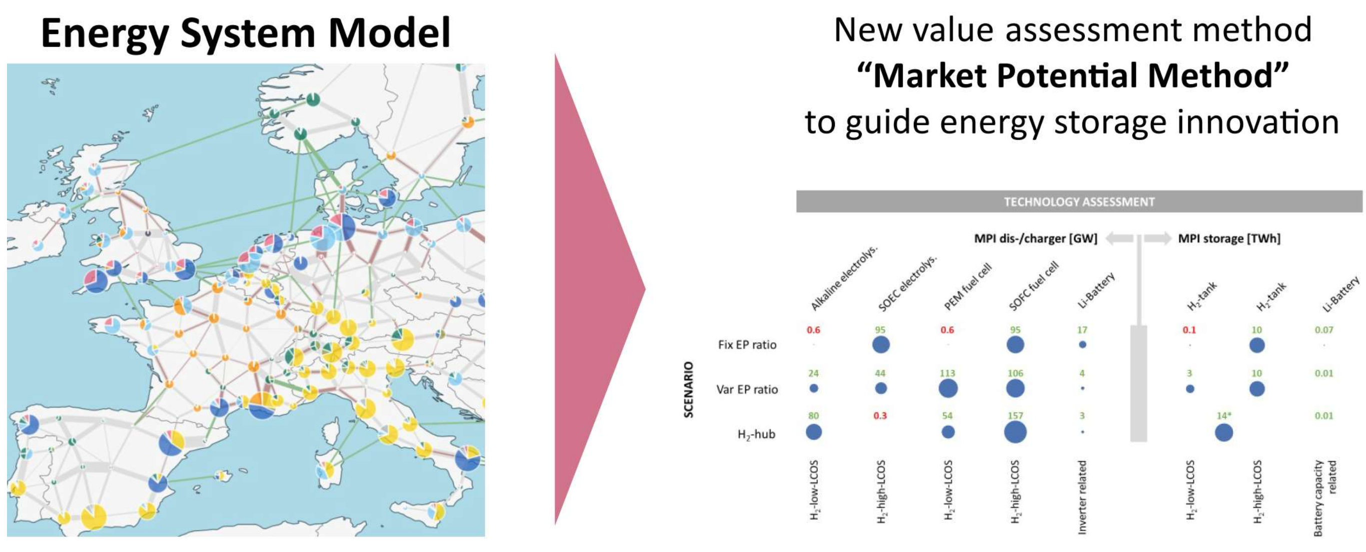
Graphical Abstract

Beyond cost reduction: Improving the value of energy storage in electricity systems.

Maximilian Parzen[1,*], Fabian Neumann[2], Addrian H. Van Der Weijde[1], Daniel Friedrich[1], Aristides Kiprakis[1]



Highlights

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- Review of evaluation methods for energy storage identifies need for new approaches.
- Pitfalls of cost approaches are identified in an European electricity system.
- Formulation of new 'market-potential method' to identify value of storage.
- Increasing storage design-freedom impacts technology value and system benefit.
- The 'market-potential-method' is useful for research and industry.

Beyond cost reduction: Improving the value of energy storage in electricity systems.

Maximilian Parzen[1,*], Fabian Neumann[2], Addrian H. Van Der Weijde[1], Daniel Friedrich[1], Aristides Kiprakis[1]

[1] *University of Edinburgh, Institute for Energy Systems, EH9 3DW Edinburgh, United Kingdom*
[2] *Karlsruhe Institute of Technology (KIT), Institute for Automation and Applied Informatics, Karlsruhe, Germany*
**Corresponding author email: max.parzen@ed.ac.uk*

Abstract

An energy storage technology is valuable if it makes energy systems cheaper. Traditional ways to improve storage technologies are to reduce their costs; however, the cheapest energy storage is not always the most valuable in energy systems. This paper reviews techno-economic storage valuation methods and expands them by the introduced 'market potential method'. The market potential method derives the value of technologies by examining common deployment signals from energy system model outputs in a structured way. We apply and compare this method to cost evaluation approaches in a renewables-based European power system model, covering diverse energy storage technologies. We find that characteristics of high-cost hydrogen storage can be equally or even more valuable than low-cost hydrogen storage. Additionally, we show that modifying the freedom of storage sizing and component interactions can make the energy system 10% cheaper and impact the value of technologies. The results suggest to look beyond the pure cost reduction paradigm and focus on developing technologies with value approaches that can lead to cheaper electricity systems in future. One practical and useful value method guiding energy storage innovation could be the 'market potential method'.

Keywords: Energy storage, Energy system modelling, Techno-economic analysis, Hydrogen, Battery, Technology development

1. Introduction

In the face of global ambitions to reduce greenhouse gas (GHG) emissions, the energy transition characterised by increasing shares of wind and solar power will benefit from more energy storage in the future electricity system [1–3]. How many benefits can be delivered depends, among others, on how future technology will be designed. Consequently, research and development (R&D) must adapt the techno-economic design of energy storage systems to be most beneficial.

A traditional approach to improve energy storage design is to reduce the cost of its devices [4]. The cost can be absolute in €or relative defined. The latter is typically related to energy (€/kWh) and power (€/kW) quantities. In particular, in the material science and chemistry literature, cost reductions of energy storage are a pivotal element, alongside maintaining other storage characteristics such as a 'sufficient' high efficiency, power and energy density, and safety [5, 6]. Though, what is 'sufficient' high is often unclear. Only if one energy storage outperforms the other in all characteristics one can define it as superior technology; otherwise, more expensive energy storage with suitable technical characteristics can compete as well (as will be demonstrated in Section 4). Fortunately, material science literature has recognised one of the key challenges that energy storage depends on different applications and the interaction with the energy system [7].

Alternatives to cost reduction approaches are approaches that maximise profits and whole system benefits (see Section 2). However, none of them focus on what probably matters the most: designing technologies that more likely reduces the average electricity bill.

This study aims to close this research gap by introducing a method which fundamental objective is to reduce the average electricity bill. A key economic metric in this context are total system costs. Only if we can achieve a total system cost reduction in reality, it is possible to reduce the average electricity bill, freeing up money for alternative investments that could be used to increase social welfare. Tools that aim total system cost reductions are energy system models which are applied in this study. These models can minimise investment and operational costs in the whole energy system and therefore be complementary used to guide technology design such as for energy storage.

The scope in this study regarding the energy storage value is limited. In general, energy storage systems can provide value to the energy system by reducing its total system cost; and by reducing risk for any investment and operation. This paper discusses total system cost reduction in an idealised model without considering risks. Reducing risk in a real power system can be seen as option value [2] leading to a more optimal investment and operation. Further, included are only energy balance benefits within a European power system model. Sacrificing subhourly signals relevant to address grid stability benefits, but including hourly up to seasonal arbitrage based scarcity signals relevant to address short and long-term balancing benefits (described in Section 3.3).

The paper distinguishes from and contributes to existing literature in the following way:

- We review and discuss techno-economic approaches that are currently used to evaluate and compare energy storage technology in Section 2. Included are cost, profit and system-values analysis.

- We show that current cost metrics can be misleading for technology design decisions. Section 4.2 and 4.3 show that a high levelised cost of storage (LCOS) hydrogen storage can be equally or even more valuable than a low LCOS one from the system perspective. We draw this conclusion by observing deployment of low and high LCOS hydrogen storage systems in a least-cost power system investment planning model.

- We extend the system-value approaches by the newly developed 'market potential method' in Section 3.1. It is further applied and discussed in Section 4. The method analyse common deployment estimations from energy models in a systematic way by looking on a set of probable scenarios in high spatial-temporal resolution over large regions such as Europe. Compared to existing alternatives that are described in Section 2, the new approach could be potentially more useful and overcomes many limitations. Research and industry could complementary apply the new approach to guide energy storage innovation.

- We show that modifying the freedom of storage sizing and component interactions can lead to significant energy system benefits (Section 4.1) and impact the system-value of a technology (Section 4.3). It underlines the impact of developing and offering adaptive components, such as charger, storage and discharger, separately instead of complete storage systems.

Our findings suggest that a narrow cost focus on designing energy storage is not enough. Future R&D design decisions should additionally use system-value insights from energy system models. The presented market potential method could be one approach to accomplish this.

2. Review on Storage Valuation Methods

This section reviews and classifies currently applied storage valuation methods, or in other words, techno-economic analysis approaches which appraise the competitiveness of energy storage including both, technicalities and economic measures.

