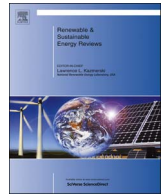




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Long-run power storage requirements for high shares of renewables: review and a new model

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ABSTRACT

The purpose of this article is twofold. First, we review model-based analyses that explore the role of power storage in energy systems with high shares of variable renewables. Second, we introduce a new model that is specifically designed for exploring long-term storage requirements. The literature survey focuses on recent contributions in the peer-reviewed energy economics and engineering literature. We compare key characteristics of the different models, provide an overview of model applications, and summarize key findings on power storage requirements. We also evaluate which system values of storage are covered by respective model analyses. Based on the literature survey, we identify common findings and key model features required for a sound assessment of future storage requirements. In order to raise complementary insights, we introduce DIETER, a new dispatch and investment model. The model contributes to the literature by capturing multiple system values of power storage related to arbitrage, capacity, and reserve provision. Further, the model is designed as an open-source tool that can be freely used and modified. Results of a first application of the new model are presented in a companion paper.

1. Introduction

An increasing use of renewable energy sources (RES) is foreseen in many countries around the world. This development is driven, among other factors, by tighter carbon constraints and growing concerns about security of supply. The power sector is often perceived as a particularly promising area for achieving high shares of renewables as compared to the heat and transportation sectors. Moreover, many other greenhouse gas mitigation options appear to be comparatively expensive. In countries where hydro, biomass or geothermal resources are limited, achieving high shares of RES in the electricity sector requires a massive deployment of variable wind and solar power generators. A cost-efficient power system that is largely based on such variable renewable energy sources not only requires an appropriate mix of different generation technologies, but also the utilization of dedicated flexibility options such as power storage or demand-side management (DSM).

In this paper, we first provide a comprehensive review of the academic literature analyzing the role of power storage and other flexibility measures to accommodate electricity generation from variable renewables deployed on large scale. For different types of models, we compare specific features, application details and central findings,

and identify relevant aspects for comprehensively modeling the interplay between variable renewable energy sources and power storage. Based on this, we introduce a new open-source model, the Dispatch and Investment Evaluation Tool with Endogenous Renewables (DIETER).¹ The model is designed to determine cost-minimizing combinations of generation, DSM, and power storage capacities as well as their optimal dispatch. In a companion paper [1], the model is applied to analyze the role of different power storage technologies in a long-term greenfield system with high shares of renewables between 60% and 100%.

We aim to contribute to the literature in several respects. First, we systematically review and compare relevant recent contributions from peer-reviewed energy economics and engineering journals that specifically deal with power storage in the context of variable renewable energy sources, such as wind and solar power. In doing so, we compare key characteristics of different models, provide an overview on the scope of respective applications, and summarize key findings on power storage requirements. We also evaluate which system values of storage are covered by respective model analyses. We discuss common findings and relevant modeling features concerning the role of storage. Based on the review, we propose a new model dedicated to exploring long-term

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¹ DIETER is an open-source model that may be freely used and modified by anyone. The code is licensed under the MIT License. Input data is licensed under the Creative Commons Attribution-ShareAlike 4.0 International Public License. To view a copy of these licenses, visit <http://opensource.org/licenses/MIT> and <http://creativecommons.org/licenses/by-sa/4.0/>. This article refers to model version 1.0.2. Different model versions and further information are provided at <http://www.diw.de/dieter>.

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Table 1
Comparison of model features.

