~.

RC	**The robustness of the case-study conclusions should be strengthened. The case study is based on one specific wind farm, one wind time series, German 2024 day-ahead electricity prices, and a fixed hydrogen price. However, the optimal electrolyzer and BESS sizing, as well as the performance gap between the rule-based heuristic and the MIL dispatch optimization, are likely sensitive to wind-resource profiles, electricity price volatility, and hydrogen price assumptions. To strengthen the conclusions, the authors are encouraged to include sensitivity analyses using at least one additional wind year, electricity price year, or hydrogen price scenario.**
AR	We thank the reviewer for this constructive comment regarding the sensitivity of our case-study results to external conditions. We fully agree that the optimal sizing configurations are highly dependent on external inputs. To address this a sensitivity analysis for the hydrogen price is integrated into the study, as shown in Figure 7. These results clearly demonstrate that the hydrogen price has a massive impact on the optimal capacities of P_{El} and W_{BESS}, which underscores that the sizing configuration reacts highly sensitively to external economic drivers. Because the design results cannot be classified as universally robust against shifting external factors, we agree that terms like "robust" or "global optimum" were misleading in this context. Consequently, we have revised the manuscript to eliminate these terms. Additionally, we have now explicitly acknowledged these sensitivities as a limitation in the revised discussion section. The primary focus of this paper is the high-fidelity modeling of the internal technical component specifications such as dynamic stack degradation and non-linear part-load efficiency curves rather than a comprehensive multi-year climatic uncertainty analysis. Developing a fully robust sizing framework capable of optimizing across multi-year weather and price scenarios is a vital next step, but it remains outside the scope of this model specific paper.
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 22, 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, line 551:* The results indicate that the ~~global~~ optimum found shifts toward larger electrolyzer and BESS capacities as the hydrogen price increases. *Page 29, line 684:* In this context, the design optimization identified a ~~global optimum~~ near-optimal solution for the electrolyzer rated power and BESS capacity of the investigated use case. *Page 30, line 720:* Alternatively, nonlinear optimization could directly integrate degradation effects into the decision-making process, although this significantly increases computational effort ~~and may hinder the identification of a global optimum~~. *Page 30, line 724:* Additionally, this work did not explore variations in electricity price profiles or wind generation time series~~, both of which can exert a substantial influence on optimal operating behaviour~~. These external drivers can exert a substantial influence not only on the optimal operating behaviour, but also on the

	resulting component sizing configurations and the performance gap between the rule-based heuristic and the MILP dispatch optimization. *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.

RC	**Correct spelling and wording issues, for example: “Bevor” → “Before,” “eighter” → “either,” “prize cannibalization” → “price cannibalization,” “European Comission” → “European Commission,” “archivable electricity price” → probably “achievable electricity price,” “reasonably solution” → “reasonable solution,” and “the integrate of adaptive…” → “the integration of adaptive…”, etc.**
AR	All comments have been addressed according to the reviewer's suggestions.
AC	
	Page 5, line 128: ~~Bevor~~ Before starting the design optimization *Page 2, line 63:* ... Schnuelle et al. (2020) and Fabianek and Madlener (2024) ~~eighter~~ evaluated given… *Page 2, line 46:* Meanwhile, WF operators encounter revenue declines due to ~~prize cannibalization~~ price cannibalization and high price volatility (Bechmann und Quick 2025). *Page 2, line 40:* To achieve the European Union’s climate target of reducing greenhouse gas emissions by 55 % by 2030 (European Parliament and Council 2021), the share of renewable energy in the energy mix is planned to be increased to 42.5 % and the production of 10 million tons of green hydrogen is targeted by 2030 ~~(European Comission)~~ (European Commission 2026) *Page 1, line 27:* Firstly, the assumption of a constant ~~archivable~~ achievable electricity price over the systems lifetime leads to a 23 % overestimation of annual operational profits when compared to the more realistic electricity sales at the German day-ahead market in 2024. *Page 11, line 301:* Nevertheless, this strategy is employed to obtain a ~~reasonably~~ reasonable solution. *Page 30, line 731:* Therefore, the ~~integrate~~ 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.