This study classifies the literature into three groups: cost analysis, profit analysis and system-value analysis, which mainly differ in the objective of the metrics. Figure 1 summaries what components will be discussed. These methods are broadly employed for industry decision making, research focus consolidations and policy regulation [2, 8, 9], which underlines their importance and the impact of any improvement.

To understand the 'visible' and 'hidden' value terminology chosen to classify the literature, one should acknowledge that current markets can be considered imperfect and incomplete for multiple reasons:

- Markets are not temporally or spatially resolved. For instance, spot prices are settled over larger spatial areas and not in real-time, leading to not perfect spatial dissolved socialised grid fees [10].

- Market power can be exploited. Dominant market participants act for their profit while damaging the average participant [10].

- Forecast information are imperfect. Forecasts of demand, wind and solar generation underlies uncertainties leading to imperfect operation and planning [10].

- Other negative and positive externalities exist, related to incomplete markets which distort the price. Negative externalities are for instance, non-priced cost for carbon emission, air pollution and biodiversity losses; positive externalities are non-priced benefits such non-tracked carbon reduction benefits [10].

In this context, system-value analysis generally tends to analyse markets by partially or entirely reducing these market flaws. For instance, energy system models can cover higher spatial and temporal resolution, exclude market power, assume perfect foresight and account for externalities. However, not all models idealise. Some can also incorporate effects of imperfect and incomplete markets by adding cost and benefits related to uncertainty and non-optimal operation and investment [11–13].

'Visible values' are simply said benefits that can be priced or accounted for in real world imperfect and incomplete market such used for profit analysis. In contrast, 'hidden values' are benefits that are not yet priced or accounted for in real world markets. An example are hidden energy storage benefits for network or peak plant deferral, or reduced solar and wind power plant curtailments [14]. To track both hidden and visible values, system-value approaches use idealised models assuming perfect and complete markets.

The next subsections will clarify for each techno-economic analysis class their objectives, methods and users, and further, analyse the grade of technical detail and how the approaches handle the role of competition in uncertain future markets.

2.1. Cost analysis

We categorise the cost analysis of energy storage into two groups based on the methodology used: while one solely estimates the cost of storage components or systems, the other additionally considers the charging cost, such as the levelised cost approaches. Their objective is in general to minimise the cost metric for a particular technology or application.

An example of the first approach is represented in [15]. The energy weighted cost of a storage system (£/kWh) is minimised, without any electricity price signal, by a cost optimisation model that simultaneously maximise the round-trip efficiency of the storage. In [16, 17], instead of assuming the cost of components, they break down storage components or systems into materials and manufacturing processes. This methodology, known as process-based cost analysis, allows a deeper

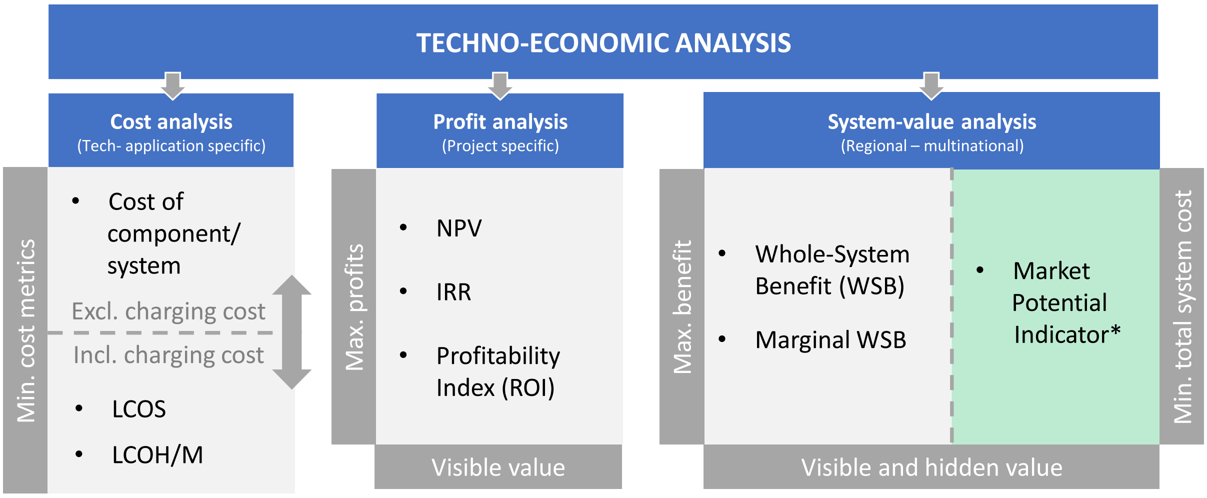

Figure 1: Classification of current techno-economic analysis methods in the context of energy storage. *Market potential indicator is a suggested decision metric and part of the new introduced market potential method. The abbreviation mean the following: levelised cost of storage (LCOS), levelised cost of hydrogen or methan (LCOH/M), net present value (NPV), internal rate of return (IRR), return of investment (ROI).

understanding of cost reductions by mass production or switching to different manufacturing methods. While both approaches do not mention competitiveness or the value of energy storage, their outputs combined with cost and benefit analysis allows finding the value of energy storage solutions.

The levelised cost approaches for energy storage include metrics such levelised cost of storage when electricity is discharged (LCOS) and LCOH or LCOM when hydrogen or methane are discharged respectively [8, 18]. All the levelised cost metrics above are similarly structured. They divide the total cost of the considered system by the discharged energy. Both parameters must be discounted to represent the time value of money [19]. We use LCOX in the following equation to indicate that the equation holds for various discharged energy forms:

$$\mathrm{LCOX} = \frac{(\sum_0^T \text{Total cost})_{Discounted}}{(\sum_0^T \text{Total discharged energy})_{Discounted}} \tag{1}$$

Thereby, the total cost typically consists of capital expenditures, operational expenditures and charging expenditures [20–22]. Sometimes additional factors are included that can impact total cost and total discharged energy such as degradation rates, taxes, or self-discharging [8].

Levelised cost like metrics are used to evaluate many applications, such as energy arbitrage, frequency regulation, voltage regulation, system restoration and operational management (i.e. redispatch). For this purpose the levelised cost like metrics assumptions must be categorised for the specific application, such charging price, operational time and power to energy ratio [8, 22].

While the 'cost of component' or 'cost of system' approach is widely used for design decisions with high technological detail [15–17], the levelised approaches forego some technological detail to inform project developer and policy about their projected competitiveness in the market [8].

Cost of component or system metrics are excellent for exploring cost reduction opportunities in great technical detail. On the other hand, LCOS-like metrics differ by being a good first indicator for the competitiveness between various technologies for a particular application.

However, the main limitation of cost-analysis methods is that cost reductions can be only a clear signal for technology improvement under the condition that the other characteristics such as efficiency and cost of each components stay at least the same or even improve. Because this lead to what we define as valuable technology. One technology that lead to total system rather than single technology cost reductions. As example, an energy storage only clearly improves if the cost reduces at least for one component such as charger, store or discharger, while the other component costs and efficiencies are not negatively influenced or even benefit. If this is not the case, a complex solution space exist for which a higher cost energy storage can lead to lower total system cost - being more valuable, see Section 4.

2.2. *Profit analysis*

The profit analysis describes methods from the investor's perspective. They tend to choose profitable energy storage projects at current energy market designs [23, 24]. Thereby, the general objective for the investor is to maximise the profit indicator for a given investment.

The inclusion of discharging behaviour and revenue streams are distinctive for profit analysis. Depending on the market design, several different revenue streams for energy storage exist. In the UK, for instance, 14 potential revenue streams exist, such as frequency response provision or wholesale market arbitrage, which can be power (€/kW) or energy (€/kWh) related [25]. In general, not every storage has access to the same revenue streams due to specific characteristics and requirements

[8]. Most studies include only the energy arbitrage service from energy storage, which means buying cheap electricity and selling it later more expensive [26]. Other studies co-optimise multiple energy services which result in higher benefits [26–28].

