How much technological progress is needed to make solar hydrogen cost-competitive?

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Dedicated to Professor Matthias Beller on the occasion of his 60th birthday

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An open-source software and Monte Carlo-based methodology for the analysis of green hydrogen production are developed. These tools are used to analyze the required technological progress for cost-competitive hydrogen production via photovoltaic + electrolysis, photoelectrochemical and photocatalytic water splitting. Based on the results, actionable targets for materials research are derived.

Abstract

Cost-effective production of green hydrogen is a major challenge for global adoption of a hydrogen economy. Technologies such as photoelectrochemical (PEC) or photocatalytic (PC) water splitting and photovoltaic + electrolysis (PV+E) allow for sustainable hydrogen production from sunlight and water, but are not yet competitive with fossil fuel-derived hydrogen. Herein, open-source software for techno-economic analysis (pyH2A) along with a Monte Carlo-based methodology for modelling of technological progress are developed. Together, these tools allow for the study of required technological improvement to reach a competitive target cost. They are applied to PEC, PC and PV+E to identify required progress for each and derive actionable research targets. For PEC, it is found that cell lifetime improvements (> 2 years) and operation under high solar concentration (> 50-fold) are crucial, necessitating systems with high space-time yields. In case of PC, solar-to-hydrogen efficiency has to reach at least 6% and lowering catalyst concentration (< 0.2 g/L) by improving absorption properties is identified as a promising path to low-cost hydrogen. PV+E requires ca. 2 or 3-fold capital cost reductions for photovoltaic and electrolyzer components. We hope that these insights can inform materials research efforts to improve these technologies in the most impactful ways.

Main Text

Producing green hydrogen at a cost that is competitive with fossil fuel-derived hydrogen is one of the major challenges for transitioning to a hydrogen economy.[1] There are promising technologies for converting solar energy and water to hydrogen, such as coupling of photovoltaic and electrolysis (PV+E),[2] photoelectrochemical (PEC)[3,4] and (particulate) photocatalytic (PC)[5] water splitting (see Figure 1). These technologies, however, cannot currently produce hydrogen at a cost that is competitive with hydrogen derived from steam reforming.[6,7] Hence, the question arises what and how much technological progress is required to reach a point of competitiveness? Understanding these requirements can inform (materials) research efforts, focusing them on the areas that are most impactful for quickly improving green hydrogen production routes.

Techno-economic analysis (TEA) is a helpful tool in this regard: it allows for economic modelling of various (hypothetical) production processes, providing insight into how process parameters affect the levelized cost of hydrogen ($LCOH_2$, herein expressed using the unit \$/kg(H_2)). In the literature, various techno-economic studies of hydrogen production from solar energy can be found.[6–12] Broadly speaking, they can be classified into three categories:

1. Modelling of state-of-the-art technologies to obtain an estimate for the current $LCOH_2$[6,11]
2. Modelling of hypothetical future technologies to obtain an estimate for a potential future $LCOH_2$[13,14]
3. Learning curve analysis based on learning rates to model the decrease of $LCOH_2$ over time[9,10]

Modelling of state-of-the-art or potential future technologies provide valuable single-point cost estimates and also reveal the impact of individual parameters through sensitivity analysis. However, they do not capture the trajectory of technological progress. Learning curve analysis does model the evolution of $LCOH_2$ over time but if faces two important limitations: firstly, historical data is often needed to derive reasonable estimates for the learning rates. It is therefore most reliable for mature technologies and challenging to apply for technologies which have not yet been widely deployed.

Secondly, learning curves do not provide straightforward insight into which aspects of technological progress are actually responsible for the modelled $LCOH_2$ decrease.

Aside from these methodological aspects, there is also a major practical challenge encountered in the TEA literature: techno-economic models are often implemented in custom environments (e.g. Excel sheets or programming scripts which are not publicly available) due to the lack of standardized tools. This leads to reduced transparency and hinders reproduction as well as comparison of literature results. It also creates overhead effort which goes into creation of these custom environments.

Given this backdrop, the present study has three major goals:

1. Creation of the pyH2A open-source software as a transparent and reproducible tool for techno-economic modelling. Partly based on the H2A model developed by the U.S. Department of Energy,[15] it allows for flexible modelling of various hydrogen production pathways.
2. Development of the Monte Carlo based development distance methodology to capture how technological progress affects the $LCOH_2$. Furthermore, this methodology can be used to determine which progress is required to reach cost-competitive hydrogen production. It is inspired by the previous use of Monte Carlo for uncertainty quantification,[6] and the use of contour plots to study how simultaneous change of multiple parameters impacts the $LCOH_2$.[14]
3. Application of this methodology to PV+E, PEC and PC, determining for each how much and which technological progress is needed produce hydrogen at a cost-competitive level. These insights are then used to derive actionable research targets for each technology.