RC2

RC	**1) The treatment of downstream hydrogen demand is insufficiently specified. In particular, it is unclear whether hydrogen demand is assumed to be fixed over time (e.g., annually, monthly, or daily). One would typically expect the hydrogen to be supplied to specific industrial clusters with relatively fixed consumption profiles. While the hydrogen storage tank and pipeline network may act as buffers enabling operational flexibility, the paper does not clarify whether total hydrogen demand must be fully met. Alternatively, it remains unclear whether hydrogen demand is assumed to be flexible or whether unmet demand can be supplied by other hydrogen production facilities.**
AR	In this case study, we assume that the produced hydrogen is injected into a public hydrogen grid. Consequently, the hydrogen network is modeled as an infinite sink, meaning that the system does not face a predefined time-varying or constant demand constraint that would require explicit fulfillment or lead to unmet demand. While the underlying model framework proposed by Reichartz et al. (2024b) is capable of incorporating specific industrial consumption profiles or transport logistics such as trailers, these features were deliberately excluded to focus on the model of the systems components, degradation, and operation. We have clarified this modeling assumption in the revised manuscript to avoid any ambiguity regarding the demand-side constraints.
AC	Page 21, line 523
	Consequently, we assume that produced hydrogen will be compressed and delivered to the hydrogen grid via pipeline, where the hydrogen grid is modeled as an infinite sink.

RC	**2) Section 2.1: How fast do HRES (or WHP) require electrolyzers to operate? What ramp-rate or other characteristics would you expect from an electrolysis plant to follow the daily wind profile? Is PEM the only technology that fits these requirements?**
AR	PEM electrolyzers are characterized by a high load range and highly dynamic response times, with ramp rates typically ranging within seconds. This allows them to follow the variable output of wind farms almost instantaneously. In our model, we apply an hourly resolution, which is appropriate for evaluating the seasonal and daily economic dispatch of the hybrid system. Given the high load and ramp-rate flexibility of PEM technology compared to the hourly time step, we assume that the electrolyzer can track the average hourly power output of the wind farm without significant latency. While alkaline electrolysis (AEL) technology is a viable alternative for hydrogen production, it exhibits slower response characteristics and higher minimum load requirements. Consequently, PEM technology is selected due to its superior dynamic flexibility.
AC	-
	-

RC	**3) Section 2.1.3: Eq. 10-14 are not clear. It would help the reader first to introduce the voltage and Faraday efficiencies (eq. 11 and 12), and then derive eq. 10 using the variables from 11 and 12. Equations 13 and 14 also use different variables, not connected to eq. 10-12, making it hard to link equations to each other.**
AR	We have fundamentally restructured Sect. 2.1.3 to improve the mathematical readability. Following the reviewers suggestion, we first define the Faraday and voltage efficiencies as fundamental components, then derive the cell efficiency as their product, and finally integrate the auxiliary efficiency to define the overall system efficiency. All variables are now consistently defined across the sequence of equations.
AC	Page 8, Section 2.1.3
	The efficiency of the electrolysis cell is modeled by considering the voltage efficiency and the Faraday efficiency. First, the Faraday efficiency η_F reflects losses due to gas diffusion and is defined as the ratio between the real hydrogen flow $\dot{n}_{\mathrm{H_2}}$ and the ideal hydrogen flow $\dot{n}_{\mathrm{H_2,ideal}}$, following Eq. (10): $\eta_F = \frac{\dot{n}_{\mathrm{H_2}}}{\dot{n}_{\mathrm{H_2,ideal}}}$. (10) With the ideal hydrogen flow determined by Faraday's law based on the cell current density i_{cell}, the active cell area A_{cell}, the Faraday constant F, and the number of electrons transerred per hydrogen molecule formed z, calculated according to Eq. (11) (Yodwong et al. 2020): $\dot{n}_{\mathrm{H_2,ideal}} = \frac{i_{\mathrm{cell}} \cdot A_{\mathrm{cell}}}{z \cdot F}$. (11) Second, the voltage efficiency η_V describes the ratio between the thermoneutral potential U_{th} and the actual cell voltage U_{cell} (Hernández-Gómez et al. 2020):

