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How can energy-system models inform technology development? Insights for emerging energy-storage technologies

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A R T I C L E I N F O

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A B S T R A C T

Energy-system models (ESMs) are used often to support policymakers, system operators, or investors, but much less for offering guidance to technology developers. This paper contributes to bridging the gap between the ESM discipline and technology developers. For the example of emerging energy-storage technologies, we identify and categorise information needs of technology developers. Moreover, we discuss, which information needs can be met by an advanced analysis of ESM results, and which needs require fundamental model developments. We demonstrate the capabilities of an advanced analysis for an application study using a model that optimises investment and dispatch to assess energy-storage technology requirements in a fully decarbonised European power system. Our analysis provides insights regarding requirements and opportunities of energy-storage technologies in terms of design parameters, operational patterns, and target markets. We show that technologies with low-cost power, *e.g.*, lithium-ion batteries (LIB), are designed with low energy-to-power (E2P) ratios, while those with low-cost energy (*e.g.*, H_2) have high E2P ratios. Concerning operational patterns, low-E2P energy-storage technologies cycle frequently (up to daily for LIB and vanadium-redox flow batteries), whereas H_2 featuring a high-E2P cycles only a few times per year. Moreover, we find that requirements and cycling frequencies vary strongly between different target markets driven by their underlying electricity systems. We conclude that an advanced analysis can make a contribution to bridging the gap between ESMs and technology developers. Future work should improve the representation of technological details and develop inverse modelling approaches for technologies in very early development stages with still highly uncertain parameters.

1. Introduction

Energy systems around the world are transitioning towards sustainable energy to reduce emissions and limit the effects of climate change [1,2]. In this context, both governments and private actors worldwide invest enormous resources into developing clean-energy technologies to provide and improve the necessary technologies to realise a functioning, climate-neutral, global energy system [3]. Therefore, governments need to be informed about the benefits of spending public resources, companies need information to manage their technology-development portfolios, and there may also arise the need for universities or research institutions to (re)direct their research programmes to maximise societal benefits [4,5].

Successful energy-technology developments lead to adoption decisions by energy-market participants, resulting in benefits for the energy system and its sustainable transition as well as profit for the technology adopters. Hence, it is worthwhile to shed light on decision making by different market actors in the energy sector, particularly concerning decisions on the development and use of energy technologies under uncertainty [6,7]. Tension is growing between economic growth and increasing energy-transition costs pressuring energy budgets [8,9]. Therefore, it will become increasingly important to assess the economic

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and system benefits of energy technologies during earlier stages of technology development and implementation [10–12].

1.1. Background and motivation

The analysis of energy technologies can help to improve the quality of government decisions in the energy field [13]. Consequently, energy-system models (ESMs) have been developed and used for decades [14, 15]. ESMs can be classified as either top-down or bottom-up. Top-down models employ a macro-economic approach, which considers the whole economy (of the analysed region), but neglects some technical characteristics of the energy systems. Conversely, bottom-up models focus solely on the energy sector (many only on the electricity sector), but aim to realise a rather detailed representation of existing and future energy technologies [16–18].

Over 50 years of experience with them demonstrates the opportunities and limitations of ESMs. The objective of using an ESM cannot be to predict accurately future energy systems, *e.g.*, the development of electricity prices or the technology mix over the next 20+ years. The experience with ESMs makes clear that we should model for insights rather than for specific trajectories [19,20]. There are several reasons why we should restrict the use of ESMs to this objective, starting with the trivial fact that even extremely sophisticated models are simplifications of reality. However, most important is the insight that the future (energy system) is not fixed, but will be influenced by the decisions that are taken today. This leads to the main objective of ESMs: selecting more rational actions today by identifying robust decisions [21].

With regard to the target audience, ESMs are applied primarily to provide decision support to policymakers, and much less to inform energy-technology developers. This is surprising, because technology developers would benefit from guidance that can be provided by ESMs, *e.g.*, on the probability of a sufficient return on investment or requirements for novel technologies from the perspective of the system or market [22,23]. We posit that the lack of collaboration between the ESM discipline and technology developers may be at least partially due to a gap in technology readiness levels (TRLs) on the spectrum between established technologies that are operational and emerging technologies that are undergoing development, demonstration, and testing. Bottom-up optimisation or simulation models, which represent technological details of energy technologies, seem to be the tool of choice for informing technology developers. These models work best for technologies with high TRLs (*e.g.*, TRL 7 and above), because meaningful estimates of the costs and efficiencies of such technologies, which are key input parameters for ESMs, are available within reasonably small ranges. This reality explains also why ESMs are used frequently to support decision making of investors (*e.g.*, utilities) in the energy sector, which invest usually in relatively high-TRL technologies. However, for emerging technologies, *e.g.*, with TRL 5 and below, estimations of cost or efficiency are often impossible or carry enormous uncertainty.[1]

In this paper, we focus on energy-storage technologies, which is particularly relevant because the availability of affordable, location-independent, resource-conserving, and scalable energy storage remains an unsolved challenge in transitioning to carbon-free energy systems [24–26]. There are a number of studies, including our own, that analyse energy-storage requirements for energy systems. However, these studies are aimed mostly at providing high-level decision support to policymakers by analysing feasible and economically efficient technology mixes for future energy systems that meet predefined policy goals [27–30]. This does not mean necessarily that the ESMs that are used are not suited to support technology development. However, minimally, this means that the results that are reported are not geared towards the needs of technology developers. Absent appropriate input from the ESM discipline, technology developers frequently need to make rather crude assumptions about the potential behaviour of "their" technology in the market [31–33]. Thus, to narrow the gap between the ESM discipline and technology developers, we gather researchers from both disciplines to prepare this paper, which discusses information that is needed from the perspective of technology developers for the example of energy-storage technologies. Moreover, the objective is to highlight, which information needs can be met by an advanced analysis of ESM results, and which needs require fundamental model developments.

[1] We acknowledge that uncertainties concerning future technology costs are high also for established technologies. The uncertainty is significantly higher for emerging technologies, however.

1.2. State of the art

The existing literature on techno-economic analyses of energy-storage technologies and their behaviour in energy systems falls largely into one of three broad categories: (i) studies focusing on energy-storage cost, (ii) studies focusing on profit maximisation of energy-storage technologies using electricity prices as exogenous inputs, and (iii) studies focusing on energy-storage-technology needs from an energy-system perspective. The state of the art will be summarised briefly for each of these categories in the following subsections.

1.2.1. Studies focusing on energy-storage cost

These studies compare the *costs* of different technologies, while the technologies' market values and market-based revenue opportunities typically are not assessed in detail. These studies are conducted mostly by the technology-development disciplines. Hence, such studies typically are technologically detailed. In these studies, the economic evaluation of technologies typically involves calculating metrics such as the specific investment cost or the levelised cost of storage (LCOS).

For example, Georgiou et al. [32] consider pumped-thermal energy storage (PTES),[2] which they assume to operate 365 cycles per year (one cycle per day). Going beyond such studies, of interest to us here is to explore whether there is a need for or whole-system benefit of such a technology operating at this frequency. Smallbone et al. [31] calculate the LCOS of a PTES system and find that these are in a similar range as those of compressed-air energy storage and vanadium-redox flow batteries, when assuming 365 cycles per year. They consider a fixed "energy-to-power" (E2P) ratio[3] of 8 hours and an exogenously fixed ratio of 1.25 between the charging and discharging power capacities. In their sensitivity analysis, Smallbone et al. [31] emphasise that the LCOS is sensitive to assumptions on the operating profile as well as the assumed costs and efficiency. Likewise, McTigue et al. [34] explore recuperated PTES systems and estimate how the LCOS changes with varying charging and discharging durations. Their analysis shows that the minimum LCOS is achieved when the ratio between the charging and discharging durations is approximately 1.4. Recent technical investigations, including the works of Dumont and Lemort [35], Frate et al. [36] and Dai et al. [37], combine energy storage with thermal waste energy recovery, often utilising heat sources at temperatures between 50°C and 90°C. Such configurations, however, combine aspects of energy storage systems and energy upgrading/conversion devices. In their LCOS calculation, Dai et al. [37] assume 365 cycles per year with a charging duration of 10 hours and a discharging duration of 6 hours.

Mersch et al. [38] consider adiabatic compressed-air energy storage (ACAES), which—similar to PTES—is a type of thermo-mechanical energy-storage technology [39]. The authors focus on evaluating different technical configurations without modelling the energy system

[2] PTES also is referred to as a Carnot battery, pumped heat energy storage or, less specifically, power-to-heat-to-power energy storage.

[3] The E2P ratio is defined as the quotient of the energy storage capacity (measured in MWh) and the discharge power (measured in MW) of energy storage. Hence, E2P is measured in hours. See Eq. (9) for a mathematical definition.

in which the ACAES is integrated. Instead, the energy storage is optimised for maximum roundtrip efficiency and minimum specific capital costs, assuming fixed charging and discharging durations of 3, 6, and 9 hours and power ratings of 10 MW, 50 MW, and 100 MW. Similarly, Barbour et al. [40] investigate a 500-kW, 2-MWh ACAES system, which is assumed to be charged over night and discharged during the daily evening peak demand. The energy storage is charged every day between 2:00 and 6:00, remains fully charged during the following 10 hours, and then is discharged between 16:00 and 20:00, before sitting idle between 20:00 and 2:00. Sciacovelli et al. [41] investigate the transient operation of an ACAES system assuming similar daily cycles as Barbour et al. [40]. The system is assumed to be charged between 3:00 and 13:00 and discharged between 18:00 and 22:00. Bashiri Mousavi et al. [33] also model the transient operation of an ACAES system. They assume that the energy storage is charged for 6 hours before being discharged immediately for 4 hours. In our study, we go beyond these assumptions by proposing to consider information from ESMs in the design and evaluation of different energy-storage systems.