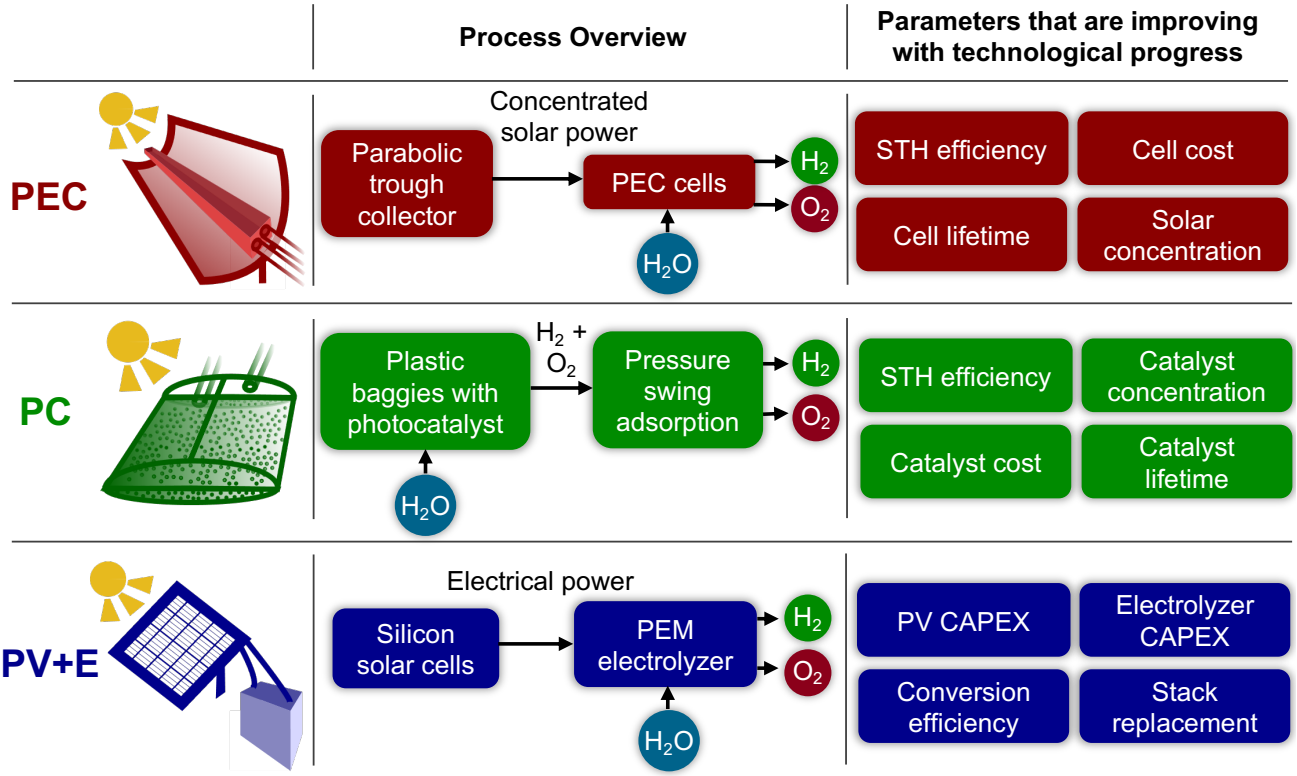

Figure 1 Overview of photovoltaic + electrolysis (PV+E), photoelectrochemical water splitting (PEC) and photocatalytic water splitting (PC) for green hydrogen production along with relevant parameters for technological progress. Abbreviations: "PEM" proton-exchange membrane, "CAPEX" capital expenditure, "STH" solar-to-hydrogen.

Methodology

pyH2A open-source software

pyH2A is an extensible framework for techno-economic analysis of hydrogen production, implemented in Python. It is open-source, with the source code available on GitHub (https://github.com/jschneidewind/pyH2A). Input parameters are provided in a plain text file and different technologies are modelled by invoking plugins. These feed information into the central discounted cash flow calculation, from which the $LCOH_2$ is obtained. Any given techno-economic model can be interfaced with various analysis modules to perform cost breakdown, sensitivity, waterfall or Monte Carlo analysis. A detailed description of the general pyH2A methodology is provided in SI Section 2.

Hydrogen production technologies

This study focuses on photophysical/photochemical technologies for converting solar energy and water to hydrogen, namely photovoltaic + electrolysis (PV+E), photoelectrochemical (PEC) and photocatalytic (PC) water splitting. There are other promising solar hydrogen production pathways, such as those based on thermal[16] or biological processes for water splitting[17] or by utilizing biomass as a feedstock.[18] While these routes are outside the scope of the present work, the described methodologies can also be applied to them.

For each selected technology, a hydrogen production plant with a design capacity of ca. 1 metric ton(H_2)/day was modelled over its entire lifetime, obtaining the $LCOH_2$. The financial input parameters shared by all models can be found in SI Section 6.2.