Authors	Reference	Model name	Type of model	Type of program	Time resolution	Transmission model ^a	Other sectors ^{a,b}	Reserves ^a	Demand-side flexibility ^b	Software/ solver	Open-source
Dispatch and investment models											
Pfaffmann et al (2014)	[12]	MRESOM	Cost min	LP	Hourly, full year	–	–	–	–	Not specified	–
MacDonald et al (2016)	[13]	NEWS	Cost min	LP	Hourly, 3 full years	Transport model	–	[Yes]	–	GAMS/ CPLEX	–
de Sisternes et al (2016)	[4]	IMRES	Cost min	MILP	Hourly, 4 weeks	–	–	Yes	–	CPLEX	–
Safaei & Keith (2015)	[14]	–	Cost min	LP	15 min, full year	–	–	–	–	MATLAB	–
Budischak et al (2013)	[15]	RREEOM	Cost min	Enumeration	Hourly, 4 full years	–	EV, [heat]	–	–	Not specified	–
Hart & Jacobson (2011)	[16]	–	Cost min	LP	Hourly, 2 full years	–	–	Yes	–	MATLAB/ CVX	–
Ludig et al (2011)	[17]	LIMES	Cost min	LP	4–96 time slices	–	–	–	–	GAMS/ CPLEX	–
Haller et al (2012)	[18]	LIMES	Cost min	LP	49 time slices	Transport Model	–	–	–	GAMS/ CPLEX	–
Haller et al (2012)	[20]	–	Cost min	NLP	12 time slices	DC load flow	–	–	–	GAMS/ CONOPT	–
Fürsch et al (2013)	[22]	DIMENSION	Cost min	LP	24 time slices	Transport model & DC load flow	[Heat (CHP)]	–	–	GAMS/ CPLEX	–
Jägemann et al (2013)	[23]	DIMENSION	Cost min	LP	4 type days	Transport model	[Heat (CHP)]	–	–	GAMS/ CPLEX	–
Bussar et al (2014, 2015, 2016)	[24–26]	GENESYS	Cost min	Evolutionary	Hourly, 3–5 full years	Transport model	–	–	–	C++	Yes
Nagl et al (2013)	[27]	–	Cost min	LP	Hourly, 30 type days	Transport model	[Heat (CHP)]	–	–	Not specified	–
Pfenninger & Keirstead (2015)	[29]	Calliope	Cost min	LP	550 time slices	Transport model	–	–	–	Python/GLPK or GUROBI	Yes
Egerer & Schill (2014)	[30]	ELMOD	Cost min	MILP	Hourly, 336 h	DC load flow	–	–	–	GAMS/ CPLEX	–
Babrowski et al (2015)	[31]	PERSEUS-NET-ESS	Cost min	MILP	Hourly, 288 h	DC load flow	EV	–	Load shift by EV	GAMS/ CPLEX	–
Steffen & Weber (2013)	[32]	–	Cost min	Theoretical model	Hourly, full year	–	–	–	[Load curtailment]	Closed-form solution	Not applicable
Genoese & Genoese (2014)	[33]	PowerACE	Agent-based	MILP	Hourly, full year	–	–	Yes	–	Java/ GUROBI	–
Pape et al (2014)	[34]	–	Cost min	LP/MILP	Hourly, full year	Transport model	EV, power-to-heat	Yes	Load shift by EV	Not specified	–
Dispatch models with exogenous generation portfolios											
Denholm & Hand (2011)	[35]	REFlex	RES max	–	Hourly, full year	–	–	–	–	VBA	–
de Boer et al (2014)	[36]	–	Cost min	Not specified	Hourly, full year	–	–	[Yes]	–	Not specified	–
Edmunds et al (2014)	[37]	Energy PLAN	Simulation	–	Hourly, full year	Transport model	–	–	–	Delphi Pascal	Yes
Jentsch et al (2014)	[38]	–	Cost min	MILP	Hourly, full year	DC load flow	Power-to-heat	–	EV, heat pumps	Not specified	–
Schill (2014)	[39]	–	Cost min	LP	Hourly, full year	–	–	[Yes]	–	GAMS/CPLEX	–
VDE (2012)	[40]	–	Cost min	MINLP	Hourly, full year	AC model	–	[Yes]	–	Not specified	–
AGORA (2014)	[41]	–	Cost min	MINLP	Hourly, full year	Transport model	–	Yes	Load shift & curtailment	Not specified	–