	$\eta_V = \frac{U_{\text{th}}}{U_{\text{cell}}}$ (12) The product of both efficiencies yields the cell efficiency η_{cell}, which relates the energy content of the produced hydrogen, based on the lower heating value ΔH_{H_2} to the electrical input power, following Eq. (13): $\eta_{\text{cell}} = \eta_V \cdot \eta_F = \frac{\Delta H_{\text{H}_2} \cdot \dot{n}_{\text{H}_2}}{U_{\text{cell}} \cdot i_{\text{cell}} \cdot A_{\text{cell}}}$. (13) ~~The efficiency of an electrolysis cell η_{cell} is described by multiplying the voltage efficiency η_V and the Faraday efficiency η_F by the ratio of the produced hydrogen to the input power following Eq. (10).~~ ~~$\eta_{\text{cell}} = \eta_V \cdot \eta_F = \frac{\Delta H_{\text{H}_2} \cdot \dot{n}_{\text{H}_2}}{U_{\text{cell}} \cdot i_{\text{cell}} \cdot A_{\text{cell}}}$, (10)~~ ~~where ΔH_{H_2} is the lower heating value and $\dot{n}_{\text{H}_2}$ the real mass flow of hydrogen. η_V is defined as the ratio between the thermally neutral potential U_{th} and U_{cell}, given in Eq. (11) (Hernández-Gómez et al. 2020).~~ ~~$\eta_V = \frac{U_{\text{th}}}{U_{\text{cell}}}$ (11)~~ ~~η_F reflects losses due to gas diffusion and is correlated to $\dot{n}_{\text{H}_2}$ and the ideal mass flow of hydrogen $\dot{n}_{\text{H}_2,\text{ideal}}$, following Eq. (12):~~ ~~$\eta_F = \frac{\dot{n}_{\text{H}_2}}{\dot{n}_{\text{H}_2,\text{ideal}}}$, (12)~~ ~~with the ideal mass flow calculated by Eq. (13) (Yodwong et al. 2020):~~ ~~$\dot{n}_{\text{H}_2} = \frac{i_{\text{cell}} \cdot A_{\text{cell}}}{z \cdot F} \cdot \eta_F$. (13)~~ Finally, ~~E~~equation (14) shows the overall efficiency of an electrolyzer η_{El} with multiple cells and stacks and can be calculated by η_{cell} and an additional efficiency for auxiliary structures η_{Aux} such as water and heat management systems (Cheng et al. 2025; Lu et al. 2023; Tofighi-Milani et al. 2025): $\eta_{\text{El}} = \eta_{\text{cell}} \cdot \eta_{\text{Aux}} = \frac{\Delta H_{\text{H}_2} \cdot \eta_F}{U_{\text{cell}} \cdot z \cdot F} \cdot \eta_{\text{Aux}}$, (14) where η_{cell} is substituted to a combination of Eq. (10) and (13).

RC	**4) Some of the abbreviations (like RV and MIL) are used before they are defined.**
AR	"RV" is now introduced, when its first mentioned on page 6, line 143. Besides the abstract, "MIL" is first mentioned in Section 1on page 4, line 102, where it is introduced. It was introduced twice (again on page 15, line 395). The latter introduction was deleted.
AC	
	Page 6, line 143: …and a reference value (RV) describing the average expected electricity price achieved over the lifetime of the WF. *Page 15, line 395:* This subsection introduces the ~~mixed-integer linear (~~MIL~~)~~ operation optimization…

RC	**5). Section 2.2.3: You mentioned the voltage level of 2.5 V at which the stack should be replaced. What is the nominal voltage of one cell at nominal current, nominal temperature, and at the beginning of life? The comparison of the start point and the end point would be helpful to understand this value. Also, the choice of this voltage level is not clear: "the maximum cell voltage of PEM electrolyzers ranges between 1.65 and 2.5 V at a nominal current density of 2 A cm⁻²." - It ranges depending on what and how it justifies the choice of the replacement level of 2.5 V?**
AR	We agree that providing the initial cell voltage at the beginning of life (BOL) and clarifying the rationale behind the 2.5 V end-of-life (EOL) threshold significantly enhances the transparency of our model assumptions. Under nominal operating conditions, which include a current density of 2 A cm^{-2}, a cell temperature of 80 °C, an anode pressure of 1.013 bar, and a cathode pressure of 13.78 bar, the empirical polarization curve model yields an initial cell voltage of 1.93 V. This value corresponds to an initial stack efficiency of 64 %. The voltage range of 1.65 V to 2.5 V reported by Buttler and Spliethoff (2018) reflects the wide technological diversity of commercial stacks spanning an efficiency range between 50% and 76%. In our methodology, the 2.5 V level is implemented as a techno-economic upper limit for stack replacement because degradation-induced overvoltages, cause the cell voltage to rise. Reaching the threshold of 2.5 V corresponds to the minimum efficiency bound of 50% defined in the literature. To