This category of technical studies is valuable for the design and comparison of different technologies, but faces certain limitations. First, different revenue streams are not considered in the calculation of the LCOS. Given that private investors value profitability, which may be substantial despite high costs, an analysis of potential revenues is important when making investment decisions. Finke et al. [15] make a similar argument in the context of renewable-energy investments. Second, the assumptions regarding the energy-storage technologies' operation profile can influence significantly the economic results. Information from ESMs can be valuable to ensure that these assumptions are aligned well with energy-system needs. Third, static assumptions regarding operation profiles and electricity prices cannot capture the potential feedback of technology characteristics on the entire energy system. Cebulla et al. [42] show and this paper confirms that the number of full cycle equivalents (FCEs) per year,[4] that is economically viable for the energy-storage owner and beneficial to the energy system in which it operates depends on the E2P ratio of the energy storage. The optimal choice of E2P ratio depends on the costs of energy-storage capacity and charging and discharging power of the technology as well as characteristics of the underlying energy system (*e.g.*, shares of renewable and flexible generation and other energy storage). The underlying energy system may be driven by the costs and efficiencies of available energy-storage technologies. Static assumptions on energy-storage operation are unable to reflect such feedbacks [15].

1.2.2. Studies focusing on profit maximisation of energy-storage technologies

This category of studies involves analysing energy-storage technologies using a profit-maximising approach relying upon exogenous (typically historical) electricity prices as an input. Such studies are conducted both by technology developers and energy-market analysts, as the profit maximisation reflects (at least to some extent) the perspective of investors.

For instance, Frate et al. [43] compare different energy-storage technologies based on data from the Italian market. The authors consider E2P ratios between 4 and 10 hours and varying round-trip efficiencies. Their results suggest that the investigated technologies are not economically viable as of the time of the study. However, potential technology improvements or energy-market changes could enhance their economic feasibility. Similarly, Spodniak et al. [44] investigate key factors that influence the economic viability of large-scale, centralised energy storage in day-ahead electricity markets of Germany, United Kingdom, and Scandinavia. The study considers E2P ratios between 1 and 13 hours. The study finds that the specific revenues (in Euro per MWh storage capacity) are highest for an E2P ratio of 1, and that storage revenues from arbitrage in the spot market are higher in Germany and United Kingdom compared to Scandinavia, which can be explained by abundant hydroelectric storage already being available across Scandinavia. Braeuer et al. [45] assess the profitability of battery energy storage for German small- and medium-sized enterprises. They find significant potential profits when considering revenue streams from the provision of primary control reserve compared to a case wherein batteries arbitrage spot-market energy-price differences only. Laterre et al. [46] conduct a techno-economic analysis of Carnot batteries for energy management in residential settings. They find that in cases where heat pumps and thermal-energy storage are needed to supply residential heating demand, adding a heat engine to provide electricity can be financially attractive. Chen et al. [47] analyse the economic viability of underground hydrogen-storage systems for long-duration grid-scale electricity storage and find that profitability can be achieved for an appropriate mix of revenue streams.

While these approaches can indicate potentially attractive markets and applications of energy-storage systems, the profitability is assessed on the basis of exogenous, typically historical, electricity-price time series of the corresponding markets. Thus, such studies are unable to capture the future development of electricity prices, including potential feedbacks between the market and energy storage deployment. In contrast, Sioshansi et al. [48] study the value of electricity storage in an eastern United States of America (US) market and explicitly compare the arbitrage value with and without considering the feedback effect of energy storage arbitrage on electricity-market prices. However, this analysis is based on an ordinary-least-squares estimate of an assumed linear price-demand relationship using historic prices of one month. Dynamic changes in the underlying electricity system are not considered.

1.2.3. Studies focusing on energy-storage-technology needs from an energy-system perspective

The final category are studies aimed at analysing energy-storage needs from an energy-system perspective. Such studies use ESMs to consider dynamic energy-system interactions.

Weitemeyer et al. [49] examine the energy system's demand for energy storage as a function of the share of renewable energy generation. Considering different existing energy-storage technologies with varying efficiencies, costs, and capacities, they show that inter-seasonal energy storage is only a part of the least-cost energy system design for electricity systems with more than 80% of electricity being supplied by renewable energy. Babrowski et al. [50] investigate the spatio-temporal development of energy-storage demand in Germany and identify future energy-storage demand, especially in the vicinity of offshore wind generators. Solomon et al. [51] investigate the need for energy-storage technologies in future electricity systems in California and Israel with renewable energy supplying 90% of electricity. Arbabzadeh et al. [52] focus on the impact of energy storage on the curtailment of renewable-energy generation and show that in California, energy storage can increase carbon-emissions reductions due to expanding the supply of renewable energy by 20%. Moser et al. [27] present comprehensive sensitivity analyses of the impact of energy-storage costs and capacities on energy-storage demand in different regions of Europe. They find that hydrogen storage is deployed mostly in regions with high wind-electricity shares, while batteries are more distributed throughout Europe. Mutke et al. [30] analyse installed capacities of different energy-storage technologies in Europe with different decarbonisation targets. They report the results at an aggregated European level and assess the impact of bioenergy and transmission-line expansion on energy-storage requirements. Heredia-Fonseca et al. [53] use an ESM to identify and analyse 100% renewable energy pathways for the Indian state of Goa. Their study is focussed on energy-technology mixes along the pathway rather than operational details.

[4] FCEs per year is calculated as the total energy discharged over one year (in MWh) divided by the invested energy storage capacity (in MWh), and is dimensionless. See Eq. (10) for a mathematical definition.

All of these system-level approaches allow us to study least-cost future electricity systems including the interactions between existing and emerging technologies in the system under different constraints. However, while providing useful information, they do not focus explicitly on the needs of technology developers, who may seek to gain insights into a different set of questions. Based on our discussions with technology-development researchers, we identify the following three categories of information needs (note that they are not mutually independent).

First are design parameters. A technology developer may seek to understand trade-offs between technology performance (efficiency) and costs, which can help to prioritise development directions (*i.e.*, a low-cost/low-performance as opposed to a high-cost/high-performance technology). This possibility is explored by Olympios et al. [54] in the context of heat-pump systems, for example. In the specific context of energy-storage technologies, other design details that may be of interest to technology developers include required E2P ratios (*i.e.*, the need for short- or long-duration energy storage) or the number of FCEs per year as an indication for the required cycle stability.

Second are operational patterns. Specifically, dispatch curves can inform required ramping capabilities and provide insights into part-load dispatch as well as (dis)charging speeds, which is relevant to understand the importance of design-point as opposed to average efficiency. Moreover, future electricity-price profiles and spreads can inform economic viability.

Third are target markets. Investment requirements and prospective market volumes can inform which markets and technology mixes of the underlying power systems are most promising for a given energy-storage technology.

Most existing system-level studies, however, are not designed towards informing technology developers and addressing their needs. Exceptions beyond the aforementioned study by Olympios et al. [54] on domestic heating systems, are the works of Cebulla et al. [42] and Sepulveda et al. [26]. Cebulla et al. [42] analyse the capacity requirements, spatial distribution, and dispatch of energy storage in an European electricity system with high penetrations of renewable energy. Specifically, their model enforces a constraint that a minimum of 80% of electricity supply be from variable renewables, which their solution satifies exactly. Because they do not require a fully renewable electricity-system design, their target energy system still includes fossil-fueled generators. Sepulveda et al. [26] analyse the so-called design space of long-duration energy-storage technologies. By varying a selection of design parameters of such technologies, they focus on technology costs and efficiencies. Through a multi-parameter analysis, they identify minimum efficiencies and maximum costs that long-duration energy-storage technologies need to meet to be deployed and provide value to the energy system. Their analysis is limited to considering two US elecricity systems, which limits insights into which geographical characteristics drive their findings.

In summary, while most studies of the first two groups are technologically detailed, they are not designed to capture dynamic interactions with electricity markets, which will change fundamentally during the coming decades. These changes stem mainly from the evolving technology mix of underlying electricity systems (as they transition towards sustainable supply mixes), which will change the (marginal-)cost structures of electricity supply. In contrast, models that are used in the third group of studies are designed explicitly to capture such dynamics. However, these studies are intended typically to support policymakers or investors, but are often not aimed at providing results that offer guidance to technology developers.

1.3. Contributions of the paper and research questions

This paper contributes to narrowing the gap between ESM and technology development for the example of energy-storage technologies. Gathering researchers from both disciplines, this paper seeks to highlight, which information is needed from the perspective of technology developers, which information needs can be met by an advanced analysis of ESM results, and which needs require fundamental model developments. In contrast to the work of Cebulla et al. [42], we formulate a constraint on emissions and focus on fully decarbonised electricity systems. Compared to the work of Sepulveda et al. [26], we investigate explicitly the impact of the underlying electricity systems' technology mixes (*e.g.* solar- as opposed to wind-dominated). Moreover, we provide detailed information on operational patterns and expected market volumes.

More specifically, we consider the following four research questions, two of which are application-oriented (A), while the other two are methodological (M).

(A1) What are future requirements and opportunities of different energy-storage technologies in a fully decarbonised European electricity system in terms of design parameters, operational patterns, and target markets?
(A2) What technological and geographical characteristics drive the identified design parameters, operational patterns and target markets?
(M1) What insights for technology developers can be derived by advanced analysis of ESM results without targeted model modifications?
(M2) What novel methodological developments are required to bridge further the gap between ESMs and technology development?

We distinguish explicitly between insights that can be provided without targeted model modifications (M1) and insights that require fundamental model development (M2), because novel model developments may be perceived as a burden. Advancing the analysis of ESM results without targeted model developments, however, can typically be realised at relatively low effort, which means that such advancements can have a potentially wide and immediate impact in terms of transferring ESM results to technology developers.