(continued on next page)

Table 1 (continued)

Authors	Reference	Model name	Type of model	Type of program	Time resolution	Transmission model ^u	Other sectors ^{a,b}	Reserves ^a	Demand-side flexibility ^b	Software/ solver	Open-source
Models focusing on sector coupling and soft-linked approaches											
Jacobson et al (2015)	[56]	LOAD MATCH	Heuristic	–	30 s, 6 years	–	Heat, transport, industry	–	[Load shift]	Not specified	–
Després et al (2016)	[5]	POLES, EUCAD	Cost min	MIQCP (EUCAD)	2/12 type days	Transport model	Oil, natural gas, coal, hydrogen	Yes	[Load shift]	Vensim, GAMS/CPLEX	–
Poncelet et al (2016)	[53]	TIMES, LUSYM	Cost min	MILP (LUSYM)	12 time slices, (quarter-hourly)	–	–	–	–	GAMS/CPLEX or GUROBI	–
Krakowski et al (2016)	[58]	TIMES	Cost min	Not specified	84 time slices	Transport model	Industry, commerce, EV	[Yes]	Demand elasticity & load shift	Not specified	–
Palzer & Henning (2015)	[60,59]	REMod-D	Cost min	Iterative	Hourly, full year	–	Heat, [natural gas]	–	Flexible heat demand	Delphi	–
Koch et al (2015)	[61]	PowerFlex	Cost min	MILP	Hourly, full year	DC load flow	Heat, EV	[Yes]	Load shift, flexible heat demand	GAMS/CPLEX	–
This article and companion paper											
Zerrahn & Schill (2017)	–	DIETER	Cost min	LP	Hourly, full year	–	– ^c	Yes	Load shift & curtailment	GAMS/CPLEX	Full source code & data

Notes: The table does not include references [42,43] and the group of time-series based models as most categories do not apply to these approaches. ^aSquare brackets indicate a stylized representation of the model feature. ^bAbbreviations: Electric Vehicles (EV), Combined Heat and Power (CHP). ^cModel extension with electric vehicles presented in [64].

storage requirements. This model not only focuses on the wholesale market, but also considers balancing reserves, the requirements of which are endogenously determined, depending on the deployment of variable renewables. We further include a novel representation of demand-side management, which may be considered one of the main competitors of power storage with respect to the provision of short-term flexibility. To do so, we build on a DSM model formulation recently introduced in the literature [2], which is applied in a large-scale model for the first time. Aside from DSM and different power storage technologies, which can be freely optimized with respect to their energy to power (E/P) ratio,² the model comprises further flexibility options such as flexible thermal plants, dispatchable biomass generators, and oversizing as well as curtailment of variable renewables. Importantly, the model is able to reflect three distinctive system values of storage and other flexibility options: an arbitrage value, a balancing value, and a capacity value. At the same time, the model is set up as parsimonious as possible in order to remain traceable and to allow for extensive sensitivity analysis.

The remainder is structured as follows. We first review, compare, and discuss the relevant literature in Section 2. Subsequently, Section 3 introduces the analytical formulation of the new model. We briefly discuss the model's contribution and its limitations in Section 4. The final Section 5 concludes.

2. Literature review

The analysis of electricity or, more generally, energy systems with high shares of variable renewables spawned a broad literature featuring a variety of modeling approaches. Power storage and other flexibility options are important aspects of such exercises. Between the ends of traceability and the degree of technical, economic or spatial detail, there is always a trade-off depending on which features a particular focus is laid on—power system models are generally suited to their application. In this section we review some recent contributions analyzing the roles for power storage in energy systems dominated by variable renewables.³ This review synthesizes common findings within the academic literature on the needs for storage to accommodate high shares of variable renewables. Moreover, it identifies relevant aspects in terms of modeling features to soundly address how storage and other flexibility options interact in a renewable-dominated system.