For photoelectrochemical (PEC) water splitting, hydrogen production is achieved by concentrating sunlight using parabolic trough collectors and focusing it on PEC cells, which are in a transparent enclosure with water. Irradiation of the PEC cells leads to hydrogen and oxygen production on opposites sides of cell, so that pure hydrogen can be obtained (see Figure 1, PEC). State-of-the-art properties of the PEC cells are based on devices by Kistler *et al.*[3] and Khan *et al.*[4] using a III-V absorber. The layout of the hydrogen production plant is based on Pinaud *et* al. (type 4 - PEC).[13] A detailed description of the process can be found In SI Section 5.1 and all input parameters are available in SI Section 6.5.

In photocatalytic (PC) water splitting, a particulate photocatalyst is mixed with water and placed in plastic baggie reactors, which are exposed to sunlight.[13,19,20] Action of the photocatalyst leads to production of a H_2/O_2 mixture, which is separated using pressure swing adsorption[13] to obtain pure hydrogen (see Figure 1, PC). The CDot/C_3N_4 photocatalyst reported by Liu *et al.*[5] is used as a state-of-the-art reference and the plant layout is based on the "type 1 – single bed" design described by Pinaud *et al.*[13] SI Section 4.1 contains a detailed process description and input parameters can be found in SI Section 6.4.

Coupling of silicon solar cells with an off-grid proton-exchange membrane (PEM) electrolyzer is the basis for photovoltaic + electrolysis (PV+E). Electrical power from the solar cells is fed to the electrolyzer to produce pure hydrogen from water (see Figure 1, PV+E). The plant model is based on the one reported by Yates *et al.*[6] A process description can be found in SI Section 3.1 and input parameters in SI Section 6.3.

Monte Carlo/development distance methodology

The aim of the Monte Carlo/development methodology is to model how simultaneous progress for multiple parameters of a technology affects the $LCOH_2$. For a given technology, this is accomplished in four steps (see also SI Section 2.4.4):

1. Selection of parameters that improve with technological progress (selected parameters are shown for each technology in Figure 1). For every parameter, a base value, which represents the state-of-the-art, is defined. Furthermore, a limit value is defined, which represents the limit which can possibly be achieved with future progress.
2. A large number (in this case 50,000) of random parameter value combinations are generated. Each parameter value is within its [base, limit] interval. This leads to 50,000 different models, each with random values for the selected parameters.
3. For each model, the normalized distance of its parameter values to the base case is calculated. "Base case" means that all parameter values are equal to their base values (normalized distance is 0), while "limit case" means that all parameter values are equal to their limit value (normalized distance is 1). Details on the distance calculation can be found in SI Section 2.4.4.1. This metric is herein referred to as "development distance", since it is an indicator for the amount of technological development that is represented by a given model.
4. The full discounted cashflow calculation is performed for every model to obtain the corresponding $LCOH_2$.

With this methodology, a dataset of 50,000 models for every technology is obtained. Each model has a unique combination of parameter values, an associated development distance and $LCOH_2$.

Together, the datapoints map the entire trajectory from the state-of-the-art (base case) to future technologies (limit case). The Monte Carlo/development distance methodology is implemented in pyH2A.

The tables in Figure 2 show the base and limit values for the selected parameters of each technology. For PEC the parameters are: STH efficiency, solar concentration factor, cell cost ($/m^2(PEC cell)) and cell lifetime (in years). For PC, catalyst concentration (g(Catalyst)/L), catalyst cost ($/kg(Catalyst)), STH efficiency and catalyst lifetime (in years) were selected. Selected PV+E parameters are: PV CAPEX ($/kW(PV)), electrolyzer CAPEX ($/kW(Electrolyzer)), conversion efficiency (kg(H_2)/kWh(Electricity)) and stack replacement cost (as a fraction of electrolyzer CAPEX). In the SI, sources/rationales for each selected base/limit value can be found (PEC: SI Section 5.1.4, PC: SI Section 4.1.4, PV+E: SI Section 3.1.3).

Limitations

There are several limitations for the methodology employed in this study:

1. The limit values for the Monte Carlo/development distance modelling must be assumed since it is not possible to know which parameters values will actually be achieved in the future. The choice of limit values affects the development distance: choosing very optimistic limit values, for example, makes models with intermediate values appear at shorter development distances. This means that comparing the development distance values for different technologies is only valid if the limit values for each are equally "difficult" to achieve. As this notion is challenging to quantify, the development distance should always be seen in the context of the underlying base and limit values, especially when comparing technologies. Importantly, however, the choice of limit values does not affect the analysis of the required parameter values to achieve a given cost target. In this case, the limit values only determine which part of the parameter space is explored.
2. The present models only calculate the cost of hydrogen production, thus the cost for transport of storage is not considered.

3. For all calculations, the plant size (1 metric ton H_2/day) and location (Dagget, CA, USA) are fixed. Hence, scaling and geographical effects on the $LCOH_2$ are not considered.
4. In this study, only a cost analysis of hydrogen production is performed. Other important aspects, such as modelling of life-cycle greenhouse gas emissions[21] and net energy analysis[22] are not included.