The remainder of this paper is structured as follows. Section 2 describes the model and data that are used to illustrate the potential role of ESMs in informing technology development. Section 3 addresses research questions A1 and A2 by presenting the results of the advanced analysis on energy-storage-technology requirements for the application study that is considered in this paper, which is geared towards supporting technology developers. Section 4 addresses research questions M1 and M2 by discussing wider methodological insights for both technology developers and energy-system modellers. Section 5 concludes this paper and provides an outlook on future research requirements.

2. Methods and data

This paper builds on a European electricity-system model for the year 2050, that is presented by Mutke et al. [30] and used to inform policymakers with highly aggregated results. The innovation of this paper lies in an extended analysis that informs energy-storage-technology developers. This is achieved by analysing and interpreting previously unconsidered, disaggregated results, particularly nationally and temporally resolved data. Thereby, we can disentangle which information needs of technology developers can be answered by innovated analysis, and which ones require innovated modelling.

2.1. Energy-system-optimisation framework: Backbone

The linear optimisation model that is used for the analysis that is in this paper represents the electricity systems of 21 European countries during the 2050 target year at hourly resolution with a specified CO_2-reduction target. The model is built using the open-source energy-system-optimisation framework, Backbone, which structures networks using nodes, grids, units, and lines [55]. Most countries are represented

Fig. 1. Geographical region under study; black lines represent borders between nodes.

by one node, whereas Germany is modelled with 10 nodes, as is depicted in Fig. 1. Backbone is formulated using General Algebraic Modelling System (GAMS) and openly available.[5] The optimisation problem is solved using CPLEX. An extensive mathematical description of the full framework can be found in the original publication by Helistö et al. [55]. A mathematical description of the model used in this study is provided by Mutke et al. [30, Appendix A]. To provide a basic understanding of the underlying optimisation framework that underlies this paper, this section provides simplified forms of the objective function and selected constraints.

The objective function:

$$\min \sum_t \left(c_t^{\mathrm{VOM}} + c_t^{\mathrm{fuel}}\right) + c^{\mathrm{FOM}} + c^{\mathrm{invest}}; \tag{1}$$

minimises total system cost, which consists of costs for variable operation and maintenance, c_t^{VOM}, and fuel, c_t^{fuel}, both of which depend on time-t operation, as well as fixed operation and maintenance, c^{FOM}, and investment, c^{invest}, both depending on capacities. The objective is minimised assuming perfect foresight. The model uses a brownfield planning approach, where natural-gas and nuclear generators are assumed to be installed already (coal and oil generators are decommissioned), based on historical capacities, while investment in renewable generation and energy-storage technologies is optimised endogenously to achieve decarbonisation at least cost. Thereby, CO_2 emissions have an upper limit of zero, *i.e.*, we focus on the "C100" scenario of Mutke et al. [30], which yields a fully decarbonised European electricity system.

Investment cost:

$$\begin{aligned} c^{\mathrm{invest}} = & \sum_{g\in G} \alpha_g \cdot \mathrm{CAPEX}_g \cdot v_{n,g}^{\mathrm{invest}} \\ & + \sum_{s\in S} \alpha_s \left(\mathrm{CAPEX}_s^{\mathrm{power}} \cdot v_{s,n}^{\mathrm{max}\ +/-} + \mathrm{CAPEX}_s^{\mathrm{energy}} \cdot v_{s,n}^{\mathrm{max\ SoC}}\right); \end{aligned} \tag{2}$$

considers the invested capacity, an assumed per-unit CAPEX, and an annuity factor, α, of all generators, $g \in G$, and energy-storage technologies, $s \in S$. Power and energy capacities are distinguished for energy-storage investments.

The generation technologies that are available for endogenous investments are onshore and offshore wind, solar photovoltaic, and bioenergy. The energy-storage technologies that are available for endogenous investments are lithium-ion batteries (LIB), vanadium redox-flow batteries (VRFB), adiabatic compressed air energy storage (ACAES), and hydrogen storage (H_2). These four technologies are considered as they represent a range of technologies with different characteristics and potential uses. Batteries are continuing to experience significant cost reductions and technological development and offer are a competitive option for short-term load balancing of variable renewable energy. These characteristics apply particularly to LIB and VRFB [30,56]. Compressed air energy storage (CAES) is a promising technology for mid-term energy storage with additional efficiency improvements that are expected through adiabatic designs [57]. H_2 storage is a promising long-term energy-storage technology [58]. The H_2 energy storage that we model includes a polymer electrolyte membrane (PEM) electrolyser for charging, *i.e.*, hydrogen generation, and a hydrogen gas turbine for discharging, *i.e.*, re-electrification. We assume that the size of the energy reservoirs and power rating for all energy-storage technologies can be determined independently, which amounts to having the E2P ratios determined endogenously. For H_2, the charging and discharging capacities also can be determined independently, while for LIB, VRFB, and ACAES, there is no distinction between the two, meaning that their ratios are fixed equal to unity [59,60].

Energy balance is enforced at each network node, n, and during each time step, t:

$$v_{n,t}^{\mathrm{generation}} + v_{n,t}^{\mathrm{transfer}} + v_{n,t}^{-} = p_{n,t}^{\mathrm{demand}} + v_{n,t}^{+}; \tag{3}$$

where $v_{n,t}^{\mathrm{generation}}$ is total generator output, $v_{n,t}^{\mathrm{transfer}}$ is net energy transfer, $v_{n,t}^{-}$ energy released by discharging energy storage, $p_{n,t}^{\mathrm{demand}}$ electricity demand, and $v_{n,t}^{+}$ energy that is used for charging energy storage.

For each energy-storage technology, s, at each node, n, the ending time-t state of charge, $v_{s,n,t}^{\mathrm{SoC}}$, can change due to charging, $v_{s,n,t}^{+}$, discharging, $v_{s,n,t}^{-}$, both of which account for efficiencies, $\eta_{s,n}^{+}$ and $\eta_{s,n}^{-}$, respectively, and self-discharge losses, $\sigma_{s,n}$:

$$v_{s,n,t}^{\mathrm{SoC}} = (1-\sigma_{s,n}) v_{s,n,t-1}^{\mathrm{SoC}} + \eta_s^{+} v_{s,n,t}^{+} - \frac{1}{\eta_{s,n}^{-}} v_{s,n,t}^{-}. \tag{4}$$

The three decision variables that represent the state of charge, charging, and discharging also have lower and upper bounds:

$$0 \le v_{s,n,t}^{\mathrm{SoC}} \le v_{s,n}^{\mathrm{max\ SoC}} \tag{5}$$

$$0 \le v_{s,n,t}^{+} \le v_{s,n}^{\mathrm{max}\,+} \tag{6}$$

$$0 \le v_{s,n,t}^{-} \le v_{s,n}^{\mathrm{max}\,-}. \tag{7}$$

Cyclic boundary conditions are enforced for all energy-storage technologies, whereby their initial states of charge are determined endogenously but must match their ending states of charge:

$$v_{s,n,0}^{\mathrm{SoC}} = v_{s,n,T}^{\mathrm{SoC}}. \tag{8}$$

Such a constraint allows for seasonal energy-storage use between the beginning (*i.e.* time $t = 0$) and end (*i.e.* $t = T$) of the model horizon.

2.2. Data

The analysis in this paper is based on a European electricity-system model for the year 2050, including electricity-system data for 21 European countries [30]. The data used for the analysis consists of the following two main components. First is the open-source model PyPSA-Eur [61], which is the main data source for existing (real-world) conventional generators, transmission capacities, demand, and weather time series (which correspond to year-2013 data), and nodal clustering. The second is techno-economic data, most importantly costs, CAPEX, technical lifetimes, and efficiencies, which are synthesised from various sources by Mutke et al. [30]. Table 1 summarised these data for investable energy-storage technologies. For H_2, Table 1 shows two values each for "$\mathrm{CAPEX}_{\mathrm{power}}$", "Overall efficiency", "Lifetime" and "Annualised $\mathrm{CAPEX}_{\mathrm{power}}$". The first of the two values refers to the PEM for charging, *i.e.*, hydrogen production, whereas the second value refers to the hydrogen gas turbine for discharging, *i.e.*, re-electrification. Further details of the underlying model data are provided by Mutke et al. [30].

[5] https://gitlab.vtt.fi/backbone/backbone

Table 1
Techno-economic input data of the four energy-storage technologies that are available for investment. $CAPEX_{power}$ indicates the investment costs of 1 kW combined charging and discharging power (except for H_2, where both capacities can be determined independently). $CAPEX_{energy}$ indicates the investment costs of 1 kWh of energy-storage capacity, which can be sized independently of the power capacity. The quotient of the two is E2P CAPEX ratio, where for hydrogen storage we have added 1 kW charging and 1 kW discharging capacity in the denominator. Using the lifetime and a discount rate of 7%, the annualised CAPEX (in €/kW(h)/a) is calculated. Note that the E2P CAPEX ratio does not change with annualising the CAPEX, except for hydrogen storage. All data are taken from Mutke et al. [30].

Energy-storage technology	$CAPEX_{power}$ (€/kW)	$CAPEX_{energy}$ (€/kWh)	E2P CAPEX ratio (1/h)	Overall efficiency (%)	Lifetime (a)	Annualised $CAPEX_{power}$ (€/kW/a)	Annualised $CAPEX_{energy}$ (€/kWh/a)
LIB	74	155	2.095	93	17	7.58	15.87
VRFB	333	96	0.288	81	23	29.54	8.52
ACAES	823	48	0.058	70	45	60.49	3.53
H_2 [a]	267 // 767	0.5	0.0005	78 // 60	13 // 28	31.96 // 63.20	0.06

[a] Hydrogen generation with PEM, re-electrification with gas turbine.