The profit analysis typically evaluates energy storage projects with capital budgeting techniques based on discounted cash flow methods to acknowledge the time value of money [19]. The energy storage literature uses multiple project assessment metrics: present value (PV) is employed to calculate the feasible cost of a storage project [23], net present value (NPV) to evaluate the profitability of a project [14, 29], and internal rate of return (IRR) to determine at which discount rate or opportunity cost a project is viable [26, 30]. NPV and IRR are good investor signals when investment capital can be accessed easily. However, when investment capital is limited, projects should be evaluated by a profitability index, which relates the discounted benefits to the cost [19]. Many energy storage studies, therefore, investigate energy storage by the profitability index [19], which is also termed cost-benefit ratio [31, 32], NPV-ratio [33], return of investment (ROI) [34], return on equity (ROE) [24], all giving the signal of how much money can be achieved per investment. Another common metric in context of energy storage is the payback period [30, 35, 36], which [19] judges to be an illustrative but not useful factor for investment decisions. Finally, when multiple energy storage technologies with different lifetimes are evaluated and compared, such as in [29, 32, 36], an equivalent annual annuity metric is recommended [19]. For instance, one could break down the NPV to an equivalent annual annuity where the highest annuity is the preferable project.

The main limitation of the profit analysis is that it misses the 'hidden' or wider power system cost and benefits of energy storage. Because it only focuses on the 'visible' cost and benefits at the current market design. Future energy markets might internalise 'hidden' benefits, such evident by market design efforts to address the previously hidden greenhouse gas emission costs. Hidden cost and benefits are, for instance, savings due to investment deferral of network upgrades or peak plants, or when fewer curtailments increase the value of renewable generators [37]. Employing a hybrid method of profit and system-value analysis, the authors in [14] added social or 'hidden' benefits to the NPV metrics, which are not directly accounted for in the market design. This lead to a higher value of energy storage solutions. The drawback of the approach is that many assumptions are made and added exogenously to the NPV characteristics ignoring the spatial and temporal heterogeneity of the hidden cost and benefits. What may be a good assumption at one location at a specific time must not be the case at another location at the same or another time. Including these variables endogenously, as some energy system models do, can help anticipate better infrastructural changes and reduce risks.

As a result, the profit analysis is a useful method to investigate a storage project's value and competitiveness at present for a specific location at current market designs. This might be sufficient for investors to assess short-term projects at specific locations. However, when one looks at the value of energy storage in the long term or across many regions, the following system-value approach can give some extra insights.

2.3. System-value analysis

As previously stated, the system-value analysis estimates the value of energy storage which are 'visible' and 'hidden' at existing markets, for longer time horizon and large spatial regions by considering perfect and complete markets in the analysis. Energy system models are used for the system view which optimises investment and operation of generators, networks and storage or demand response units at the same time to accomplish the objective of minimising total system cost. The results of such analysis are nowadays mostly applied for policy recommendations. However, they also reveal insights for technology design. For instance, it was found that high capacity factor wind turbines can be equally desired in an optimal energy system as their less capital intensive alternative technology with lower capacity factors – having smaller hub heights and shorter blade lengths [38, 39].

The system-value approaches are important to identify benefits of energy storage. But not all energy system models considering the same benefits. For instance, [3] neglects network expansion, missing significant network expansion cost savings from storage deployment [2]. On the contrary, the authors in [2, 40] use a model that incorporates generation, network, and system operations savings from energy storage in the UK.

The whole-system benefit (WSB) given in €/year and the marginal WSB given in €/kW or €/kWh are two inspiring concepts how to attach a system-value to the energy storage in power systems [2, 3, 41**?**]. Both concepts share a comparison of a none or existing storage scenario with one that includes an energy storage expansion. Such approaches are also known as counterfactual scenarios [42]. Thereby, the total system cost difference between the scenarios is the WSB that the energy storage creates [40]. When the marginal WSB curve, given in €/kW or €/kWh, is integrated by the respective storage unit (in kW or kWh), then the WSB is obtained. The marginal WSB is described as vital since it provides the upper-cost limit for energy storage for a given amount of installed storage [43]. Only if the marginal value is above its marginal cost the storage is an economically viable option and should be installed. Additionally, to the WSB and its marginal value, the authors in [43], extended the concept by the differentiation of the benefits in net and gross benefit. The gross benefit excludes the investment cost of energy storage while the net benefit includes them. Thereby, the gross value method is used to create a benchmark of how much the cost can rise for a given technology. The net benefit analyses the holistic-value for a specific storage case.

Both WSB methods above lead to insightful results. For instance, (i) that every additional installed energy storage capacity decreases its marginal value; (ii) that the value of energy storage can suffer from competition with other flexibility providers, such as demand response or bi-directional charging of electric vehicle; and finally (iii) that energy storage benefits can be decomposed into its origins such as network and peak capacity savings [2, 40].

The major drawback of the WSB approaches is that they are unsuitable as evaluation metrics to signal between multiple storage alternatives what technology is more competitive. The WSB approaches seem to work correctly only for a single energy storage design. When multiple energy storage units are included in the WSB analysis at the same scenario and with variable sizing for each location, it becomes difficult with counterfactual approaches to allocate benefits. Or in other words, it becomes unclear which energy storage at what location is responsible for certain energy storage benefits at a specific time. As a result, WSB approaches are not useful to assign a value to one particular storage or to compare multiple storage technology candidates.

In the next section, the 'market potential method' aims to extend the existing system-value literature to circumvent the above issue and give decision-maker signals even under complex competition situations. In short, the new approach moves away from assigning monetary values directly to individual energy storage units, but instead focuses on the optimised quantity. Meaning that a storage is likely to be valuable when a certain amount of storage is built. As in Section 4.4 discussed, the quantity appears to be another useful metric for industry and research when systematically applied.

3. Methodology

The methodology section is built up as follows. First, the new system value assessment method, the 'market potential method' is defined in theory. Second, an experimental model setup for hydrogen and battery storage is described that compares cost and system-value analysis approaches. Finally, to carry out the experiment the power system model PyPSA-Eur is introduced with its problem formulation, set of scenarios and model input data.

3.1. Market potential method

The 'market potential method' attempts to expand the existing system-value methods to give more useful signals of which storage technology is valuable in existing or future energy systems. Figure 2 illustrates that the 'market potential method' consists of: first, the 'market potential indicator' which corresponds to the expanded power or energy capacities of a storage component such as charger, discharger or capacity unit; second, the 'market potential criteria' which seek to support design-decision making of storage technologies.

3.1.1. Market potential indicator

The foundation of the introduced method is the market potential indicator (MPI). The MPI is not a new metric. It is a result of energy system models that analyse scenarios in future energy systems and describes the total quantity of a particular storage technology in a cost minimised electricity system [3, 44, 45]. However, the MPI has never been a central metric to improve, compare and explore storage designs in detail; it was rather used to inform policymakers and market participants about probable energy futures to reduce investors risk [45]. We utilise the MPI to guide technology innovation with probable scenarios and market potential criteria.

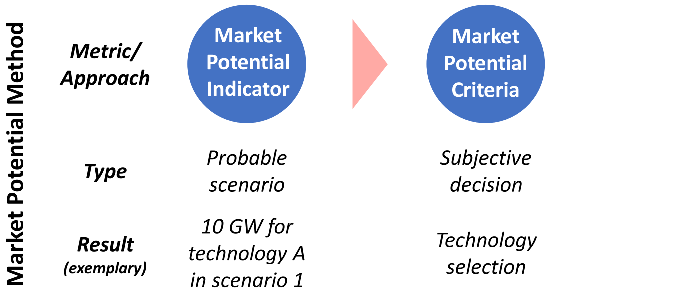

Figure 2: Description of the Market Potential Method. First a market potential indicator is derived for a single or multiple possible scenarios. The market potential indicator is then used by an entity through a market potential criteria to support design-decisions making on energy storage technology.

The market potential can be either aggregated or disaggregated. In the context of energy system models, we define the disaggregated MPI of a storage unit as optimised (or expanded $t-t_0$) power or energy related size at a region. Thereby, the market potential focuses on the storage component c, which represents a charger, discharger or store unit. The over a region i aggregated MPI is determined by:

$$\mathrm{MPI}_{t-t_0,c} = \sum_{i\in\mathbb{N}} (\mathrm{MPI})_{t-t_0,c,i} \qquad [MW \text{ or } MWh] \tag{2}$$

It is crucial to consider the MPI by components rather than by a fixed-sized storage system for mainly two reasons. First, grid-scale energy storage can be highly scalable and adaptable [46, 47]. For instance, electrolysers (MW), steel tanks (MWh) and fuel cells (MW) composing hydrogen storage systems can be freely scaled and combined. And in a H_2-hub operation, two different electrolyser could feed the same H_2-storage tank. Second, energy storage system components–for instance based on hydrogen–are not required to be at one location. Indicated by [18], hydrogen pipelines can become an economically viable option when large amounts of hydrogen need to be transported. Its integration means that hydrogen electrolyser and fuel cell are not required to be located at one place. Consequently, because storage components can be independently scaled, adaptable in operation and do not require co-location, it seems advisable to optimise them separately.