Results and Discussion

Development distance and $LCOH_2$

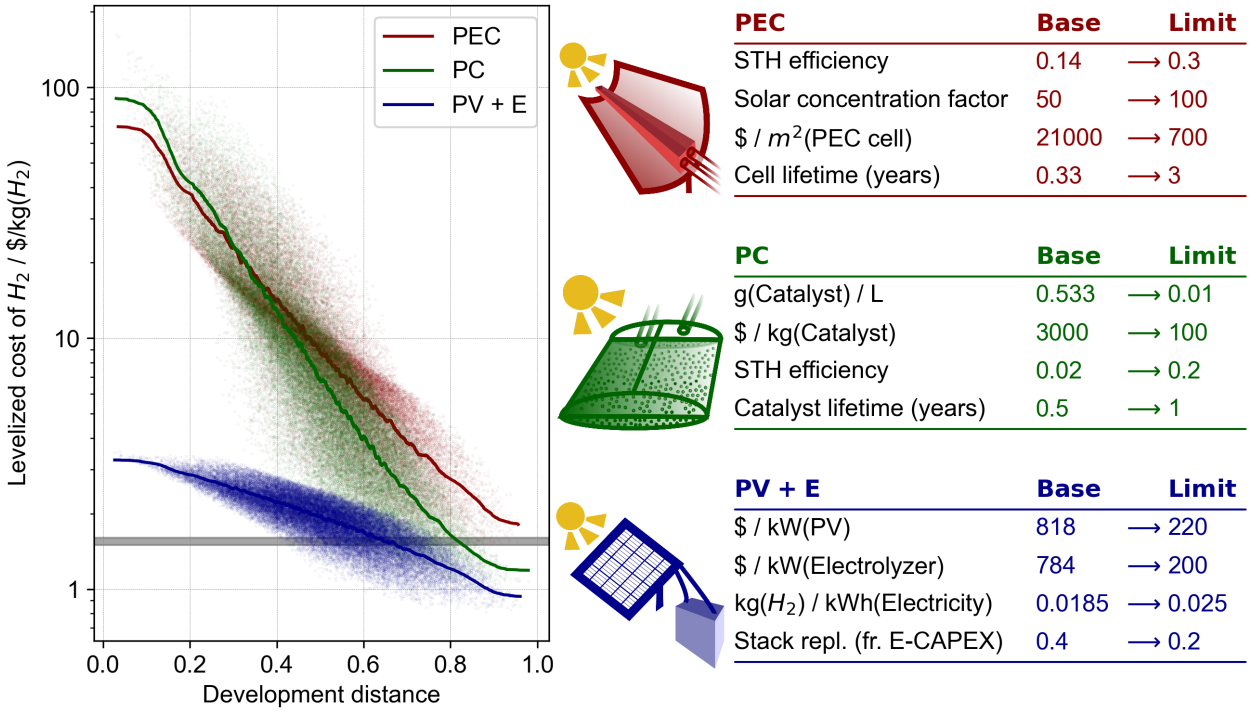

Figure 2 Relationship of development distance and $LCOH_2$ (log scale) for PEC, PC and PV+E. The grey bar indicates the target cost range (1.5 – 1.6 \$/kg(H_2)). Savitzky-Golay smoothed trendlines are shown as solid lines. For each technology, parameters that constitute the respective development distance are shown on the right, along with their base and limit values. For details see SI Section 2.4.4.2. "Stack repl. (fr. E-CAPEX)" stands for "Stack replacement cost (fraction of electrolyzer CAPEX)".

The relationship between development distance and $LCOH_2$ provides an overview of technological progress' impact on hydrogen cost. Figure 2 plots the development distance of each random model against its associated $LCOH_2$, along with a smoothed Savitzky-Golay trendline for each technology. The shown data reflects the entire trajectory from the current state-of-the-art (base case, development distance of 0) to the limit technologies (development distance of 1).

PEC and PC have a very high $LCOH_2$ for the base case in excess of 100 \$/kg(H_2). However, the $LCOH_2$ for both drops exponentially with increasing development distance, as indicated by the linear trend in the logarithmic plot. Such an exponential decrease points at a strong interaction between the selected parameters, leading to multiplicative effects. In case of PC, for example, improving both the

206 STH efficiency and catalyst concentration produces a multiplicative cost reduction. It can also be
207 seen that the $LCOH_2$ decreases more steeply for PC compared to PEC.
208 PV+E has a much lower $LCOH_2$ of around 3.6 \$/kg(H_2) for the base case. Increasing development
209 distance, however, leads only to a roughly linear cost reduction (sublinear in logarithmic plot),
210 indicative of weak interactions between selected parameters. In contrast to PEC and PC, parameter
211 improvements (such as PV or electrolyzer CAPEX reductions) are largely independent of one
212 another and do not produce multiplicative effects.