2.3. Advanced analysis of ESM results

We focus our analysis of model results and draw insights from the following three sets of decision variables that are optimised by the ESM. The first is the invested capacity, $v_{g,n}^{\text{invest}}$, of (renewable) generators. The second is the invested charging and discharging power, $v_{s,n}^{\max +}$ and $v_{s,n}^{\max -}$, respectively, and energy-storage capacity, $v_{s,n}^{\max \text{SoC}}$, of energy-storage technologies. The third is hourly operational time series of generators and energy storage. In particular, we focus on the charging and discharging behaviour, $v_{s,n,t}^{+}$ and $v_{s,n,t}^{-}$, respectively, and state of charge.

In addition to these model outputs, we use the following three ancillary metrics to draw further insights regarding technology developers' needs, as is described in Section 1.2. The first ancillary metric is the energy-to-power ratio $\text{E2P}_{s,n}$ of each energy-storage technology, s, at each node, n, which is defined as:

$$\text{E2P}_{s,n} = \frac{v_{s,n}^{\max \text{SoC}}}{v_{s,n}^{\max -}}; \tag{9}$$

which is the ratio between invested energy-storage and discharge-power capacities of energy storage. The second is the number of full-cycle equivalents, $\text{FCE}_{s,n}$, which is calculated as:

$$\text{FCE}_{s,n} = \frac{\sum_{t=0}^{T} v_{s,n,t}^{-}}{v_{s,n}^{\max \text{SoC}}}; \tag{10}$$

and is defined as total energy that is discharged during the model horizon divided by the invested energy-storage capacity. The third metric is residual load, which is computed as:

$$\text{RL}_{n,t} = p_{n,t}^{\text{demand}} - \sum_{g \in R} p_{g,n,t}^{\text{cf}} v_{g,n}^{\text{invest}}; \tag{11}$$

and is defined as demand minus the potential generation of all variable renewable generators (*e.g.*, PV solar, onshore and offshore wind, and run-of-river hydroelectric generators). Potential generation is defined as capacity built multiplied by capacity factor, $p_{n,t,r}^{\text{cf}}$, and R is defined as the set of renewable technologies.

As part of our analysis, Section 3.2 presents and discusses associations between residual load calculated according to Eq. (11) and the state-of-charge profiles, $v_{s,n,t}^{\text{SoC}}$, as obtained from Eq. (4). In addition, we present histograms of the charging and discharging behaviour, $v_{s,n,t}^{+-}$, for each energy-storage technology and discuss how this is driven by geographical and technological characteristics at selected nodes.

3. Results of the application study

This section presents the outcomes of the advanced analysis of ESM results. Such results usually are not reported in system-level studies, but they are valuable for technology developers. Consequently, this section addresses research questions A1 and A2, where the application study is based on the European power systems model that is described in Section 2.

To establish a baseline and provide fundamental results for the fully decarbonised electricity system that is modelled, Mutke et al. [30] discuss the aggregated electricity mix and energy-storage capacities. They observe the following trends. With decreasing emissions, natural-gas generation is replaced by renewable electricity supply, while total electricity generation increases due to increased energy losses that are associated with energy-storage use. Energy storage capacities increase with decreasing emissions, with LIB being built first and, for all decarbonisation targets except 100%, having the greatest capacity. H_2 capacities increase drastically from 0 GW in the cost-minimal case without an emission target to up to approximately 300 GW at 100% CO_2-emission reduction. VRFB and ACAES are built only for CO_2-emission reductions above 80%, with capacities always below 15 GW. Fig. 2 summarises annual electricity generation by technology and country in the fully decarbonised scenario.

In the following, this section goes beyond these findings by presenting disaggregated modelling results for the four endogenously investable energy-storage technologies to inform technology development. As discussed in Section 2, we show results regarding design parameters (*e.g.*, E2P ratios and FCEs, *cf.* Section 3.1), operational patterns (*cf.* Section 3.2), and target markets (*cf.* Section 3.3).

3.1. Design parameters: Analysis of energy-storage E2P ratios, FCEs, and investment costs

The E2P ratio is a key investment decision of our ESM that characterises an energy-storage system. Fig. 3 shows the optimal E2P ratios of different energy-storage technologies for each country. The E2P ratios change significantly between the different technologies: the E2Ps of H_2 is between 300 h and 1000 h, of ACAES is between 15 h and 20 h, and of VRFB is between 5 h and 7 h. These E2P ratios depend only weakly on the country. For LIBs, the E2P in solar-rich countries, such as Italy and Spain, is approximately 5 h, whereas it is 2 h–3 h in wind-rich Ireland and Great Britain. Consistent with the findings of Cebulla et al. [42], different optimal E2P ratios of different energy-storage technologies can be explained by their power- and energy-capacity investment costs. Technologies with relatively low CAPEX for energy capacity and high CAPEX for power have high E2P ratios and *vice versa*. Fig. 4 shows a clear negative, non-linear, relationship between optimal E2P ratios and E2P CAPEX ratios, which are defined as $CAPEX_{energy}/CAPEX_{power}$. The difference between E2P ratios for solar- and wind-rich countries can be explained by the different roles of LIB in these countries: in solar-rich countries, LIB mainly shifts energy from the midday solar peak into the evening hours, while in wind-rich countries LIB mainly balances short-term wind fluctuations to meet demand and minimise electrolyser capacity (which is used to charge H_2 energy storage). This result shows that the underlying system influences the requirements for energy-storage technologies, although the effect is much weaker than the effect of the investment costs of power and energy-storage capacity.

Fig. 5 shows FCEs for selected countries and all storage technologies. The figure reveals a strong connection between optimal investment and dispatch decisions, namely an opposite trend of invested E2Ps

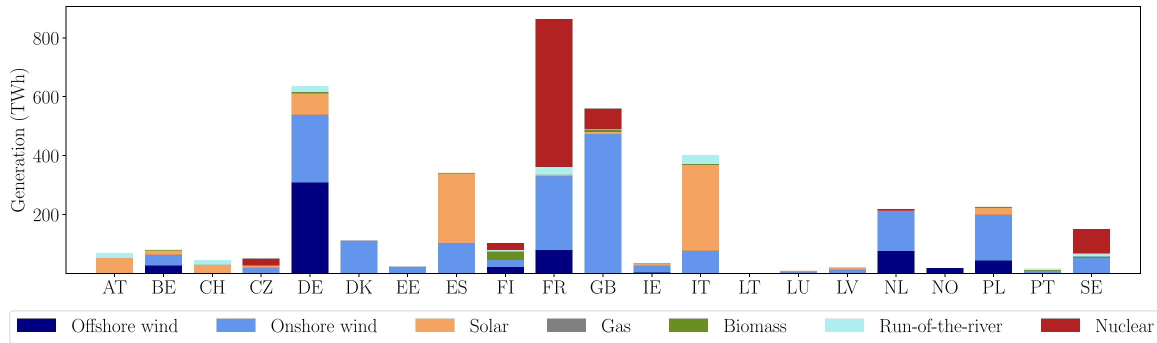


Fig. 2. Electricity-generation mix per country.

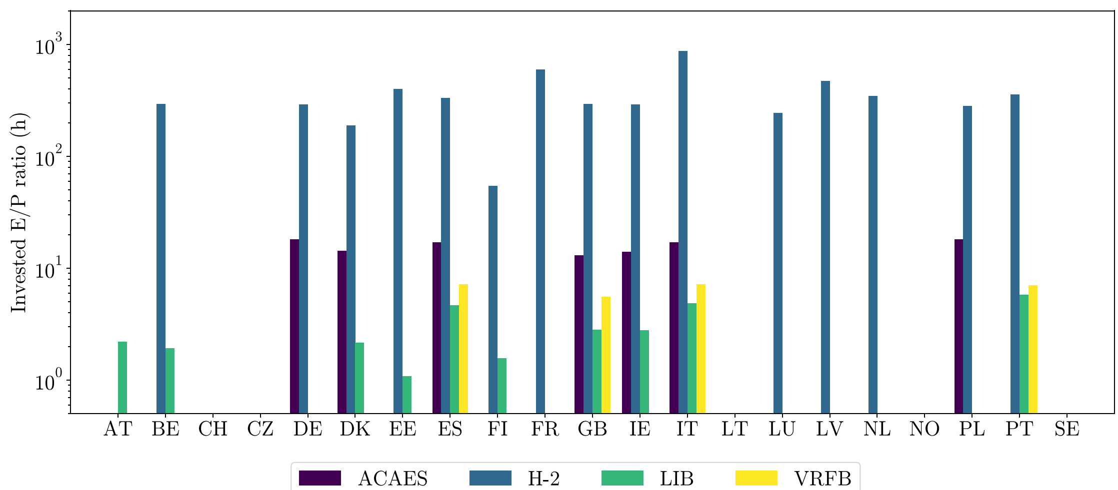


Fig. 3. Invested E2P ratio (log scale) per technology and country.