3.1.2. Scenario selection and dealing with uncertainty

The use of energy system models is subject to uncertainty as predicting the future with certainty is impossible. It is impossible because we can make decisions that impact the future such as done by agreeing on multilateral CO_2 targets which improved renewable energy deployment and led to learning by doing cost reductions effects [4]. Nevertheless, analysing a broad range of future scenarios can reduce uncertainty [48].

The market potential method in linear programming models relies on possible and probable scenarios. Many different ways exist to create 'possible' scenarios which differ in the set of deterministic input assumption and constraints [48, 49]. However, a possible future does not necessarily mean that it is a probable one. A good approach to develop scenarios that can be expected in future is to follow the ones which are provided and encouraged by either national or multinational institutions - and engage in public consultations if they require changes [45]. An example of the latter one is the European Network of Transmission System Operator for Electricity (ENTSO-E) which provides every two year an update on multiple, currently three, 'realistic' pathway scenarios based on storylines towards the European agreed targets - known as Ten-Year Network Development Plan (TYNDP) [45]. Transparency in energy modelling, also from trusted institutions, is a key requirement to lower uncertainty [50].

Scenarios can be additionally selected to investigate multiple technology designs. For instance, technology manufacturer might be interested in such analysis to guide energy storage innovation.

This study includes for the purpose of technology assessment three different hydrogen design constraints and two different charger and discharger technologies which are described in more detail in Section 3.3. While this study uses an exemplary 100% GHG emission reduction scenario that is sufficient for the research purpose, future work should include probable scenarios such given by national or multinational institution as ENTSO-E.

3.1.3. Market potential criteria

The 'market potential criteria' give the market potential indicator its meaning and can help with decision-making. The criteria includes three simple rules. In an optimised energy system model with many if not all technological alternatives, the technology with:

- $MPI = 0$, for one scenario is unlikely valuable.
- $MPI > 0$, for one scenario is probably valuable.
- $MPI > 0$ in multiple scenarios reduces uncertainty.

Additionally, the positive MPI magnitude can be used as supportive decision criteria to set flexibly own rules to deal with uncertainty. This can be for example the 'threshold' or the 'bigger is better' rule described below:

- $MPI > X$ or 'threshold rule'. Where a company or institution decides what minimum market potential X must be achieved. For instance, an alkaline electrolyser needs to have 1 GW market size to be an attractive technology for a company.
- $MPI_A > MPI_B$ or 'bigger is better' rule. Where if two technologies A and B are compared, the one with higher market potential is more likely to be valuable.

Figure 9 illustrates how the market potential criteria could be applied as decision support tool. The illustrative example could lead to the anticipative decision of a technology manufacturer or research institution to focus rather on the first two technologies than the latter ones.

Only with the criteria one can systematically analyse the market potential indicators and reduce risk. Together, the market potential indicator and criteria build the market potential method.

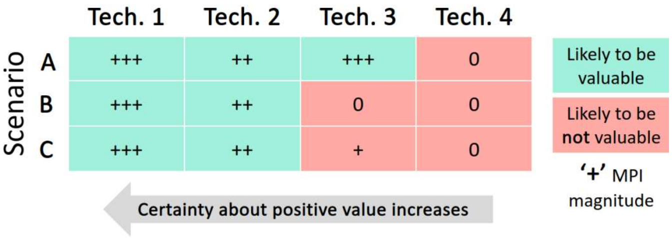

Figure 3: Qualitative illustration of market potential criteria applied to a set of scenarios and technology options. The "+" indicates the MPI magnitude. Additionally, the threshold rule is set to a single plus, meaning that for instance a company requires at least two plus to consider a technology as potential candidate to manufacture or start R&D activities.

3.2. Model structure and data

The open European transmission system model PyPSA-Eur is adopted to determine the value of various energy storage systems in a European electricity system. PyPSA-Eur is an adaptable investment and dispatch model built on the core model PyPSA that combines high spatial and temporal resolution. The suitability of PyPSA-Eur for operational studies and long-term power system planning studies is described in [13, 51, 52].

PyPSA-Eur covers the European transmission model and processes electricity system data from diverse sources. Existing conventional generators, transmission lines, substations, and hydro storage systems, as well as planned network reinforcements, are included with their size and location. Wind and solar based technologies are greenfield optimised, which means that existing solar and wind capacities are disregarded. The time series for wind and solar generators are derived from satellite and earth observatory data [51]. In regards to power demand, the load time series are collected from ENTSO-E data for each country, and redistributed by GDP and population over the regions. A spatial resolution of 181 nodes matched with an hourly resolution across a full year, accounts for the complex spatio-temporal patterns of renewables and grid congestion events that shape investment decisions [53].

In terms of market economics, the model assumes perfect competition and foresight for one reference year. A detailed model description is included in [51, 52]. Here, we only highlight the key features and constraints. The objective of the model is to minimise the total system cost in the European electricity system on transmission level. The total system costs consists of

- investment costs, which includes annualised capital cost of onshore and offshore wind turbines, storage components and both HVAC and HVDC transmission lines, and
- operating costs, which includes fixed operation and maintenance, and variable operating cost.

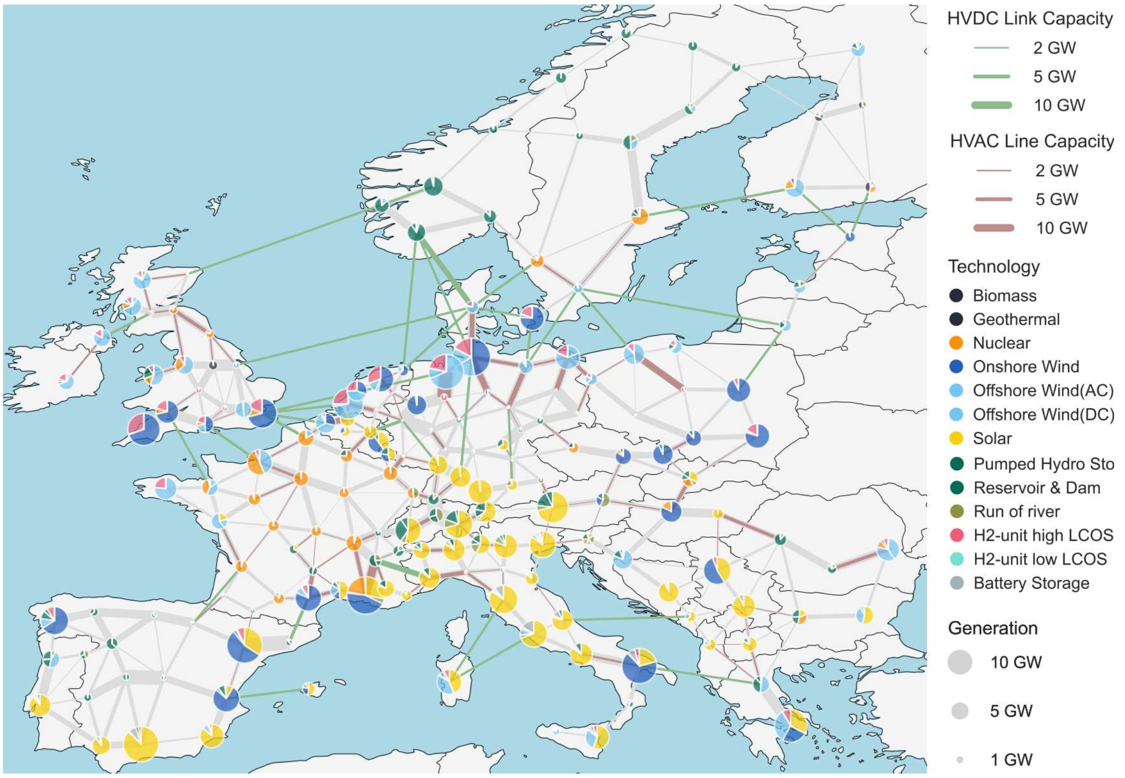

Figure 4: Optimal generation, storage and network expansion under a 100% emission reduction scenario and technology data for 2030. Light grey lines showing the existing installed network capacity.