213 **Models in the target cost range**

214 To be cost-competitive on the global market, solar hydrogen has to reach the cost range of hydrogen
215 derived from steam methane reforming (SMR), which is currently the dominant hydrogen production
216 route.[9] SMR hydrogen is produced at costs ranging from 1-2 \$/kg(H_2).[9] For this study, we
217 therefore defined the target cost range for cost-competitiveness as 1.5-1.6 \$/kg(H_2), which is
218 indicated as a grey bar in Figure 2. It can be seen that PV+E crosses into the target cost range at the
219 shortest development distance. PC also reaches it at somewhat longer distances while PEC seems to
220 mostly level off above it. To gain insight into the requirements for cost-competitiveness, we turn to
221 a more detailed analysis of the models for each technology that fall into the target cost range.
222 Figure 3 shows the development distance distribution of all models with a $LCOH_2$ in the target cost
223 range. From this analysis, we can obtain the mean development distances that are required to achieve
224 cost-competitiveness. As already indicated by Figure 2, PEC displays the longest mean development
225 distance (0.86, standard deviation: 0.043) and only a very small number of models actually reach the
226 target cost range (low frequency values on the y axis). The high mean development distance means
227 that almost all potential for technological improvement has to be exhausted in order to produce
228 hydrogen at the defined target cost. PC shows a significantly shorter mean development distance of
229 0.72 with a relatively broad distribution of models from 0.5 to 0.85 (standard deviation: 0.076). This
230 implies that, while a significant amount of progress is required, the target cost can be achieved
231 without having to use all of the innovation potential. In case of PV+E, the shortest mean

development distance of 0.61 is observed with an equally broad distribution compared to PC (standard deviation: 0.080). Within the assumptions of this study, the shortest mean development distance indicates that PV+E requires the least amount of technological progress to reach cost-competitiveness.

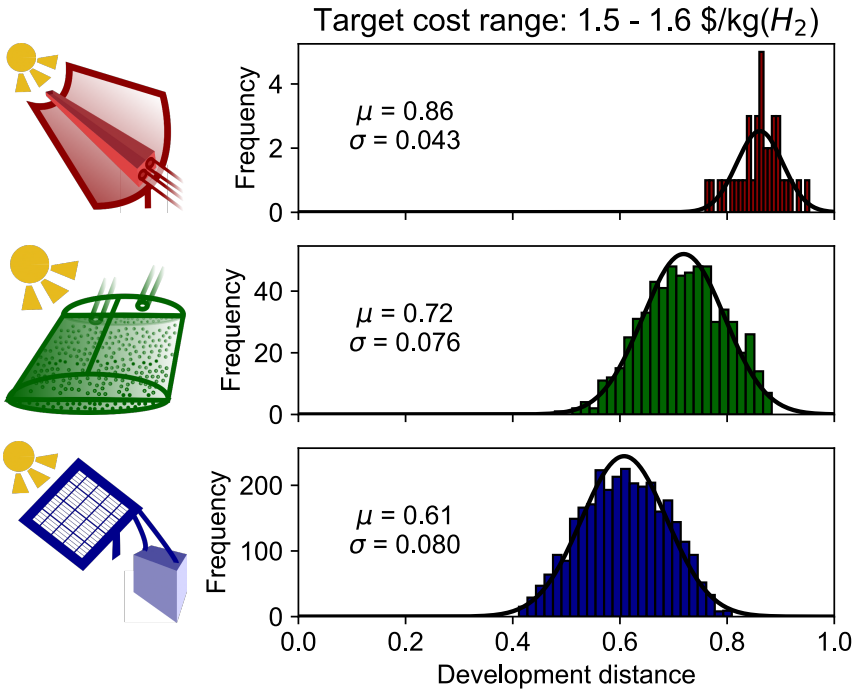

Figure 3 Histograms showing development distance distribution of models within the target cost range for each technology (top: PEC, middle: PC, bottom: PV+E). A fitted and scaled normal distribution is shown for each histogram (black line), with the corresponding mean (μ) and standard deviation (σ) shown as inlets. For details, see SI Section 2.4.4.3.

Required progress and research targets

Analysis of the development distances provides on the overall picture of (required) technological progress. To derive actionable insight, especially for informing research and development efforts, it is important to understand how much the underlying technological properties have to advance to achieve cost-competitive hydrogen production. To this end we can analyze the specific parameter values of models which reach the target cost range. In the following, the corresponding data will be visualized using colored scatter plots: each model with an $LCOH_2$ in the target cost range is shown as a colored dot, with its (x, y) position and color determined by its parameter values (the fourth

parameter which has been varied in the Monte Carlo simulation is not shown). For reference, the base case is also shown as a labelled and colored dot. From this visualization we can see which combinations of parameter values give rise to models with cost-competitive hydrogen production.