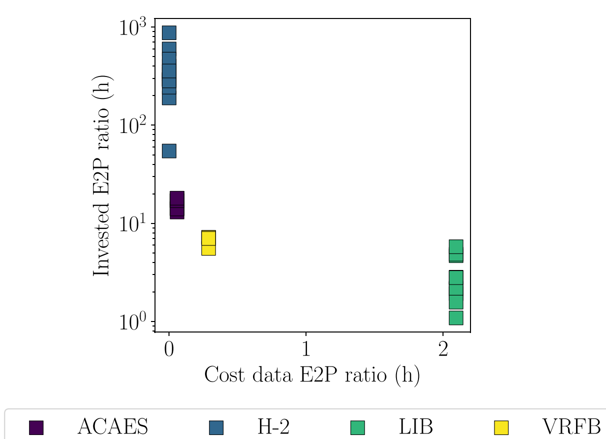


Fig. 4. Relationship between invested E2P ratio and E2P-cost ratio across all countries. The horizontal axis shows the ratio of capacity-specific energy cost divided by capacity-specific power cost. Here, capacity-specific means that both the enumerator and denominator comprise annualised CAPEX (*cf.* Table 1) and annual fixed operation and maintenance cost. Only the vertical axis has a logarithmic scale and only four different E2P-cost ratios are attained, due to the spatially homogeneous cost assumptions that are given in Table 1.

and dispatched FCEs. Whereas LIB and VRFB have over 200 FCEs per year, ACAES has below 100, and H_2 below 10. Similarly, LIB in solar-rich countries exhibits a higher number of FCEs than those in wind-rich regions. The different FCEs of LIBs between solar-rich and wind-rich countries stem from the different roles that the technology plays in these regions.

These findings can inform technology developers in multiple ways. First, they reveal the inverse relationship between E2P-cost ratios realised in the development and the invested E2P ratios in the optimised system. An energy-storage technology with relatively high (low) E2P-cost ratio (*cf.* Table 1) will likely realise a low (high) E2P ratio in optimal market- or system-based investment decisions. Moreover, such a technology will likely realise a high (low) number of FCEs in optimal market- or system-based dispatch. Conversely, if developers see, for technical reasons, a high potential for an energy-storage technology in realising many (few) FCEs in operation, then it needs likely to be built with a low (high) E2P ratio and must, therefore, be developed towards low power CAPEX (low energy CAPEX). It is important to note that different technologies have inherent limitations to their design and cost structures. For instance, LIB will never achieve the same energy CAPEX as H_2 energy storage. A supplementary analysis focusing on the relationship between the E2P ratios and FCEs is provided in the Appendix.

Secondly, the findings have an important impact on potential business models and the associated risk for energy-storage operators. Energy storage with only few FCEs are reliant upon revenue that is earned during these few FCEs. This means also that they depend strongly on prices and price spreads during only a few periods of time and may be subject to revenue risk if those parameter forecasts are incorrect. Conversely, energy storage with many FCEs have many more opportunities to generate market revenues. For example, energy storage with daily cycles can benefit from daily electricity-price fluctuations between on- and off-peak periods and can generate profits more regularly.

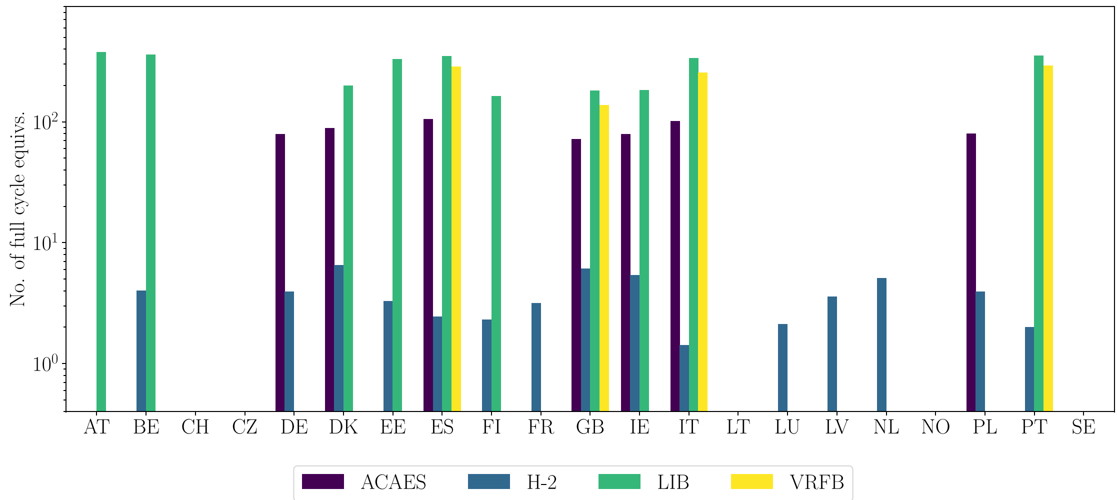


Fig. 5. Number of FCEs during the modelled year.

3.2. Operational patterns: state-of-charge profiles and associations with residual load

We examine in greater detail the operational role of different energy-storage technologies, beyond the discussion that is presented in Section 3.1. Fig. 6 shows time series of the residual load and the state of charge of all four expandable energy-storage technologies for Great Britain and Spain, which are wind- and solar-rich regions, respectively. Spain's residual-load profile is dominated by the typical intra-day fluctuation of solar irradiation. Conversely, Great Britain's residual load is dominated by inter-day and inter-week fluctuations in wind availability. Consequently, LIB and VRFB in Spain follow diurnal cycling patterns, thereby exhibiting significantly more and more predictable cycles than their counterparts in Great Britain.

In Spain, the operation of H_2 energy storage is dominated by one seasonal cycle. Conversely, H_2 energy storage in Great Britain have a great number of smaller cycles, which are related periods with differing wind speeds. ACAES provides flexibility on time scales of days to weeks. Often during solar-rich months in Spain, however, only half of the available H_2 and ACAES capacities are utilised, with energy storage cycling between half-filled and empty. Conversely, LIB and VRFB typically are filled and emptied entirely during each cycle in both countries.

These time series inform developers regarding the operational requirements for energy-storage systems under system-optimal dispatch beyond the aggregated that are FCEs summarised in Section 3.1. The time series provide information on the operational behaviour and changes of different technologies (*i.e.*, frequency of part- as opposed to full-load dispatch), which is important to assess trade-offs between design-point and off-design efficiencies. For example, Fig. 6 shows that LIB in Spain are operated in a quite regular daily cycle, while the operation of the ACAES is much more irregular. The time series provide an indication also of the required energy-storage durations, which can help to assess how self-discharge affects the economic viability of the technologies. Such an analysis is an important step beyond common engineering practice, where calculations rely often on estimated times. Especially for energy-storage systems that contain a thermal element, *e.g.*, ACAES and PTES, such considerations can influence outcomes significantly.

Furthermore, the time series provide insights into the relationship between charging and discharging power and time, which is important for technology developers. For instance, energy storage that charges slowly during 10 h and then discharges rapidly during two hours must be designed very differently compared to one that charges and then discharges during six hours each. Such considerations are particularly important for energy-storage technologies, such as PTES, where the energy storage size (*i.e.*, the E2P ratio) can be scaled independently given specific charging and discharging components. It is important to note, however, that discharging time and power are connected: when neglecting energy losses, discharging power can be increased with reduced discharging time, or *vice versa*.

In addition and complementary to the chronological presentation of the time series for residual load and state of charge in Fig. 6, Fig. 7 shows histograms of charging and discharging behaviour for the considered energy-storage technologies. The figure thereby compares the charging and discharging behaviour between GB as a wind-rich country (Fig. 7(a)) and Spain as a solar-rich country (Fig. 7(b)). Positive values (right side within each diagram) represent charging, whereas negative values represent discharging. Fig. 7 shows that the different energy-storage technologies are used very differently in the two countries.

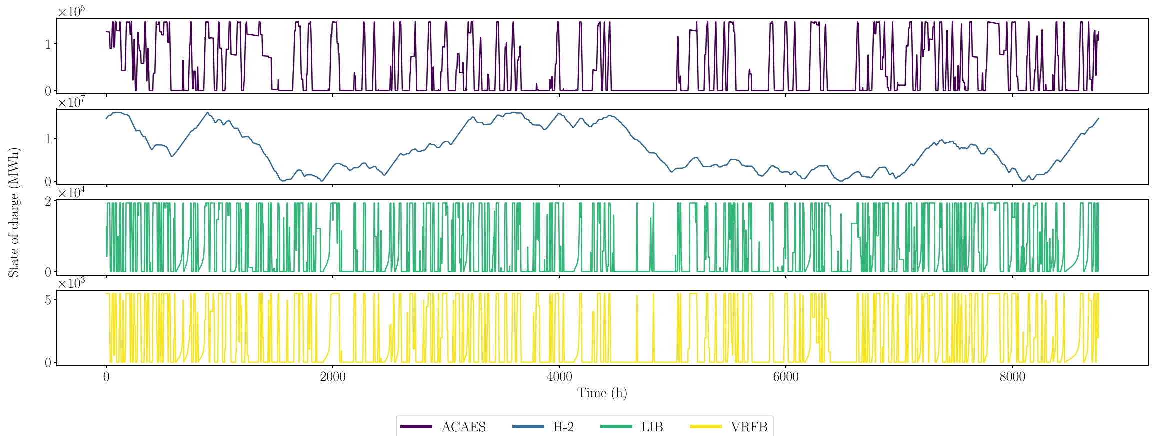
ACAES are charged/discharged at full load in around 900 h per year and hardly ever at partial load in Great Britain. In Spain, charging at full load occurs in more than 2000 h per year and discharging at full load occurs in around 1700 h. Similarly to Great Britain, charging or discharging at partial load occurs rarely only. Note, however, as illustrated in Fig. 8, the invested discharge capacity of ACAES in Spain is on the order of magnitude of 10^2, whereas it is on the order of magnitude of 10^4 in Great Britain.

H_2 energy storage in Spain is charged at full load during approximately 1400 h per year, whereas it is discharged at full load during about 700 h per year. In Great Britain, H_2 energy storage is charged at full load during about 2000 h and discharged during approximately 700 h per year. In contrast to Spain, however, H_2 energy storage is charged and discharged at partial load very frequently. The invested discharge capacity of H_2 energy storage in Great Britain exceeds the capacity invested in Spain roughly by a factor of 10.