The objective is subject to

- nodal power balance constraint that guarantee that supply equals demand at all times,
- linearised power flow constraints modelling the physicality of power transmission,
- Solar and wind resource constraint that limit the theoretical generation time-series. We chose a single weather year for our analysis; however, this can be extended for a more robust prediction of weather year anomalies or variations [54].
- Renewable availability constraint which restricts solar and wind technical potential based on environmental protection areas, land use coverage and a distance criteria.
- Emission constraint introduces a limit of carbon dioxide CO_2 equivalent emission in the model that impacts technology investment and generation.

The model has many adjustable constraints. This study does not include the available unit commitment (UC) constraints, since the purpose of this paper does not justify extra computational burdens. These computational burdens are introduced by the mixed-integer formulation of UC constraints which losses convexity and hence, leads to a nonlinear program that requires more efforts to solve. However, if a more detailed technological performance in a high renewable electricity system with nuclear power plants is important, this UC formulation should be included [55].

For the input cost and technical assumptions, the documented dataset provided in [56] is used, referring to an electricity system scenario in 2030. We only adjusted the dataset of [56] by the battery and hydrogen storage system inputs summarised in Table 1 and Table 2.

Table 1: Power related energy storage model inputs representing 2030 data

Energy storage components	Electrolysor		Fuel cell		Battery Inverter
LCOS Scenario	[Low]	[High]	[Low]	[High]	[-]
Investment [EUR/kW_{el}]	339	677	339	423[b]	209[c]
FOM[a] [$\%/year$]	2	3	2	3	3
Lifetime [a]	25	15	20	20	10
Efficiency [%]	68	79	47	58	90
Discount Rate [%]	7	7	7	7	7
Based on Ref.	[9] Alkaline	[9] SOEC[d]	[57] PEM[e]	[57, 58] SOFC[f]	[58, 59] Li-Ion Battery[g]

[a] Fixed operation and maintenance cost
[b] Includes fuel cell stack replacement after 10 years which cost 30% of initial cost
[c] Includes 80 EUR/kW balance of plant, mainly assigned to wiring and connection [59]
[d] Solid-Oxide Electrolyser
[e] Proton Exchange Membrane or Polymer Electrolyte Membrane
[f] Solid-Oxide Fuel Cell
[g] Lithium-Ion Battery

3.3. Energy storage scenarios

This study looks at three different constraint energy storage scenarios in one fully emission free energy system scenario. As explained in Section 3.1.2, one energy system scenario is just exemplary chosen and sufficient for this research. Multiple

Table 2: Energy related energy storage model inputs representing 2030 data

Energy storage components	H_2 storage		Battery storage
LCOS Scenario	[High]	[Low]	[-]
Investment [EUR/kWh_{el}]	8.4	8.4	188[b]
FOM[a] [$\%/year$]	-	-	-
Lifetime [a]	20	20	10
Efficiency [%]	-	-	-
Based on Ref.	[58]	[58]	[59]
	H_2 steel tanks		Li-Ion Battery

[a] Fixed operation and maintenance cost
[b] Includes 81 EUR/kW for engineering, procurement and construction costs [59]

system scenarios from trusted organisations such as ENTSO-E should be applied if technology decision are to be made with the MPM. This section goes through the key scenario design elements.

Starting with the energy storage scenarios, Figure 5 describes the storage scenario design. First, technical and economic parameters are chosen as model input for each storage component (see Table 1 and Table 2) to represent a low and high levelised cost of storage (LCOS) case for a classical LCOS calculation of a hydrogen storage system. Afterwards, the resulting techno-economic details are inserted in the model environment into three scenarios. The scenarios differ mainly in technological design freedoms. 'Fix EP ratio' is the most constrained energy storage scenario having a fixed energy-to-power ratio of 100 h for the hydrogen and 4h for the battery storage technology – applied in a similar range in research [8, 23, 60]. Whereby charger and discharger size are equally set. 'Variable EP ratio' optimises for the hydrogen storage unit each component size, charger, storage and discharger so that the energy-to-power ratio is variable. The battery is constrained in flexible sizing as charger and discharger represent the same component, namely the inverter, so that the battery storage can only size inverter and battery capacity related design separately (see Battery component size variables x, y, x in Figure 5). While both, fix and variable EP ratio scenario, optimise hydrogen low LCOS and high LCOS components separately, the 'H_2-Hub' scenario permits cross operation of hydrogen technologies. This can be thought of as a H_2-Hub, having at one location techno-economically different low and high LCOS charging and discharging technologies that operate the same hydrogen storage.

This study creates energy storage scenarios that focus on energy arbitrage benefits under spatially resolved perfect and complete markets. Scarcity signals relevant to seasonal balancing are considered through 'unconstrained' locational marginal prices also known as nodal prices. These nodal prices can increase to extremely high prices such as more than 20000 €/kWh and let energy storage be optimised as seasonal reserve, shifting cheap energy of one season to times of high prices. As introduced in Section 2, the complete market considerations includes the often unaccounted or 'hidden' values of energy storage systems, such as:

- Avoided investment cost of network expansion
- Avoided investment and operational cost of dispatchable generators
- Increased power plant utilisation/ less curtailment

Emission targets play for the energy storage market potential a vital role. To keep the comparability between scenarios and a decent amount of market potential for energy storage, we set in all scenarios the CO_2 emission reduction target to 100 %.

Figure 4 shows an example of the optimised European electricity landscape for the variable energy-to-power ratio scenario, which is minimised in terms of total system costs in a 181 bus spatial resolution. One should note that the network structure is based on ENTSO-E data which is aggregated to show realistic line capacities between the buses.

Different to [61], the scenarios include the existing European nuclear power fleet, but acknowledge the German, Spanish, Belgium and Swiss nuclear exit. The inclusion of nuclear power plants reduces the required VRE capacity expansion and at the same time, increase the share of dispatchable power plants. A measure that reduces energy storage demand. However, the flexibility of nuclear plants is overestimated in this study as typical ramp rates reaching up to 36%/h and minimum allowable power of 20% per nominal power [62] are ignored. It implies that this study will tend to underestimate the energy storage potential.

Further, similar to [63], an equity constraint is included that requires every country to produce at least 80% of its total electricity demand, leading to a smooth distribution of generators in whole Europe. This constraint is motivated by the fact that political leaders avoid depending entirely on electricity imports, though, are willing to trade a considerable amount to handle the trade-off between economic benefits of importing cheaper electricity and the costly independence of supply from other countries.

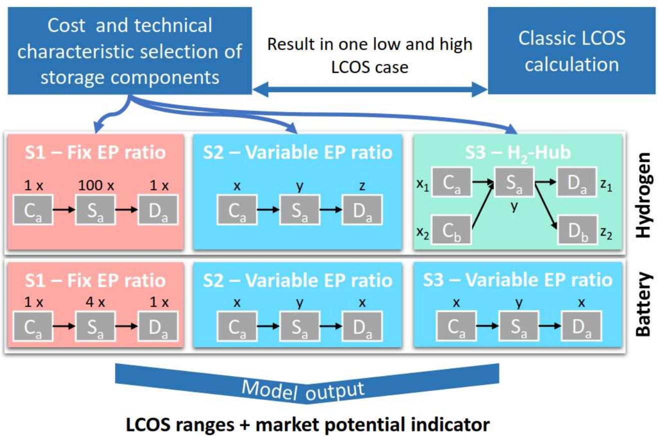

Figure 5: Description of scenarios set up. The cost and technical storage parameter are chosen once and serve as input for all storage scenarios. Scenario 1 shows the fix energy-to-power ratio of the hydrogen and battery unit a. In Scenario 2 and 3 all components can be freely scaled, though, the battery is constrained to the same charger to discharger ratio. Further, The 'b' in the $H_2 - Hub$ scenario indicates a new technology.

The network expansion is constrained to a volume of 25% compared to the existing network capacity, acknowledging the increasing political difficulty to develop new transmission lines.

A limited network expansion can potentially lead to higher storage demand [64]. Further constrained are hydro storage technologies. These are based on real power plant data, though, are deactivated for capacity expansion due to natural limitation in many regions.

4. Results and Discussion

4.1. Relaxing design constraints of energy storage and its benefits

As the introduction of the cost and value analysis scenarios, the impact of design freedom on the storage components and the total system is discussed in this section.

Increasing design freedom of energy storage can lead to significant benefits in the electricity system. When investigating the competitiveness of energy storage, many studies assume that the energy to power ratio is fixed [3, 21]. Though a fixed-sized storage unit seems to be far away from an optimal solution. A way to prove this is to investigate the total system cost reduction in energy system models as applied in the following.