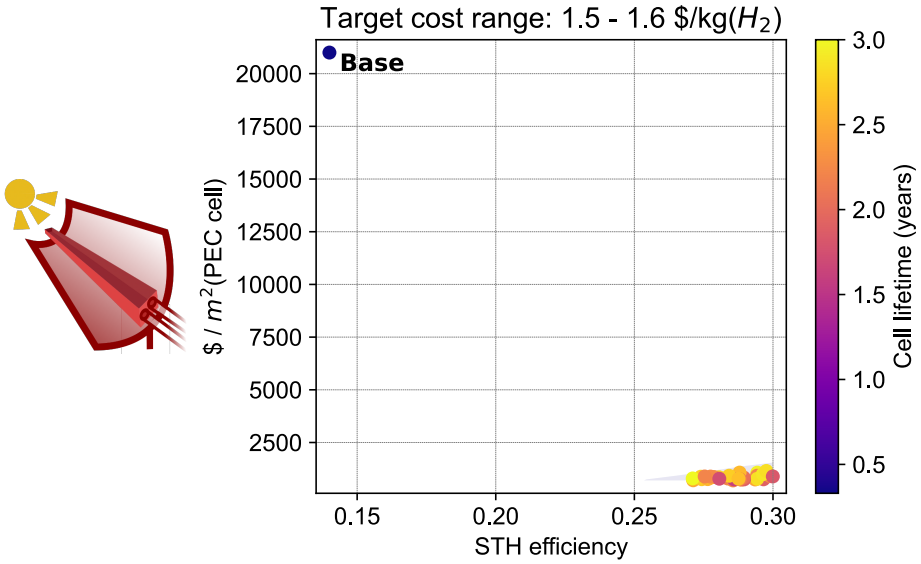

Figure 4 Colored scatter plot showing parameter values of PEC models within target cost range. For reference, the base case is shown in the top left. Light blue area illustrates largest possible region in which models can lie (for details see SI Section 2.4.4.4).

Figure 4 shows the colored scatter plot for PEC. Only a very small region of the parameter space gives rise to models in the target cost range, with this region being at the maximum distance from the base case. STH efficiency has to exceed 26%, cell cost has to be below 1500 $/m^2(PEC Cell) and cell lifetime has to exceed 2 years. The central challenge for PEC is that the PEC cells are the most expensive component of the plant for most models (see cost breakdown in SI Figure 5.2-2), but also have a short lifetime (especially compared to solar cells and electrolyzers).[23] This is because various components of the cell are exposed to a reactive chemical environment.[3] Since PEC cells are by definition highly integrated devices, most components have to be replaced together at the end of their lifetime, leading to high replacement costs (see SI Figure 5.2-1) and thus a high $LCOH_2$. Based on our results, only a combination of high efficiency (small area of cells needed for a given H_2 production), low cost and long lifetime can overcome these challenges to reach the target cost range.

It should also be noted that solar concentration is very likely necessary for low-cost H_2 production using PEC: modelling PEC without solar concentration shows that even for the limit case, $LCOH_2$ does not drop below 15 \$/kg(H_2) (see SI Section 5.4). Solar concentrators will likely be significantly cheaper than PEC cells (per m^2) for the foreseeable future. Hence, replacing PEC cell area with solar concentrator area enables effective cost reduction.[24] In the limit case, however, solar concentrator cost actually becomes the dominant factor in PEC CAPEX (see SI Figure 5.3-2). With respect to research targets these results imply the following: the lifetime of PEC cells has to be significantly improved (reaching on the order of years) to address the high costs resulting from regular replacements. Furthermore, PEC cells should be optimized to operate under high solar concentration factors (> 50) to reduce the required cell area. This implies that highly active PEC materials (absorbers and electrocatalysts) are required which have a sufficient space-time yield to convert the high incoming energy flux (peak activity likely has to exceed 400 mol H_2 h^{-1} m^{-2}(PEC cell)). It is uncertain if such progress is realistically achievable, especially to allow PEC to compete with PV+E (see below).

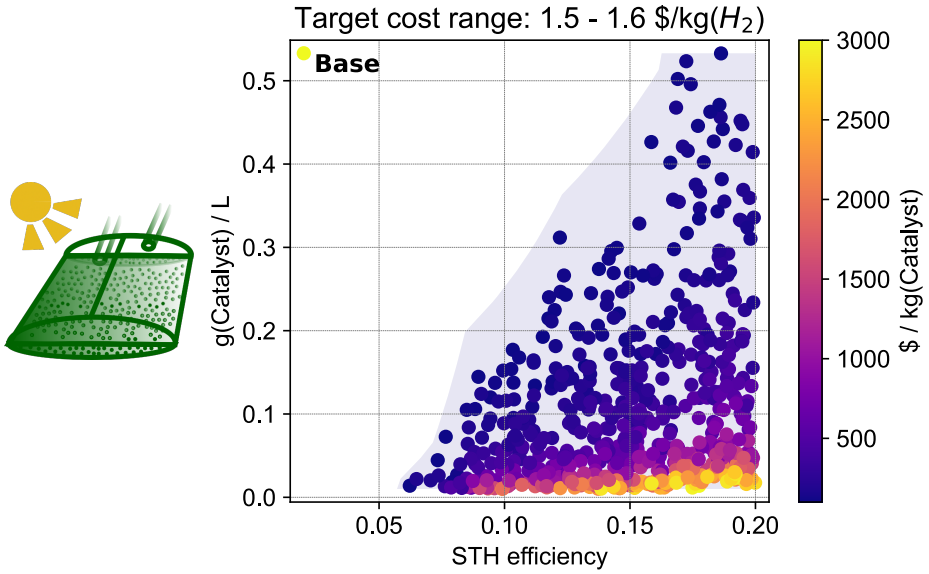

Figure 5 Colored scatter plot showing parameter values of PC models within target cost range. For reference, the base case is shown in the top left. Light blue area illustrates largest possible region in which models can lie (for details see SI Section 2.4.4.4).