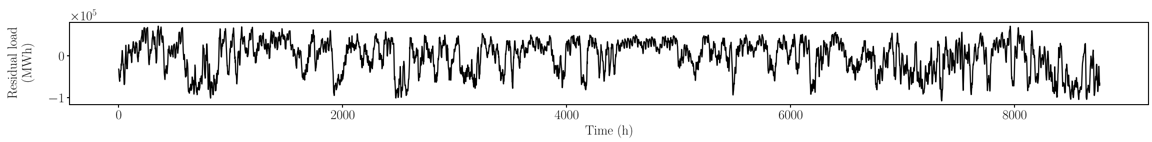
Concerning LIBs, state-of-charge changes between successive hours are negligible during around 6800 h of the year in Great Britain. During only around 200 h, LIBs are charged/discharged at full charging/discharging capacity, while they are charged/discharged at partial load much less frequently. In Spain, in contrast, LIB charging at full capacity occurs during around 1100 h, whereas discharging very often occurs at partial load (in sum more than 4000 h per year).

Concerning VRFBs, 7 shows for both countries that they are either charged/discharged at full load or not at all. Moreover, charging/discharging at full load occurs during around 2000 h each in Spain, whereas it occurs during around 700 h per year in Great Britain.

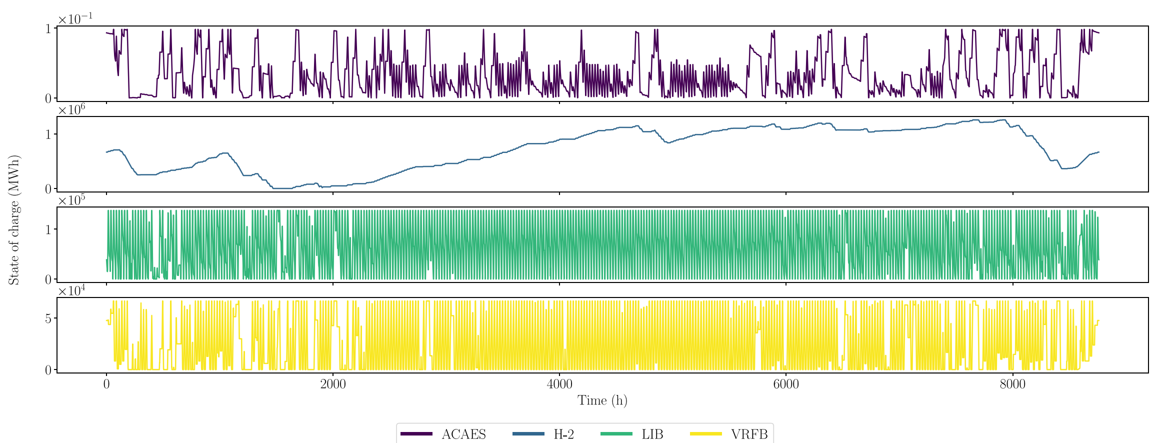
These findings provide important indications for the relevance of partial-load efficiencies as opposed to a design-point efficiency. Moreover, the findings provide insights for different use cases of different



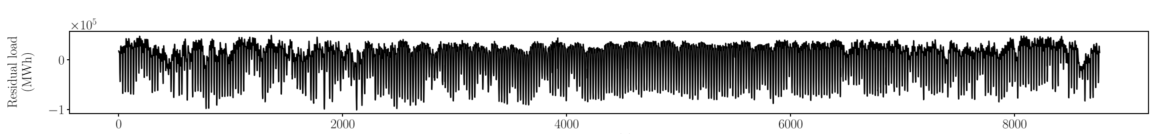
(a) State of charge of all energy-storage technologies in Great Britain (wind-rich).



(b) Residual load for Great Britain (wind-rich).



(c) State of charge of all energy-storage technologies in Spain (solar-rich).



(d) Residual load in Spain (solar-rich).

Fig. 6. Time series for residual load and state of charge of all four energy-storage technologies.

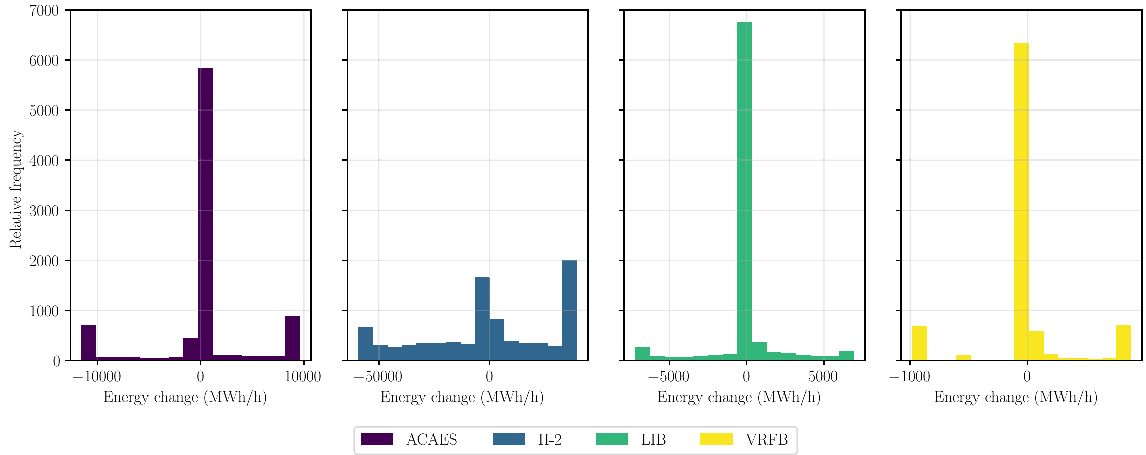
energy-storage technologies between different countries and their markets. For instance, short-term (daily) balancing of the variations of renewables is largely covered by LIBs in Spain. In Great Britain, this task is largely taken care of by H_2 energy storage. Interestingly, H_2 in Great Britain is not specifically built for this purpose. Rather, H_2 energy storage is needed to cover the demand during periods with no or low wind generation. The H_2 energy storage that is built then also provides short-term balancing services. Differences in target markets will be considered further in the subsequent section.

3.3. Target markets: spatial disaggregation and technology associations

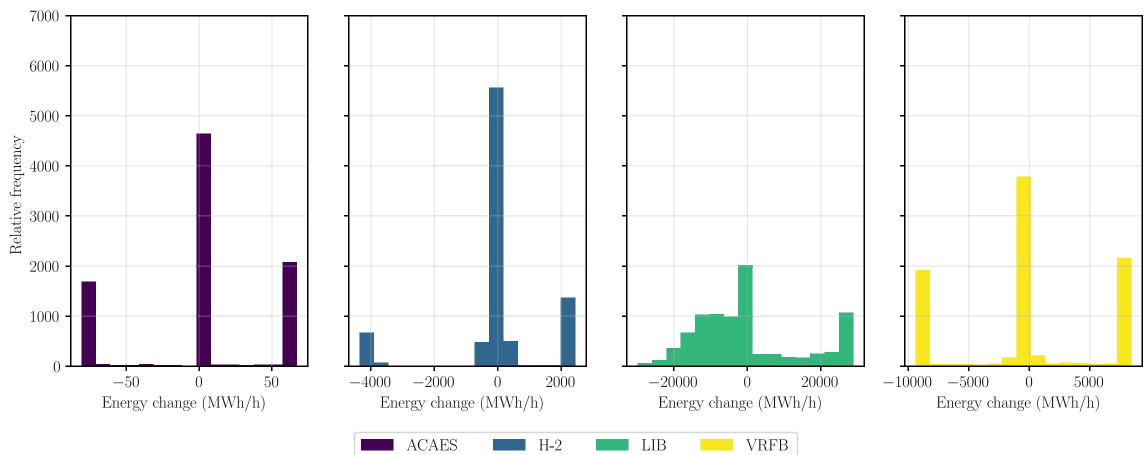
To improve understanding of promising markets for different energy-storage technologies in decarbonised energy systems, we must analyse model results at a national, disaggregated level and in the context of the renewable-energy potentials. Fig. 8 summarises power capacities of energy storage that are built in the countries that are modelled, which are grouped by renewable-energy potentials.[6]

For all wind-rich countries, H_2 is the energy-storage technology with the highest capacity, followed by ACAES or LIB, the capacities of which are mostly one or more orders of magnitude smaller. Conversely, in

[6] Following Finke et al. [15], we consider a country to be wind-rich if full-load hours of onshore wind exceed 1500 h/year and offshore wind 4000 h/year, and solar-rich if full-load hours exceed 1100 h/year. According to this classification, France is wind- and solar-rich. Because there is slightly higher wind potential, we classify it as wind-rich in Fig. 8 and this discussion.



(a) Relative frequency of energy change between two time steps for Great Britain (wind-rich).



(b) Relative frequency of energy change between two time steps for Spain (solar-rich).

Fig. 7. Histograms of state-of-charge differences, *i.e.*, charging and discharging behaviour, of the considered investable energy-storage technologies. Comparison between Great Britain as a wind-rich country (top panel) and Spain as a solar-rich country (lower panel). Positive values (right side within each diagram) represent charging, whereas negative values represent discharging.