Table 3 shows that the increasing sizing complexity seems worthwhile to consider as it can lead to per annum total system cost savings of approximately 13B€or 10% in the modelled zero CO_2 electricity system scenario while not leading to significant generation portfolio changes (see Figure 6). The total system cost thereby includes the optimisation relevant costs which consist of newly installed generation, storage and network components, including any operational costs. Another approach to comprehensively quantify the savings is by calculating the relative investment cost which divides the total system costs by the total electricity demand. It shows that the introduction of optimised sizing can lead to electricity bill savings of roughly half a cent, with the H_2-Hub scenario contributing only to negligible more savings. As a result, increasing design freedom of energy storage can be desirable for a cheaper electricity system and should be considered while designing technology.

Table 3: Annual total system costs, relative investment and curtailment data. Variable sizing of energy storage reduces the system costs by 10%.

Scenario	Total system cost	Relative investment[a]	Curtailment [% of annual demand]
Fix EP ratio	152.9 B€	4.874 ct/kWh	0.61%
Var EP ratio	139.9 B€	4.460 ct/kWh	0.73%
H2-hub	139.7 B€	4.453 ct/kWh	0.37%

[a] Total system cost per annual demand

The optimal storage design depends on the location and technology. Figure 8 shows the EP-ratio for multiple locations and technologies with relevant market potential in an optimal European future scenario.

Hydrogen charger are larger sized and reveal a wider span of EP-ratios than its discharger opponents which means that quick charging and slower release seem to be beneficial from a EU system perspective at most locations. Further, the Li-Ion batteries are optimised with a 2-4 h EP-ratio, much smaller than the hydrogen components. The reason for that heterogeneous design is that local diverse electricity system situations with its

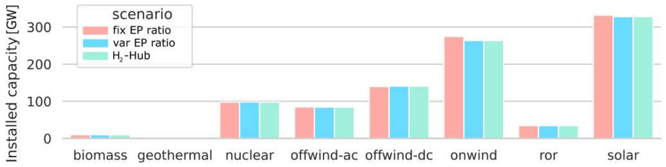

Figure 6: Absolute installed generation capacity in the exemplary 100% emission reduction scenario. The optimised capacity looks similar in all three scenarios indicating little influence of the storage scenarios on the generation portfolio. Only slightly less generation capacity is required when variable sizing of energy storage is permitted. The abbreviations 'ror' stands for run of river, offwind-ac and -dc for AC and DC connected offshore wind plants, respectively.

Table 4: Additional inputs for LCOS calculation oriented on [8].

	Hydrogen storage unit		Battery storage unit
LCOS scenario	[Low]	[High]	[-]
Discharging ratio [h]	100	100	4
Electricity price [Eur/MWh]	50	50	50
Yearly full load hours [h]	2500	2500	3400
Roundtrip efficiency* [%]	32.0	45.8	81,0
Lifetime [a]	25	15	10
Static LCOS [ct/kWh]	0.21	0.26	0.12

*calculated product from energy storage component efficiencies in Table 1

individual network constraints, supply and demand curves, as well as the different storage characteristics (see Table 1 and 2) benefit from a variety of storage scaling to reach an optimal solution that minimise the electricity bills.

4.2. Static LCOS vs modelled LCOS

The LCOS is currently an influential metrics to benchmark technology and to discuss their competitiveness. Therefore it is not surprising to see that technology design is even optimised for minimum levelised costs (see Section 2). To show the drawbacks of this measure, static and modelled values are calculated according to the methodology described in Equation 1.

The main difference between static and modelled LCOS is what assumptions are used. The static LCOS calculation uses directly assumed or exogenous variables such as for full load hours, electricity prices and energy-to-power ratios. In contrast, the modelled LCOS is based on endogenous variables which are determined by the energy system model and its inherent assumptions. It means that full load hours, electricity prices and energy-to-power ratios are determined for each location by the European power system model.

The static LCOS is calculated with the technical and economic component characteristics in Table 1 and 2, and the LCOS assumptions given in Table 4. The results of the static LCOS calculation also given in Table 4 show a 19.2% or 5 ct/kWh difference for the two hydrogen storage units, whereby the battery storage seems much more competitive.

In contrast, the modelled LCOS results are given in Figure 7 for most buses in the EU electricity system for the 'variable EP ratio' scenario. Despite having the same input cost, lifetime, discount factor and efficiency data as the static LCOS calculation, a wide LCOS range can be observed for each optimised storage unit which consists of charger, storage, discharger. The LCOS ranges are roughly between 20-100, 20-55 and 4-14 ct/kWh for the low, high LCOS H_2 unit and the battery, respec-

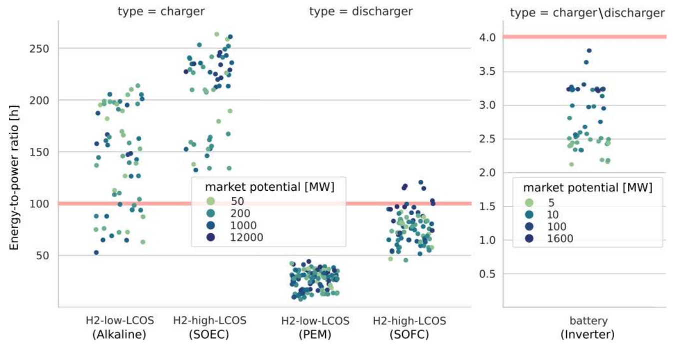

Figure 8: Optimal energy to power ratio ranges in the variable EP ratio scenario. The red line represents the fix EP-ratio scenario assumption. The energy to power ratio's are very diverse sized in the 181 buses of the European optimal future and in regards to hydrogen and not necessarily equal for charger and discharger. The electrolyser capacity is generally larger than the fuel cell capacity which means that slow charging and quick discharge at few moments is desired in the system.

tively. One reason for the wide LCOS ranges is the heterogeneous charging and discharging behaviour which is indicated by a diverse observed full load hours between 80-3000h; another one, the heterogeneous nodal prices or electricity price profiles at each region; and finally the heterogeneous sizing of the storage chain. Again, the battery technology seems more competitive under the LCOS framing while it becomes ambiguous for hydrogen with the overlapping LCOS ranges.

A minimum LCOS metrics should be never a solely technology design objective or used to argue about competitiveness. Regardless of the low or high LCOS indication, the 'variable EP scenario' shows that all included energy storages technologies are valuable. As reminder, we define a technology as valuable if it reduces the total system costs. This is the case if a technology is part of an optimised energy system. In Figure 7, all technologies reveal a market potential indicating to be required assets to achieve the minimum total system costs. As a result, instead of improving energy storage by minimising the LCOS, one could try to optimise the system-value and assess the market potential indicator. Why reducing the total system cost should be also in interest of the technology developer will be discussed in Section 4.4

4.3. Market potential method as value indicator

This section reveals the market potential indicator for each technology and scenario and evaluates it exemplary with the market potential criteria. Exemplary, because as described in Section 3.1 the MPM scenarios should be chosen according to institutional scenarios or 'beliefs' that might be more likely to impact decision making. As reminder, the scenario design of this study is described in Figure 5 and helps interpreting the results.

Figure 9 shows the total market potential indicator for all expandable storage components in the European market. How this market potential can be disaggregated over Europe is demonstrated for chargers and the variable EP ratio scenario in Figure 10.

The first scenario shows as expected a fix energy to power ratio of 100h (10TWh/95GW) for hydrogen technologies and 4h (0.07TWh/17GW) while the charging and discharging market potential are constrained to be equal for one storage unit. Surprisingly, in this scenario, the mainly optimised hydrogen technology is the high LCOS case of the static LCOS calculation, whereby, the low LCOS case reveals a negligible market potential. It means in simple terms that the high LCOS hydrogen unit is more likely to be valuable and worthwhile to design or manufacture due to the approximately two orders of magnitude higher market potential.