The articles reviewed in the following can be broadly categorized as follows: review articles (Section 2.1), analyses with dispatch and investment models (Section 2.2), studies dealing with pure dispatch models (Section 2.3), and time series model analyses (Section 2.4). While most of the articles reviewed originate from peer-reviewed scientific journals, we also include a few selected studies from the gray literature in case of particularly high policy relevance, particularly in the German case.⁴ To broaden the scope of our review, we also include a group of model analyses that deal with sector coupling, particularly between the power and heat sectors (Section 2.5). Such models typically not only focus on power storage, but deal with a broader range of energy storage technologies, including thermal storage.

In order to better compare the methodologies, applications and findings of the various analyses, we provide complementary summary tables. Table 1 compares model features, such as the general model setup, the time resolution, and—if applicable—information on the software used and the availability of the code. Table 2 compares

² The E/P ratio is the relationship between the energy storage capacity (for example, in MWh) and the power rating (in MW) of a storage technology. Technologies with E/P ratios up to around 4h are referred to as short-term storage in the following; a ratio up to around 12h qualifies as medium-term storage, and larger ratios as long-term storage.

³ Our review is based on selected contributions published through September 2016.

⁴ An extensive review of gray literature on power storage requirements in Germany is provided in [3] (in German language).

Table 2
Comparison of model applications and scopes.