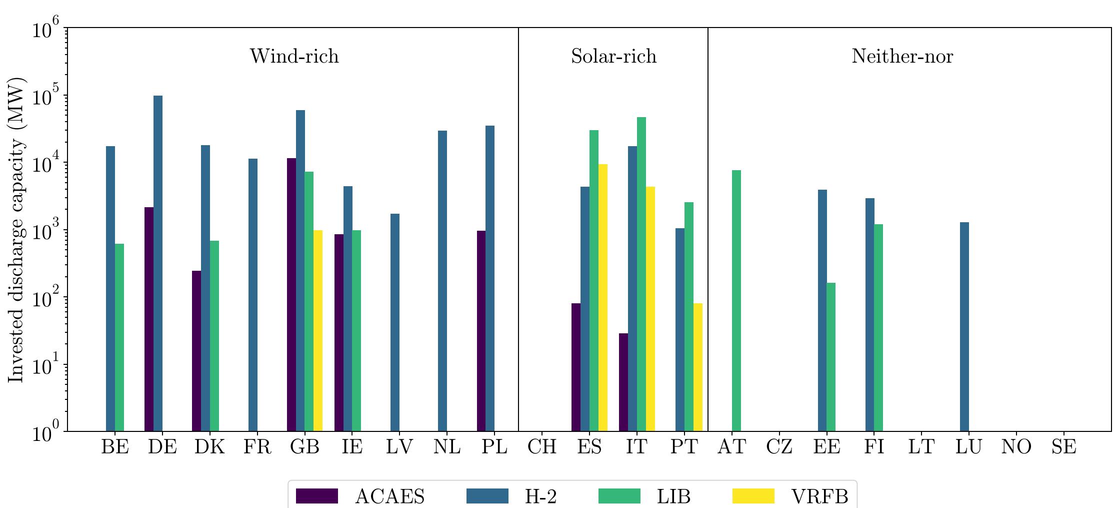


Fig. 8. Energy-storage discharging capacities for all countries grouped into wind-rich, solar-rich, or neither-nor countries.

solar-rich countries LIB has the highest capacities and many different energy-storage technologies are utilised. Further analysis shows that very high PV investments always coincide with high LIB and VRFB investments. Some countries have no or little energy-storage investments, compared to their overall generation capacity. This is due to other technologies providing dispatchable generation (*e.g.*, hydroelectricity for Switzerland, Austria, and Norway and nuclear or bioenergy for Czechia, France, and Sweden). Overall, ACAES and VRFB never dominate national energy storage capacities and VRFB are built only in solar-rich countries and Great Britain.

As VRFB is more cost-competitive (on the basis of annualised CAPEX) than LIB for E2P ratios above ≈ 3 h, we attribute the preference of LIB to its 12 percentage point higher efficiency in combination with many FCEs. As an illustrative example, for energy storage with 1 MW and 4 MWh, the annualised CAPEX difference between LIB and VRFB is approximately 8 000 €. An efficiency difference of 12 percentage points causes electricity losses of 168 MWh during 350 FCEs. Therefore, the revenue difference overcompensates financially the CAPEX difference when energy storage can earn an average arbitrage above 48 €/MWh. Such simplified calculations, however, are extremely sensitive to the underlying assumptions. Similarly, as ACAES is more cost-competitive than VRFB for E2P ratios above six hours (based on annualised CAPEX), our results suggest that the fact that ACAES systems are not built is mainly due to its 11-percentage point lower efficiency. The annualised CAPEX of H_2 energy storage is the lowest of all technologies for E2P ratios above 10 h when assuming that charging equals discharging power. Consequently, its dominance seems to be explained by its uniquely low costs for large E2P ratios that compensate for its lowest overall efficiency.

This type of analysis enables developers to identify promising target markets for their energy-storage technology while considering also the previous discussion regarding E2P ratios. For instance, energy-storage developers who consider evolving their technologies towards high E2P ratios of multiple hundreds of hours may find higher potential in markets with high wind availability and low potential for hydroelectricity and other dispatchable generation technologies, as is the case of Germany and Poland. Conversely, developers that aim for E2P ratios that are below 10 h will find greater potential for their energy-storage technologies in markets with high solar deployment, such as Italy and Spain. Such analysis guides more targeted technology development, *e.g.*, towards specific geographical, infrastructural, or regulatory conditions in promising markets. Moreover, strong cost competition between promising low-E2P-ratio energy storage technologies with high FCEs emphasises the importance of high efficiencies that technology developers must achieve while maintaining cost-competitiveness.

3.4. Limitations of the application study

As is the case for all model-based studies, there are limitations that are related to the model and the data that are used, which are important to understand when interpreting model results. We discuss the main limitations, some of which are general limitations of ESMs, whereas others are more specifically pertinent for providing guidance to energy-storage development.

The study focuses on the electricity sector, assuming exogenous energy demand. This means that sector coupling and any resulting flexibilities, which would compete with energy storage, are not considered. Therefore, exact energy-storage requirements should be interpreted with caution. Only four different energy-storage technologies are considered as investment options in the model, which means inevitably that not all emerging technologies are considered. Moreover, the charging capacities are assumed to be identical to the discharging capacities for all investable energy-storage technologies (except H_2). While this is a common assumption in ESMs [42,60,62], this simplification may lead to neglecting a real-world degree of freedom that technology developers have.

4. Wider methodological discussion

In this paper, we argue that more collaboration is needed between the ESM and technology-development disciplines. Such collaboration needs to be strengthened particularly for low-TRL technologies, to guide technology development and ensure investments in research and development are well directed. For the case of energy-storage technologies, Section 3 presents examples of an advanced analysis of ESM results that typically are not reported in ESM studies, but are valuable for technology developers.

In what follows, we address research question M1 by discussing key implications and providing insights to technology developers (Section 4.1) and energy-system modellers (Section 4.2) on which information needs can be met by an advanced analysis of ESM results, as exemplified in the previous section. Finally, in Section 4.3, we address research question M2, *i.e.*, we discuss which needs require fundamental model development.

4.1. Insights for energy-storage developers

First, LCOS alone is a not a sufficient indicator to provide guidance for energy-storage-technology development. LCOS is a cost-based metric and lacks an accurate assessment of the revenue potential of energy storage. Moreover, LCOS depends highly on the assumed utilisation of an energy-storage technology. This paper analyses the use of different energy-storage technologies based on ESM results and finds that the number of FCEs can vary from a few to a few hundred cycles per year. *Ceteris paribus*, this variance can lead to LCOS differing by a factor of 100.

Second, when considering energy-storage revenue, the use of exogenous, static prices overlooks any feedback effects between the technology that is under consideration and market outcomes. In particular, the use of historic prices overlooks the fact that price profiles and price spreads will change fundamentally as a result of the energy transition because of the changes in the technology mix of the underlying electricity system. Although we do not analyse revenues in this study, price profiles (proxied by system marginal costs) can be derived from ESMs while considering the changes in the technology mix over time. Therefore, future studies should conduct more sophisticated profitability assessments, considering both technology costs and revenues (*cf.* the works of Finke et al. [15] and Finke et al. [63] for two exemplative analyses). Such profiles allow also for assessing the market value of different technologies [15]. As a further example, such an analysis can quantify expected (additional) revenues from technology improvements to analyse if (additional) costs for such improvements (*e.g.*, larger heat exchangers for thermo-mechanical energy storage) are expected to be compensated by higher revenues.

Third, concerning research question M1, ESMs generally are capable of providing valuable information for energy-storage-technology development, accounting for dynamic energy-system interactions. Making use of the advanced analysis of ESM results presented in this paper can help identify design parameters, such as E2P ratios, that are needed from a system perspective. Our analysis shows that these may differ by more than a factor of 100, and are driven by energy-storage costs and the resource conditions and technology mix of the region where the energy storage may be deployed. In terms of operational patterns, energy-storage-dispatch profiles from an ESM provide insights into charging and discharging power and speeds, part-load dispatch, and energy-storage durations. As illustrated by the histograms in Fig. 7, the ESM results provide insights into different use cases for the considered energy-storage technologies across the different countries and their markets. For instance, some energy-storage technologies are characterised by daily cycles with fast and complete (dis)charging or by slow (dis)charging over weeks or seasons and long times with almost full energy storage. While energy-storage durations are important to assess self-discharge and the corresponding impact on overall energy-storage efficiency—particularly in the case of thermo-mechanical energy storage—(dis)charging speeds are needed to understand the importance of design-point as opposed to average efficiency. ESMs also can provide insights regarding prospective regions and markets, where market uptake of a certain technology is expected. In particular, the ESM results exhibit associations between favoured energy-storage technologies and favourable conditions for certain renewable energy sources. Moreover, ESMs can inform expected market volumes to assess if the costs of developing a technology can be expected to be recovered during the future.

Finally, to ensure that an advanced analysis of ESM results can provide meaningful guidance to technology development, high-quality, accurate technology characteristics need to be provided by technology developers. This may require multiple iterations, especially in the case of low-TRL technologies, where data are scarce or non-existent, in which case important indicators need to be estimated or predicted. On the one hand, technology costs and efficiencies are key inputs for ESMs. On another hand, as we discuss above, such assumptions depend on energy-storage-dispatch profiles. These are outputs of ESMs and drive, for instance, energy-storage durations with corresponding impacts on self discharge and material choice. These choices affect both energy-storage cost and efficiency.

4.2. Insights for energy-system modellers

ESMs are suitable not only to provide high-level policy support, but also can provide technology-development guidance including for low-TRL technologies. To provide useful support and guidance, however, the way in which ESMs are used needs to be modified. These changes concern both the output (*i.e.*, the way in which ESM results are presented) and the input (*i.e.*, the way in which model assumptions are prepared and considered) sides.

With respect to outputs, as we discuss in this paper, energy-system modellers should focus on presenting more disaggregated results that are useful for technology developers and conduct an advanced analysis of ESM results, as we do this paper, to provide the key information that developers require. For instance, total installed capacities—a standard result that is reported in ESM papers—indicate potential markets and market volumes for technologies. More important information in terms of design parameters, such as E2P ratios or expected FCEs, operational patterns, or price profiles and spreads often are missing.

With respect to inputs and energy-storage technologies, in particular, it may be insufficient to consider LIB as a short-term energy-storage technology and H_2 as a long-term technology. Such a coarse approach risks overlooking relevant gaps concerning required E2P ratios from the perspective of the system and may lead to sub-optimal outcomes. Moreover, it is important to note that ESM inputs, such as technology costs and efficiencies, depend on the dispatch mode of these technologies, which is an ESM output. In other words, using design-point efficiencies may be too optimistic and average efficiencies may be more appropriate. This means that it is insufficient for energy-system modellers to gather such key parameters from engineering publications and use them as static inputs.