In the second scenario, when all hydrogen storage components, and the battery inverter to capacity ratio, are independently scalable, one can observe a noteworthy reduction of the market potential of battery components. This means that flexible scaling of storage technologies can reduce the viable mar-

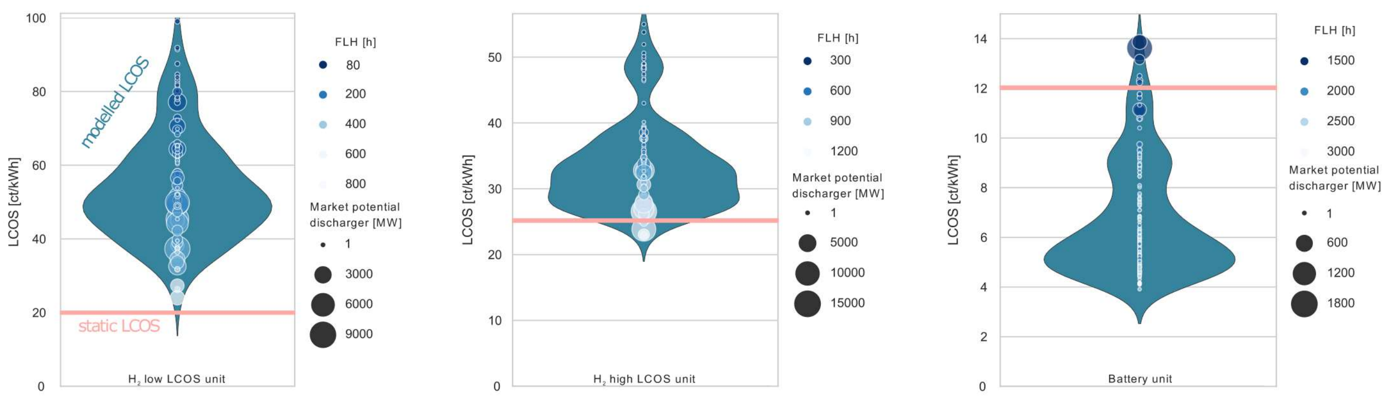

Figure 7: Static LCOS values and modelled LCOS ranges of hydrogen and battery storage. The static LCOS is marked by a red horizontal line and calculated by the assumptions given in Table 1, 2, and 4. In contrast, the modelled LCOS ranges are calculated for the 'var EP ratio' scenario for each bus in the EU network and represented as point in the Figure, showing additional full load hours and the market potential indicator for the discharging unit. The width of the violin plot shows the occurrence in the kernel density estimation which means the wider the plot the more buses are located at the respective LCOS cost range. In all cases, buses with less than 1 MW market potential or 80 FLH are removed, keeping the visualisation readable. The plot shows that the aim to minimise the LCOS can be misleading since a similar technology can be optimised and reveals a positive magnitude of market potential indicator even with higher LCOS.

ket for batteries. Further, the optimised energy to power ratio impacts the market potential for hydrogen technologies. Now, both high and low LCOS technologies possess a good market potential and seem desirable as complementary technologies. However, the variable sizing of hydrogen components leads to a market potential shift from charger towards discharger components. For a fix, variable and $H_2 - Hub$ scenario, the total amount of hydrogen charger market potential (summing low and high LCOS components) shift from 95, 68 and 80 GW to a hydrogen discharger market potential of 95, 219 and 211 GW, respectively. Making the hydrogen discharger components the clear winner of variable sizing through a rough doubling in market potential.

Concerning the $H_2 - Hub$ scenario, when components are variable sized and diverse H_2 electrolyser and fuel cell technologies can simultaneously use the same storage tank, then the market potential of storage technologies changes remarkable again. It makes the before well desirable solid oxide electrolyser as technology almost negligible in terms of market potential.

As a result, what the market potential indicator reveals is that the design freedom of storage is important to consider because it impacts the value assessment. For instance, when variable component sizing is possible, the PEM fuel cell, as well as the Alkaline electrolyser, seem to be more desirable while Li-batteries lose in importance in the electricity system.

Applying the full MPM and judging, hence, with the market potential criteria lead to the insight that all the implemented storage components can be considered as valuable. Because at least one of the scenario's possesses a positive market potential indicator. However, only the Li-battery as well as the SOFC fuel cell are the most likely valuable technologies as they are optimised in all scenario's and exceed a self-defined 1 GW threshold criteria. As reminder, such a threshold might be set by a manufacturer to define a minimal viable market for a technology worth to invest. The knowledge derived from the market potential criteria can lead to implications, for instance, that the Alkaline electrolyser manufacturer can actively mitigate their value risk by promoting variable sizing.

Finally, the presented insights underline the misleading concept of solely cost minimising technologies. Not always a technology with lowest investment or LCOS is most valuable. It can be also the more expensive technology that can lead to a cheaper future electricity system.

4.4. The relevance of the market potential method

The market potential indicator is a useful metric from a practical and computer modelling perspective for manufacturer, developer and research. First and most important reason is that the market potential is a driver for business. Successful firms want to generate money for its stakeholders and hence are driven by two things, growth and profitability. The market potential indicator for a specific product can relate the growth potential to the profitability. For instance, when a company expects to offer a future product for net costs of 10 €/kWh then it could include these cost in the energy system model with a profit and risk premium of 5 €/kWh (50%). The modelling output is the market potential indicator which is related to the profit and risk premium of 50%. As result, the market potential method can be useful for growth and profit evaluations of future storage technology.

Second, the market potential can give insights where growth markets are located and for what reason. This can be achieved since the disaggregated market potential can identify regions with future technology expansion (see Figure 10). The electrolyser distribution reveals that in many locations high and

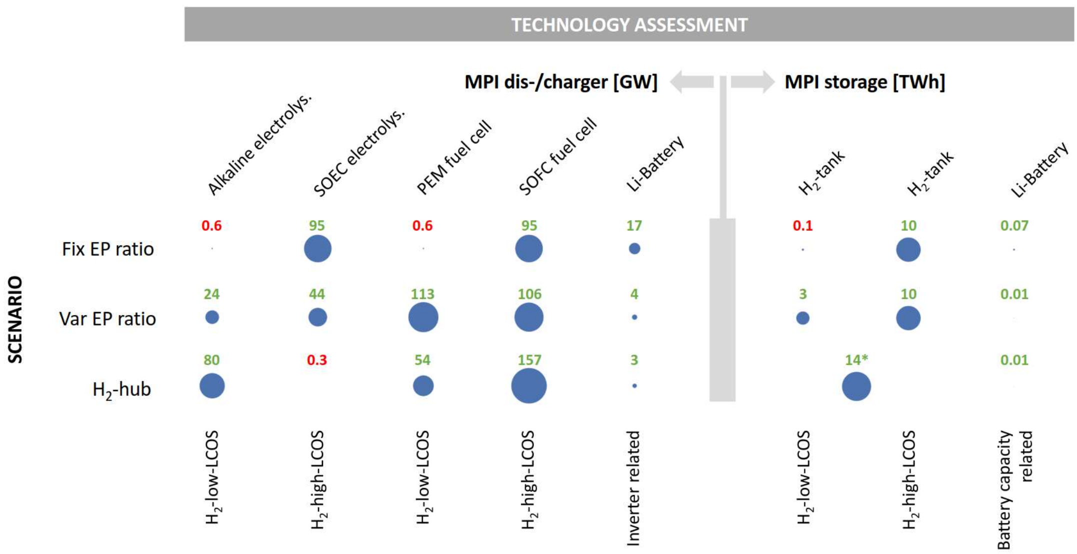

Figure 9: Market potential indicator for all charging and discharging components in Europe for three technical storage scenarios in a zero emission electricity system. Despite having the same economic and technical input data the market potential vary drastically between the scenarios. The SOFC fuel cell and Li-battery are according to the market potential method, the technologies which are most likely to be valuable in the exemplary set of scenarios. Because they have an optimised market potential indicator in each scenario. *Refers to the total shared storage capacity.

low LCOS units complement each other. Additionally, when storage components are compared to the generation distribution from Figure 4, most hydrogen units are co-located at regions with wind plants (mostly northern regions) while batteries gravitate towards solar plant optimised areas (mostly southern regions). A reason for the observed co-location might be the diurnal solar power pattern and the multi-day to weekly wind power pattern which creates a network constrained mismatch suitable for the given storage characteristics [65].