	reflect these details, the text in Section 2.2.3 has been revised to clarify the comparison between the beginning-of-life and end-of-life states.
AC	Page 14, line 352
	According to Buttler und Spliethoff (2018) the ~~maximum~~ cell voltage of PEM electrolyzers typically ranges between 1.65 V and 2.5 V at a nominal current density of 2 A cm⁻², which directly maps to lower heating value efficiencies between 76 % and 50 %, respectively. In this study, the initial cell voltage at the beginning of life (BOL) is calculated via the polarization curve model (Sect. 2.1.1) as $U_{cell}^{\mathrm{BOL}} = 1.93\ \mathrm{V}$, corresponding to $\eta_{\mathrm{cell}}^{\mathrm{BOL}} = 0.64$. Due to degradation-induced overvoltages, the required cell voltage to maintain nominal current increases over time. The stack replacement threshold is set to a maximum limit of 2.5 V, representing an end-of-life criterion where cell efficiency drops to the literature-reported minimum of 50%. ~~On this basis, a stack is required to be replaced before the maximum cell voltage of $U_{cell}^{max} = 2.5$ V is exceeded because of degradation-induced overvoltage.~~

RC	**7) Formatting errors: reference gives message "Fehler!" and reference to figure as "Fig. Figure 7".**
AR	The reference is now given correctly.
AC	Page 6, lines 162
	…, which ~~that~~ is further described in Sect. 2.2.

RC	**8) Typos: "Eighter", "Bevor", "pocc", etc**
AR	The Typos "eighter" and "bevore" have been corrected now. "pocc" is an abbreviation for point of common coupling, that is introduced on page 6, line 141. We have changed the abbreviation to "POCC" so that it aligned with the rest of the text.
AC	
	Page 5, line 128: ~~Bevor~~ Before starting the design optimization *Page 2, line 63:* ... Schnuelle et al. (2020) and Fabianek and Madlener (2024) ~~eighter~~ evaluated given… *Page 6, line 141:* …which the electrolyzer can be placed, POCC ~~pocc~~ the point of common coupling… *Table 1:* Shapefiles and points determining sh_{El}, POCC~~pocc~~, p_{H2O},p_{POD}

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	-
	-

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.

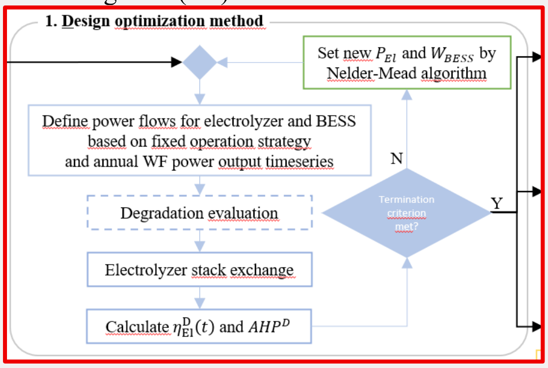
RC	**Line 120: The authors explicitly state that the methodology is an extension of the method by Reichartz et al. (2024b), with the primary contributions being a more detailed electrolyzer model and a shift in the objective function from LCOH to Annual Profit (AP). As currently presented, the work appears 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	-
	-

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 revenues estimations under these long-term average conditions.

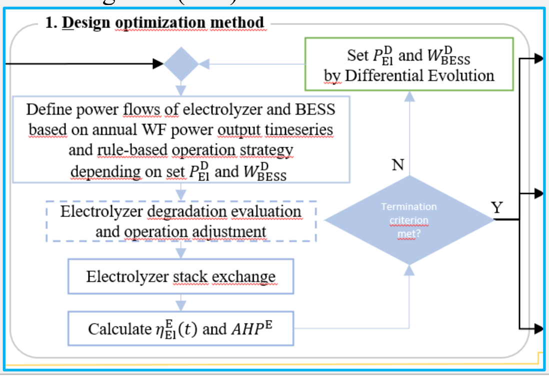
	Second, embedding a fully functional MIL operation optimization model within every single iteration of the outer global search loop (here differential evolution) increases the computational effort extremely (Eltamaly & Almutairi, 2025 DOI: 10.3390/su17062744). Furthermore, it introduces severe risks 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_{El}^{D} and BESS capacity W_{BESS}^{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. 2.2 ~~(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:

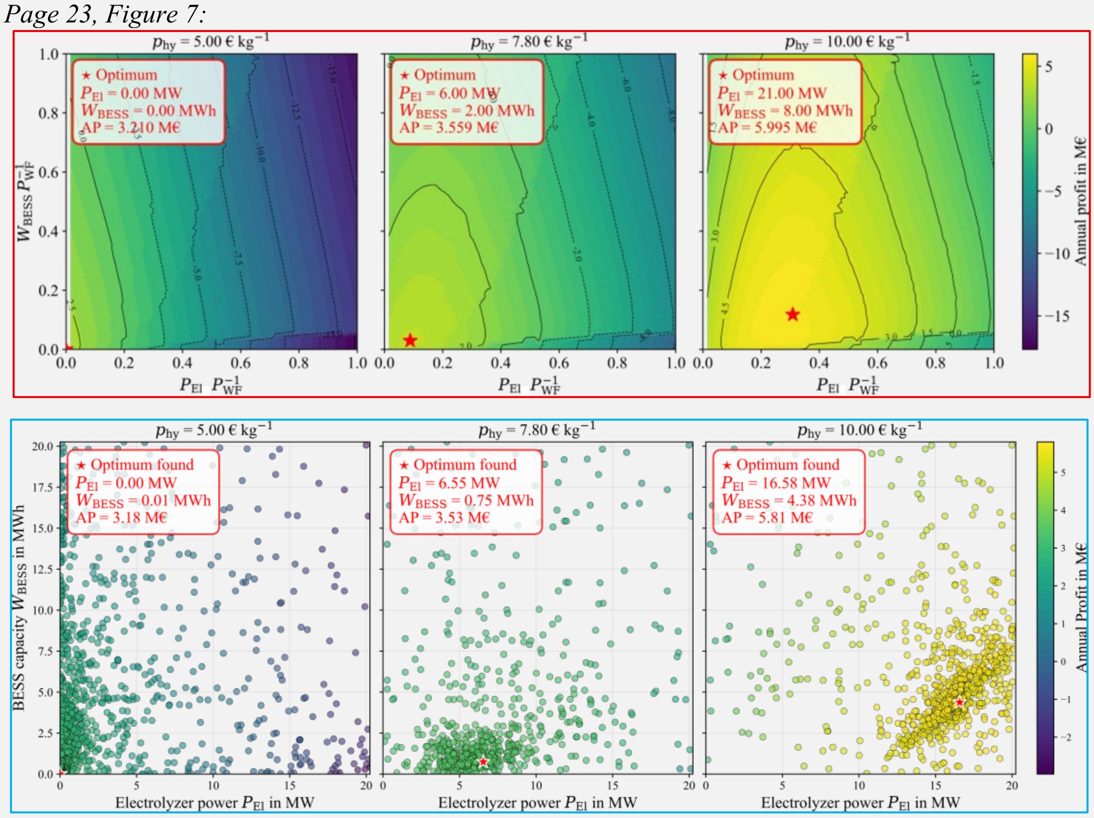


Figure 7: ~~Annual profit as function of electrolyzer rated power and rated BESS capacity over wind farm rated power for three different hydrogen prices.~~
Figure 7: Design space exploration of annual profit via differential evolution for three different hydrogen prices.

Page 24, line 557:

The optimum identified in the central panel of Fig. 7 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. 2.2 for the given use case of Sect. 3.1.~~

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):

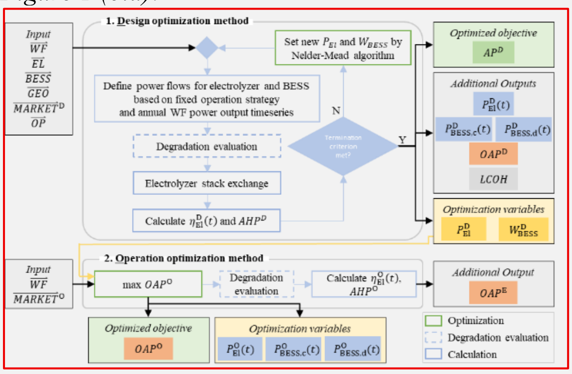
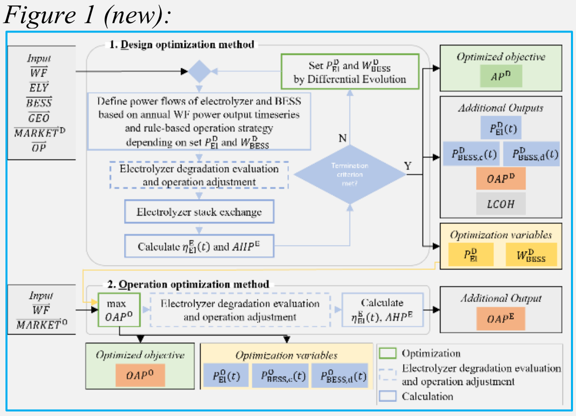