Concerning both ESM inputs and outputs, the following points are important. Efficiency and cost estimates from technology developers often have large uncertainties [34]. The same is true for almost all other ESM inputs. Therefore, the ESM community should put less focus on presenting theoretical techno-economic optima as model results, and focus more on presenting a set of near-optimal solutions [64,65], highlighting the full (technological) diversity within such a set, *i.e.*, highlighting uncertainty regarding ESM outputs. Such practice also can provide the basis for considering further interests and criteria that are relevant in reality, such as material-supply risks [66] or site availability or public acceptance [67]. The considerations of such constraints may make a shift necessary to new low-TRL technologies that go beyond the traditionally considered techno-economic sphere. Concerning ESM inputs and outputs, energy-system modellers and technology developers need to collaborate closely. Such collaboration most likely will need to be iterative. Recent research highlights the need for the ESM community to engage with policymakers, investors, and stakeholders in a more participatory way to provide more useful insights and support [68–70]. Such collaboration with technology developers also is important.

4.3. Methodological-development requirements to improve support of technology developers further

The ESM that is used in this paper identifies a least-cost solution from a central-planning perspective. While in a perfect market, the duality principle guarantees that all energy-storage technologies that are built by the ESM exactly recover their full costs through revenues from the market, there are multiple markets and revenue streams in reality [71], which may create different business cases [28]. Moreover, actors' behaviour and revenues may differ in imperfect markets. However, individual actors' decision-making, as considered in agent-based models for instance [72], is not considered here.

Moreover, the ESM that is used is a linear programme (without integer variables). This makes it hard to distinguish between several small and a few large energy-storage units. From a technology-development perspective, however, this could be an important distinction. While the consideration of integer variables is standard in many ESMs, including Backbone, such variables may yield challenges concerning the computational complexity when considering large real-world systems. In addition, the ESM is deterministic and assumes perfect foresight for a single snapshot year during the future. On the one hand, this means that no pathways or changing technology cost or efficiency assumptions resulting from technological progress over long periods of time are considered. On the other hand, this means that the model does not consider uncertainty. As discussed in this paper, however, an adequate estimation of key parameters, such as costs and efficiencies, for rather distant periods in the future involves very high uncertainties for technologies at all TRLs. Such estimation for low-TRL technologies may not be possible at all.

These limitations call for fundamental research on and development of ESMs to provide improved guidance for the development of emerging technologies. For instance, adopting an inverse modelling approach seems promising, which determines a Pareto front between technology costs and efficiency, rather than requiring these values as inputs. Methods from multi-objective optimisation can support the determination of Pareto fronts as solutions to optimisation problems with more than one objective [73]. Such an inverse approach would have the potential to indicate priorities for future technology-development activities, *e.g.*, what combinations of costs and efficiency must be achieved for a technology to enter the system. Thus, these techniques have the potential to foster closer collaboration between the ESM and technology-development communities.

5. Conclusions and outlook

ESMs are used often to support policymakers, system operators, or investors, but much less to offer guidance to technology developers. This paper aims to bridge the gap between ESM and technology development. Focussing specifically on energy-storage technologies, which are important flexibility sources for the energy transition, we discuss which type of information is needed by technology developers and highlight explicitly, which of these information needs can be met by an advanced analysis of ESM results (research question M1), and which needs require fundamental model developments (research question M2). We demonstrate the advanced analysis for an application study focusing on requirements for energy-storage technologies in a fully decarbonised European power system. The advanced analysis provides insights into design parameters, operational patterns, and target

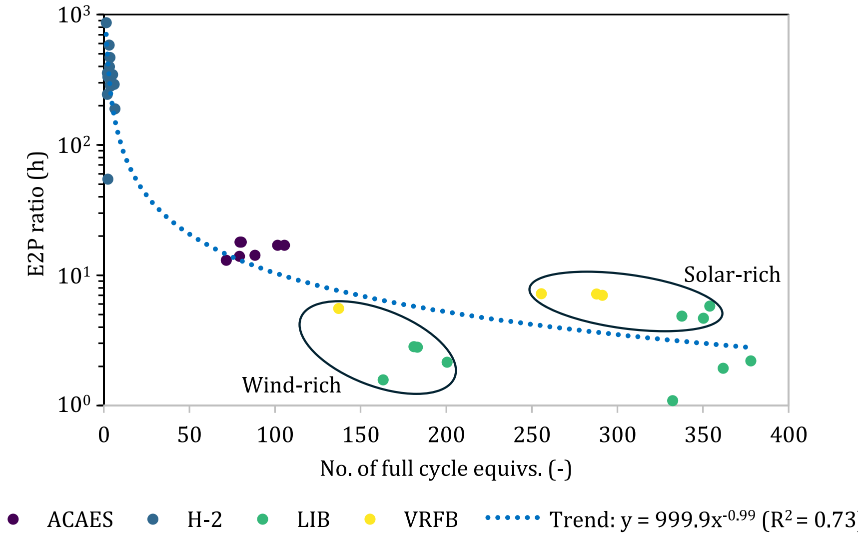


Fig. 9. Plot of E2P ratios against FCEs across all energy-storage technologies and target markets.

markets of the four considered energy-storage technologies (research question A1). Moreover, the application study shows, which (technological or geographical) characteristics are important drivers of the identified design parameters, operational patterns, and target markets (research question A2).

More specifically, the advanced analysis that is presented in this paper provides the following insights in the context of the application study. Concerning the identified design parameters, we discuss how optimal invested E2P ratios are reversed to given E2P-cost ratios, *i.e.*, technologies with low-cost power (*e.g.*, LIB) are designed with low E2P ratios whereas technologies with low-cost energy (*e.g.*, H_2) have high optimal E2P ratios. We relate this finding to operational patterns, such as optimal dispatch profiles, showing that low-E2P energy storage have many FCEs, up to the order of one cycle per day for LIB and VRFB, whereas high-E2P energy storage, like H_2, are operated with only a few FCEs per year. However, we show also that the use of energy-storage technologies can differ strongly between different regions and their markets. In terms of operational patterns, we show how typical energy-storage durations and utilisation of the available capacity are related to a technology's E2P ratio and to renewable-energy potentials and residual-load profiles. Finally, we analyse promising markets for the different energy-storage technologies and how their characteristics impact the required energy-storage technologies and their use. We show that low-E2P technologies, such as LIB and VRFB, are used more in solar-rich countries while high-E2P technologies, such as H_2, see greater investment in wind-rich countries. Moreover, we show that for LIB, VRFB, and ACAES, which follow each other as the most cost-competitive technologies with E2P ratios below 10 h, efficiency differences strongly drive optimal adoption.

We conclude that energy-technology development can benefit greatly from the information that is provided by an advanced analysis of ESM results, as is shown here for energy-storage technologies. Thus, we demonstrate the benefits of closer collaboration between the disciplines. The model that is used in this study has many common characteristics and is not fundamentally different from numerous other state-of-the-art ESMs. Certain model features and methodological developments would be beneficial for enabling this form of decision support and guidance for technology developers.

Future work could incorporate greater technological detail (*e.g.*, regarding discrete unit sizes, ramping, start-ups, and sector coupling) while maintaining or even extending a broad temporal, spatial, and technological scope. Furthermore, when describing low-TRL technologies, there is a higher uncertainty in key characteristics (*i.e.*, ESM inputs) such as costs or efficiencies. Therefore, complementary, parallel efforts based on inverse-modelling approaches to inform developers of necessary or desired cost or performance targets would be useful.

CRediT authorship contribution statement

Valentin Bertsch: Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Formal analysis, Conceptualization. **Jonas Finke:** Writing – review & editing, Writing – original draft, Validation, Software, Formal analysis, Data curation. **Katharina Esser:** Writing – original draft, Visualization, Validation, Data curation. **Leonie Sara Plaga:** Writing – review & editing, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Matthias Mersch:** Writing – review & editing, Writing – original draft, Formal analysis. **Jonathan Stelzer:** Writing – original draft. **Burak Atakan:** Writing – review & editing, Writing – original draft, Formal analysis. **Wolf Fichtner:** Writing – review & editing, Writing – original draft, Formal analysis. **Christos N. Markides:** Writing – review & editing, Writing – original draft, Formal analysis. **Ramteen Sioshansi:** Writing – review & editing, Writing – original draft, Formal analysis.

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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.

Appendix. Supplementary analysis

In addition to the analysis of E2P ratios and FCEs that is presented in Section 3.1, this appendix provides a supplementary analysis focusing on the relationship between the two. Fig. 9 illustrates the invested E2P ratios against the FCEs for the four considered energy-storage technologies. The different points for each technology each represent one target market. The dotted "Trend" line is a hyperbolic fitting curve across all technologies and markets. As shown in the legend of Fig. 9, with an exponent of −0.99, the fitted curve is very close to the standard hyperbola multiplied by 1000 (*i.e.*, it can be proxied well by the functional relationship $y = 1000/x$) and yields an R^2 of 0.73.

It is interesting to observe in Fig. 9 that the mid-term and long-term energy-storage technologies ACAES and H_2 form clearly defined clusters in the plane spanned by the FCE and E2P axes. The short-term energy-storage technologies LIB and VRFB also form clusters, but each of these clusters is split. On the one hand, short-term energy-storage technologies in wind-rich countries are typically characterised by a relatively lower number of FCEs. On the other hand, short-term energy-storage technologies in solar-rich countries are characterised by both higher FCEs and E2P ratios.

Data availability

Data will be made available on request.

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