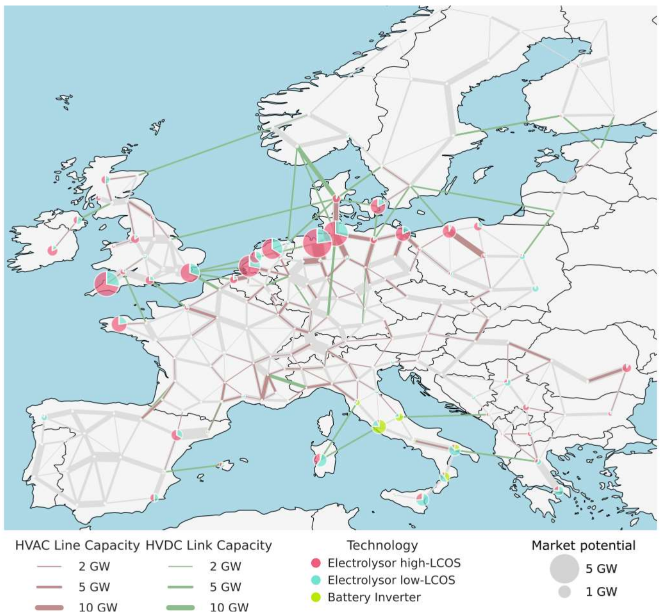

Figure 10: Optimal energy storage charger distribution in the variable energy to power sizing scenario. Showing the location of market potential in a 100% emission reduction scenario. Comparing to Figure 4, most hydrogen units are co-located with wind plants while batteries gravitate towards solar plant optimised areas [65].

Third, the market potential is useful as an indicator of future cost reductions. Because with the market potential, one can assume future technology deployment which is an implicit factor in learning by doing cost reduction effects [4] or a factor that can be incorporated into process-based cost analysis to evaluate the cost reduction potential [16, 17].

Forth, the market potential can reduce the structural uncertainty of the linear programming energy system model itself. Initial cost assumptions as model inputs are often made without knowing deployment numbers achieved in the optimisation. But it is known that larger deployment can reduce costs due to learning effects [4]. Since after the first model run the market potential can function as a cost reduction signal, one can in an iterative or sequential solution approach improve the input accuracy and, hence, lower the structural uncertainty.

Finally, the operational behaviour can be analysed with the spatial distributed market potential, due to the use of energy system models which gives operational times series of optimised technologies. These time series can be used to identify operational patterns and full load hours which both might be useful for technology design decision.

5. Critical Appraisal

What the market potential gives its power to resolve the complex value of energy storage - the energy system model - also introduces typical limitations found in this domain. The fundamental challenge of any mathematical energy model is to represent a realistic future energy system that includes all relevant physical, social and political details [66]. Current approaches encounter limitations to represent these details. For instance, models often aggregate in space, time and technological resolution to reduce the computational requirements losing some accuracy to represent future scenarios; or assuming perfect and complete markets, where actors have perfect foresight. Both deviates from what can be accomplished in reality [51] and as pointed out in the introduction it can be important to address additional values of energy storage.

These energy model limitations can be understood as (1) structural uncertainty related to the imperfect mathematical description of the physics and (2) parametric uncertainty that refers to imperfect knowledge of input values, i.e. impacted by innovation or behaviour. Both compromise every kind of mathematical models with increasing uncertainty looking into more distant future and vary from model to model [42, 64, 67]. The most important uncertainties of PyPSA-Eur are summarised in [51], for instance, that demand profiles for regions in a country are not disaggregated and only scaled by the GDP of the regions, hence, representing not local differences; or missing multi-horizon optimisation which can help to describe investment pathways and lock-in effects; or the only focus on the electricity system, missing alternative flexibility competitors from other sectors.

Nevertheless, most of the uncertainties can be reduced by improving future mathematical descriptions of the reality and by strategies to reveal remaining uncertainties [66]. This also includes the missing energy storage values of this study for sub-hourly grid services and risk confronted investment and operation. In PyPSA-Eur many of these certainty creating features can be implemented in short-term by state of the art techniques.

In context of the above-described uncertainties, this study does not seek to be the one true future. It rather shows a set of possible future scenarios with different technological design freedoms for the only purpose of comparing different storage design evaluation methods.

6. Conclusion

This study analysed recently published literature on energy storage and found three distinctive evaluation approaches to indicate how to improve energy storage. We show how these approaches work and what are their limitations. The here newly introduced market potential method is the only one which defines a valuable technology as one that reduces the total system costs or in micro-economic words, reduces the electricity bill.

The first approach found in literature coined 'cost analysis' identifies competitive storage technologies with the objective of lowest capital or levelised cost. We argue that this approach should not be used in isolation to guide storage technology development or policy recommendations. We quantified that a higher LCOS hydrogen storage can be equally or even more desired than a low LCOS hydrogen storage which questions the meaning of cost like metrics as an evaluation factor.

The second 'profit-analysis' approach aims maximal profits for storage projects. It may sound intriguing for investors at current market design without considerable electricity system changes, but when the future storage technologies are to be evaluated, this approach is likely to fail. In this context, we qualitatively explain that current market designs are incomplete and imperfect and might change due to the energy transition, leading to missing 'hidden benefits' of energy storage when looking into the future. As a result, rather than improving technology designs with cost or profit analysis methods, we could design technology with approaches that can lower the total system cost.

The third identified 'system-analysis' approach can accomplish this by also including hidden storage benefits and considering future more complete and idealistic markets. However, the review identifies a lack of practical system-analysis methods that focus on technology evaluation. The counterfactual scenario nature of existing approaches that give a monetary feeling about the system benefits constraint the usefulness. Hence, the new 'market potential method' is introduced, formulated, applied and discussed to improve technology design-decision making. The market potential method can be described as systematic deployment assessment. It focuses on components such as charger, store and discharger separately and assess how they could be scaled rather than on assessing fixed sized whole storage systems. Further, as indicator it uses the total sum of the optimised, expanded energy or power related size in a large spatial electricity system. A commonly output in energy system models that is underestimated and not yet applied to guide technology innovation. In probable scenarios the market potential method can derive through a set of criteria which technologies are potentially valuable or lead to the lowest cost energy system.

In scenarios with a high and low-cost hydrogen storage system and different grades of technological freedoms in sizing and interactions of the storage, we quantify with the market potential method that a seemingly more expensive energy storage can be the one with higher system-value. Thus, not only the cost but also the system-value of technology matters in a complex and heterogeneous electricity system.

As a secondary result, modifying the freedom of storage sizing and component interactions impacts the value of technology. For example, Li-Ion storage suffer from variable sized hydrogen storage. Likewise, increasing these design freedoms can lead to meaningful total system cost savings (10% total system cost savings compared to a fix sized storage scenario). But how variable sizing can be indicated and supported in existing energy planning is a question by itself and should be answered in future.

In summary, the market potential method has implications on practical and modelling relevant insights for manufacturer, developer and research. It can be used to

- support technology design-decision making with growth signals of magnitude and location,
- improve the technology by changing operational behaviour or adapting material or process selection to be most valuable for the energy system,
- concentrate policy endeavours to come closer to perfect market circumstances, or to
- enhance energy modelling as evaluation tool itself.

Future work can reduce the limitations of this study, such as the inclusion of sector coupling and multi-horizon optimisation. Further, this study considered energy arbitrage under perfect and complete markets. Another branch of work can include more services relevant to grid stability and risk approaches. For instance, by investigating the impact of imperfect and incomplete market conditions and higher spatio-temporal resolutions in regards to market potential method results. Finally, what might be valuable in Europe could look different in other regions. Technology developer would benefit from a global value assessment. Therefore, it is of utmost importance to expand open energy system models to cover most parts of earth.

The economist Milton Friedman said that "there is one and only one social responsibility of business–to use it resources and engage in activities designed to increase its profits so long as it stays within the rules of the game, which is to say, engages in open and free competition without deception or fraud" [68]. This might sound convenient in many cases. But in the context of developing energy technology, the game is constantly changing due to the energy transition and sector coupling, aiming complete and perfect markets. Thus, maybe it is time to look beyond the cost reduction paradigm and short-term profit focus - to develop technology that leads to lower system cost and winning the game of the future. The market potential method could contribute to this.

Code and Data availability

Code and data to reproduce results and illustrations are available on GitHub https://github.com/pz-max/beyond-cost.

CRediT authorship contribution statement

Conceptualization: M.P.; Methodology: M.P.; Software: M.P.; Validation: M.P.; Formal analysis: M.P.; Investigation: M.P.; Ressources: M.P., A.K; Data Curation: M.P.; Writing - Original Draft: M.P.; Writing - Review & Editing: M.P., F.N., A.W., D.F., A.K.; Visualization: M.P.; Supervision: M.P., D.F., A.K.; Project administration: M.P., D.F., A.K.; Funding acquisition: M.P., D.F., A.K.;

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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