Authors	Reference	Geographical scope ^{a,b}	Time horizon	Power plant portfolio	RES shares	Variable renewable technologies ^{a,b}	Types of storage ^b
Dispatch and investment models							
Pfeßmann et al (2014)	[12]	Global	2020	Greenfield	100%	Wind (onshore), PV, CSP	Batteries, power-to-methane, thermal energy storage
MacDonald et al (2016)	[13]	Contiguous U.S	2030	Greenfield	Up to 63%	Wind (onshore, offshore), PV	PHS
de Sisternes et al (2016)	[4]	Texas	2035	Greenfield ^c	Up to 70%	Wind (onshore, PV)	Generic short and medium-term storage
Safaei & Keith (2015)	[14]	Stylized (data from Texas)	Not applicable	Greenfield	CO ₂ reductions	Wind (onshore)	Mechanical and electrochemical with varying parameters
Budischak et al (2013)	[15]	PJM (U.S.)	2030	Greenfield	30%, 90%, 99.9%	Wind (onshore, offshore), PV	Batteries, hydrogen with fuel cells, EV
Hart & Jacobson (2011)	[16]	California	2005, 2050	Brownfield	18.8–82.2%	Wind, PV, CSP	Heat storage coupled with CSP, PHS (exogenous)
Ludig et al (2011)	[17]	Eastern Germany	2005–2100	Brownfield	Up to 34% wind	Wind (onshore), PV	One generic technology (PHS)
Haller et al (2012)	[18]	Europe & MENA	2010–2100	Brownfield	Up to 75%	Wind (onshore, offshore), PV, CSP	Generic medium-term and long-term storage, storage integrated in CSP
Haller et al (2012)	[20]	Stylized	2005–2100	Brownfield	Up to 100%	Wind (onshore), PV	PHS
Fürsch et al (2013)	[22]	Europe (ENTSO-E)	2008–2050	Brownfield	Up to 80%	Wind (onshore, offshore), PV	PHS, hydro reservoirs, CAES, heat storage coupled with CSP
Jägemann et al (2013)	[23]	Europe and North Africa	2010–2050	Brownfield	Up to 85%	Wind (onshore, offshore), PV, CSP	PHS, hydro reservoirs, CAES, heat storage coupled with CSP
Bussar et al (2014, 2015, 2016)	[24], [25], [26]	Europe & MENA	2050	Greenfield	100% (regional self-supply)	Wind (onshore), PV	NaS batteries, hydrogen
Nagl et al (2013)	[27]	Europe	2050	Greenfield	Up to 95%	Wind (onshore, offshore), PV	PHS, hydro reservoirs, CAES, hydrogen storage
Pfenninger & Keirstead (2015)	[29]	UK	Not applicable	Greenfield	Up to 100%	Wind (onshore, offshore), PV, tidal	Generic battery technology, PHS
Egerer & Schill (2014)	[30]	Germany	2024, 2034	Brownfield	48% (2024), 60% (2034)	Wind (onshore, offshore), PV	PHS
Babrowski et al (2015)	[31]	Germany	2015–2040	Brownfield	60%	Wind (onshore, offshore), PV	Generic battery technologies, PHS
Steffen & Weber (2013)	[32]	Germany	Not applicable	Greenfield	20%, 40%, 60%	Wind (onshore), PV	PHS
Genoese & Genoese (2014)	[33]	Germany	2020, 2030	Brownfield	34%, 39% (2020), 41%, 58% (2030)	Wind (onshore, offshore), PV	PHS
Pape et al (2014)	[34]	Europe	2050	Brownfield	88% (Germany), 82% (Europe)	Wind (onshore, offshore), PV	Batteries (Li-Ion, lead acid, NaS, redox flow), PHS, CAES, thermal storage coupled with CSP, hydrogen (cavern, natural gas grid)
Dispatch models with exogenous generation portfolios							
Denholm & Hand (2011)	[35]	Texas	Not applicable	Exogenous	Up to 80%	Wind (onshore), PV, CSP	Generic (4, 8, 12, 24 h)
de Boer et al (2014)	[36]	Netherlands	2015	Exogenous	Up to 39%	Wind (onshore, offshore)	PHS (in Norway), CAES, power-to-gas
Edmunds et al (2014)	[37]	UK	2020, 2030	Exogenous	Up to 30% wind	Wind (onshore, [offshore]), PV	Generic storage technology
Jentsch et al (2014)	[38]	Germany	2050	Exogenous	85%	Wind (onshore, offshore), PV	PHS, power-to-gas, power-to-heat, generic short-term storage
Schill (2014)	[39]	Germany	2022, 2032, 2050	Exogenous	Up to 86%	Wind (onshore, offshore), PV	Batteries (Li-Ion), PHS, power-to-gas
VDE (2012)	[40]	Germany	2020–2025, 2050	Exogenous	40%, 80%, 100%	Wind (onshore, offshore), PV	Generic short-term and long-term storage
AGORA (2014)	[41]	Central Europe	2023, 2033, long-term	Exogenous	Up to 90% (Germany), 60% Europe	Wind (onshore, offshore), PV	Generic short-term and long-term storage
Models focusing on sector coupling and soft-linked approaches							
Jacobson et al (2015)	[56]	Contiguous U.S.	2050–2055	Greenfield	100%	Wind (onshore, offshore), PV, CSP, tidal, wave	PHS, heat storage coupled with CSP, Thermal storage, hydrogen storage
Després et al (2016)	[5]	Europe, [world]	2000–2100	Brownfield	Up to around 65%	Wind (onshore), PV	Generic battery technology, PHS
Poncelet et al (2016)	[53]	Belgium	2014–2055	Brownfield	Up to around 50%	Wind (onshore, offshore), PV	Batteries (NaS), PHS, hydrogen

(continued on next page)

Table 2 (continued)

Authors	Reference	Geographical scope ^{a,b}	Time horizon	Power plant portfolio	RES shares	Variable renewable technologies ^{a,b}	Types of storage ^b
Krakowski et al (2016)	[58]	France	2012–2050	Brownfield	40–100%	Wind (onshore, [offshore]), PV, [ocean]	PHS, CAES, generic long-term storage
Palzer & Henning (2015)	[60], [59]	Germany	Not applicable	Greenfield	100%	Wind (onshore, offshore), PV	Batteries, PHS, power-to-gas, power-to-heat
Koch et al (2015)	[61]	Germany, [Europe]	2020, 2030, 2050	Exogenous	37% (2020), 51% (2030), 59%, 86% (2050)	Wind (onshore, offshore), PV	PHS, CAES, (power-to-gas)
DIETER							
Zerrahn & Schill (2017)		Stylized (German data)	2050	Greenfield	60–100%	Wind (onshore, offshore), PV	Batteries (Li-Ion, lead-acid, NaS, redox-flow), PHS, CAES, power-to-gas