For PC, a much larger region of the parameter space gives rise to models in the target cost range (see Figure 5). For cost-competitive hydrogen production, STH efficiency has to be at least 6%. Catalyst concentration can be as high as 0.5 g(Catalyst)/L, but concentrations below 0.2 g(Catalyst)/L open up much more flexibility with regards to efficiency and cost. For most cases, catalyst cost has to be below 1000 $/kg(Catalyst), except when the catalyst concentration is very low (< 0.05 g(Catalyst)/L). In all cases, the catalyst lifetime is relatively short (between 0.5 and 1 year), which necessitates regular catalyst replacements. In contrast to PEC, however, replacing the catalyst is straightforward because no other components have to be replaced with it: it can be removed from the water/catalyst mixture (e.g. by nanofiltration[25]) and new catalyst is added. Looking at research targets, this data suggests that it is crucial to lower the catalyst concentration. Systems with low catalyst concentrations can tolerate lower STH efficiencies and higher catalyst costs, while reduction of the catalyst amount also reduces resource consumption for catalyst production. To achieve lower catalyst concentrations the main consideration is the absorption behavior of the photocatalyst: it needs to have a sufficiently high absorption cross section so that most sunlight is still absorbed even when lower concentrations are employed. The demands for catalytic activity are less stringent to enable low catalyst concentrations. Even for the limit case (highest efficiency, lowest concentration), peak catalytic activity does not have to exceed 7 mol H_2 g^{-1} h^{-1} (activities on the order of 1 mol H_2 g^{-1} h^{-1} have already been achieved[26]), which corresponds to a turnover frequency of < 1 s^{-1} for a homogeneous catalyst (assuming a molar mass of 500 g/mol). Hence, light absorption performance is likely more important than highly active catalytic sites for H_2 and O_2 evolution. To identify effective paths to a cost-competitive system, it insightful to look at the parameter values of the model with the shortest development distance that reaches the target cost range: with a distance of 0.48, this model has a STH efficiency of 17.5%, catalyst concentration of 0.01 g(Catalyst)/L, catalyst cost of 2950 $/kg(Catalyst) and catalyst lifetime of 0.52 years. Hence, high catalyst cost and low lifetime can be tolerated through the combination of high STH efficiency and low catalyst concentration. These characteristics point to the potential of homogenous photocatalysts, which can be used at low

concentrations due to high molar absorptivity.[27] Furthermore, it was recently shown that it is theoretically possible for homogeneous photocatalysts to achieve dual absorber STH efficiencies (> 20%) with a single catalyst.[28] With progress on catalyst concentration and STH efficiency, there is a pathway for PC to cost-competitive hydrogen production. Due to the simple plastic baggie reactor construction, this approach has a low CAPEX (but rather high OPEX due to catalyst replacements, see SI Figures 4.2-1 and 4.3-1), which is complementary to PV+E (high CAPEX, low OPEX, see SI Figure 3.2-1) and could allow for easier construction of new plants. Safety issues due to generation of a H_2/O_2 mixture in the reactors have to be considered, but these risks were found to be manageable.[29]

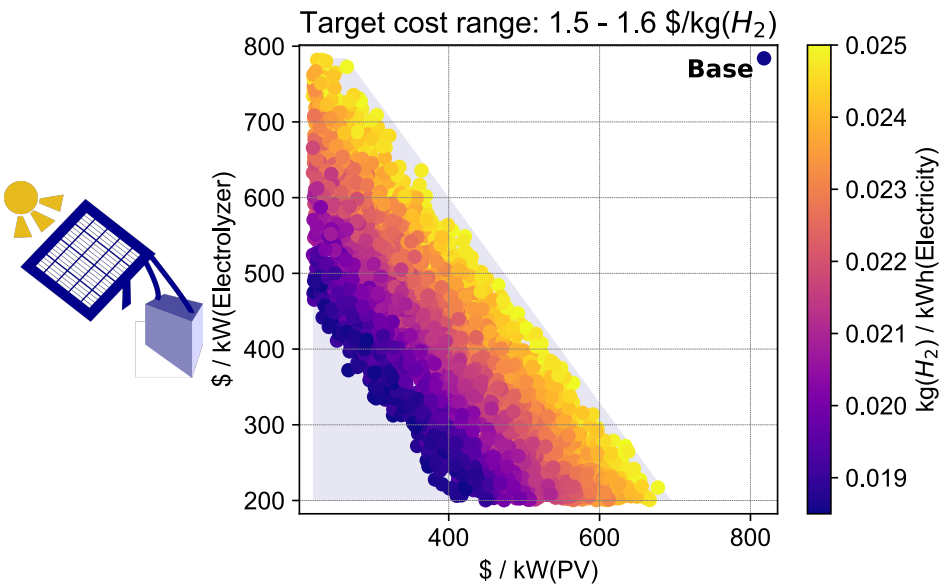

Figure 6 Colored scatter plot showing parameter values of PV+E models within target cost range. For reference, the base case is shown in the top right. Light blue area illustrates largest possible region in which models can lie (for details see SI Section 2.4.4.4).