Figure 1 (new):



	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. 2.2.3. 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. 2.3, 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. 2.3.1 and ~~neglects~~ tracks the electrolyzers degradation as detailed in Sect. 2.3.2 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. 2.3.2, 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 $\max(\mathrm{OAP}) = \max(\sum_{t=0}^{T}\left(SE(t)\cdot p_{\mathrm{elec}}(t) + SH(t)\cdot p_{\mathrm{hy}}(t) - WSC(t)\right) - DegC_{\mathrm{El}} - DegC_{\mathrm{BESS}}),$ *Page 16, line 414:* $\mathrm{DegC_{BESS}}$ denotes the degradation costs of the BESS, defined as $\mathrm{DegC_{BESS}} = \mathrm{DegC_{BESS,specific}} \cdot \Delta t \cdot \sum_{t=0}^{T}(P_{\mathrm{BESS,c}}(t) + P_{\mathrm{BESS,d}}(t)),$ (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:

2.3.3 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 -

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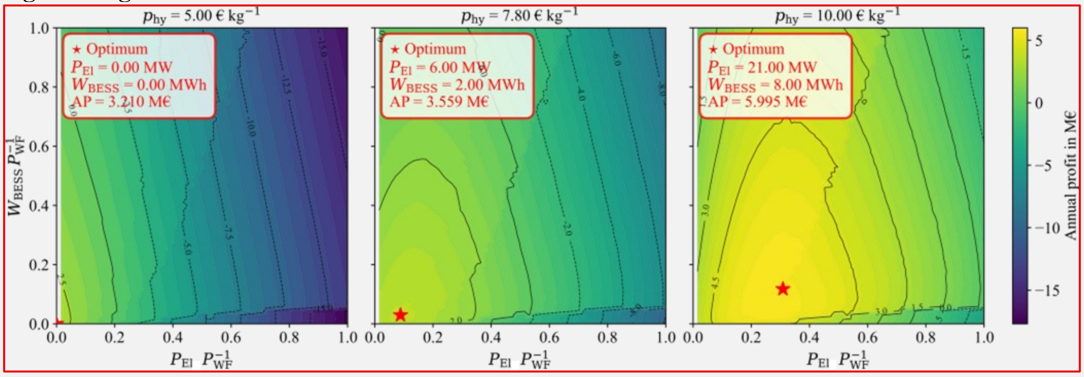
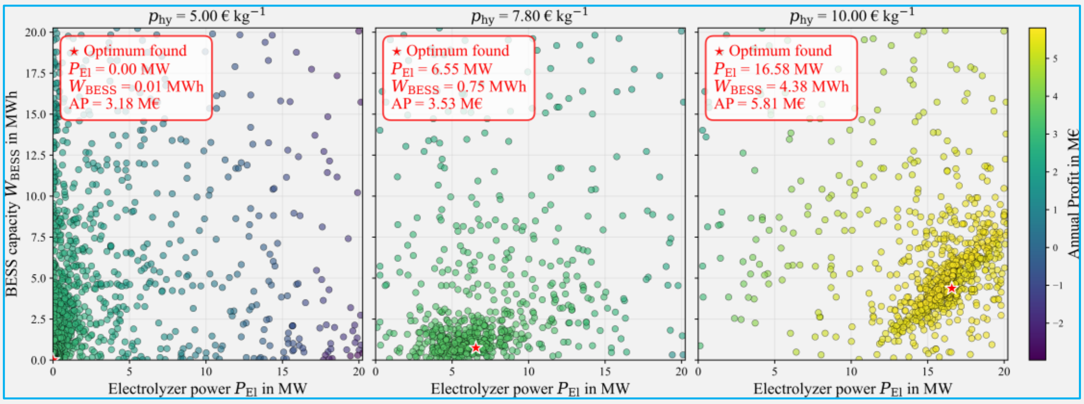
<table>
<tr><td>RC</td><td>Lines 505-510: The authors state that identifying a global optimum is "considerably more challenging" due to the non-convex nature of the problem. However, this is a weak justification in the context of current research. Established methodologies, such as convex optimization 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.</td></tr>
<tr><td>AR</td><td>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.</td></tr>
<tr><td>AC</td><td></td></tr>
<tr><td></td><td>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. 2.2 ~~(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.~~</td></tr>
</table>

	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 Fig. 7 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. 2.2 for the given use case of Sect. 3.1.~~

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	-
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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. 2.2.