PV+E shows a well-defined region of the parameter space that gives rise to models with an $LCOH_2$ in the target cost range (Figure 6). The symmetry and gradients indicate that each parameter (PV CAPEX, electrolyzer CAPEX, conversion efficiency) has a roughly linear effect on $LCOH_2$ and there are no significant interactions between parameters (which was also shown by the linear development distance/$LCOH_2$ relationship). To reach the target cost range, PV CAPEX has to be

below 650 $/kW(PV) and electrolyzer CAPEX can be as high as 800 $/kW(Electrolyzer) but only if the conversion efficiency approaches the theoretical maximum of 0.025 kg(H_2/kWh(Electricity).[6] Improving the conversion efficiency in general opens up possibilities to tolerate higher PV and electrolyzer CAPEX. However, the model with shortest development distance in the target cost range (distance of 0.41) has the base case conversion efficiency and stack replacement cost (0.0185 kg(H_2)/kWh(Electricity) and 40% of electrolyzer CAPEX), PV CAPEX of 300 $/kW(PV) and electrolyzer CAPEX of 330 $/kW(Electrolyzer). Hence, even without other improvements, it is possible to enable hydrogen production at the target cost by reducing PV and electrolyzer CAPEX 2 or 3-fold each. The implication for research and development targets is that cost reductions are key, and efficiency improvements are not strictly necessary but open up possibilities to enable cost-competitive H_2 production even with more expensive components.

Conclusion

In summary, an open-source tool for transparent and reproducible techno-economic modelling of hydrogen production, called pyH2A, has been developed. Using pyH2A, a novel Monte Carlo-based methodology was conceived and implemented, which enables the study of how technological progress impacts the $LCOH_2$ using the concept of "development distance". With this methodology it also possible to dissect the influence of specific technological parameters and determine how much each has to advance to reach a defined target cost range.

The Monte Caro/development distance method was then applied to the study of three solar hydrogen production routes: photoelectrochemical (PEC) and photocatalytic (PC) water splitting as well as photovoltaic + electrolysis (PV+E). For each, it was determined how much and which technological progress is needed to produce hydrogen at a cost level of 1.5-1.6 \$/kg(H_2) and the results were used to derive appropriate research targets.

For PEC, significant progress with respect to STH efficiency (> 26%) and PEC cell stability is required, as lifetimes of at least 2 years are needed to alleviate the high costs resulting from cell replacements. Furthermore, solar concentration is a crucial component to enable low-cost hydrogen production using PEC and cells should be optimized to operate with high solar concentration factors (> 50), necessitating highly absorbent semiconductors and highly active electrocatalysts.

For PC, STH efficiency has to exceed 6% and it is important to lower the catalyst concentration (< 0.2 g(Catalyst)/L) by developing catalysts with large absorption cross sections. With a sufficiently high STH efficiency and low catalysts concentration, high catalyst cost (> 2000 \$/kg(Catalyst)) and a short lifetime (ca. 0.5 years) can be tolerated, pointing towards the potential utility of homogeneous photocatalysts. Improvements of the photocatalyst open a path to cost-competitive H_2 production using PC, which could be a complementary technology to PV+E due to the low CAPEX of the plastic baggie reactor construction.

For PV+E, CAPEX reductions for both the photovoltaic and electrolyzer components are needed. The target cost can be reached by a 2 or 3-fold cost reduction for each (300 \$/kW(PV) and 330

366 $/kW(Electrolyzer) even without other technological improvements. Increasing the conversion
367 efficiency, however, opens up more flexibility for the cost of PV and electrolyzer systems.
368 It is our hope that these techno-economic insights inform materials research in the area of solar
369 hydrogen production, so that research efforts can be directed to improve these technologies in the
370 most impactful ways. Ultimately, these efforts will hopefully allow us to transition solar hydrogen
371 into large scale applications, providing affordable green hydrogen on a global scale.

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Author contributions: J. S. conceived and coordinated the project, developed the software, performed techno-economic modelling and data analysis, wrote the manuscript and curated the results for the supporting information and public repository.

Data availability: Original data supporting the results of this study is available at: https://github.com/jschneidewind/pyH2A

Code availability: Code developed for this study is available at: https://github.com/jschneidewind/pyH2A

Competing interests: The author has no competing interests.

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Supplementary Materials

Methods and Parameters

SI Figures 3.1-1 to 5.4-3

SI Tables 2.4-1 to 6.1-1

Original data and code: https://github.com/jschneidewind/pyH2A

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