Note: The table does not include references [42,43] and the group of time-series based models. ^aSquare brackets indicate a stylized representation of the model feature. ^bAbbreviations: (Adiabatic) Compressed Air Energy Storage (CAES), Concentrated Solar Power (CSP), Electric Vehicles (EV), Middle East and Northern Africa (MENA), Sodium-sulfur (NaS), Pumped-Hydro Storage (PHS), Pennsylvania-New Jersey-Maryland (PJM). ^c Storage exogenous.

the specifics of different model applications, including the geographical scope, the time horizon, and the types of storage considered. Finally, Table 3 provides an overview of the potential system values of power storage covered by the respective analysis (compare also [4,5]). This includes an *arbitrage value* related to shifting electricity from periods with low marginal generation costs (or economically speaking, low spot prices) to periods with higher costs. Next, we distinguish a *reserve value* related to the provision (and potentially activation) of balancing reserves; this value can only be considered in a model-based analysis if the respective model includes at least a coarse representation of such reserves. Further, storage can also provide a *capacity value* to the power system that originates from the fact that power storage can substitute other dispatchable peak capacity, or—more generally speaking—can enable lower-cost generation capacity portfolios. In contrast to models with endogenous investment decisions, pure dispatch models are generally not able to directly capture such capacity values of storage. Finally, we also include a *network-related* value of storage, which is related to potential alleviation of grid congestion facilitated by power storage, which may occur either in distribution of transmission networks. Obviously, such a value can only be captured if a model includes a proper representation of such grids.

While this literature review, necessarily, cannot be complete, we however aim at providing a comprehensive account of various model approaches, geographical regions, time horizons, and storage values covered. Geographically, the review focuses on applications in North American and European power systems.

2.1. Review articles

Specifically addressing the role of flexibility measures for electricity systems with high shares of renewables, the comprehensive overview by Lund et al. [6] points toward the different roles that the literature identifies for different types of storage and demand-side flexibility measures. Generally, storage devices with high power and low energy ratings, such as different types of batteries, are rather qualified to provide services such as short time balancing, whereas pumped hydro or hydrogen storage installations with high E/P ratios may bridge longer fluctuations. DSM is found to complement variability in time frames up to twelve hours.

A related review article [7] is dedicated to the analysis of flexibility requirements in future power systems dominated by variable renewable energy sources. It includes a review and classification of various model studies from the literature. Drawing on the findings of the studies reviewed, a summary table on the strengths and weaknesses of different options for supplying such flexibility is also provided, including various types of power storage.

With regard to the role of modeling, Pfenninger et al. [8] discuss recent electricity sector developments, that is the mass deployment of variable renewables, against the background of challenges for energy modeling features. They identify several domains to be addressed: first, the appropriate resolution in time and space; second, the proper treatment of uncertainty and transparency; third, the complexity of overlying scales; and fourth, the encompassing of social and behavioral factors. As one basic conclusion, they subsume that models should be transparently tailored to specific needs. On the same note, Haydt et al. [9] point toward the importance of incorporating sufficient information on short-term variability of renewables. Otherwise, the energy delivered by wind or solar photovoltaics (PV) could easily be overestimated.

The literature on model-based renewable integration studies is so broad that dedicated literature reviews exist even for specific model types. For example, [10] exclusively reviews analyses using the EnergyPLAN energy system model. Most of these deal with questions of integrating variable renewable power sources by means of different flexibility options, including various types of energy storage.

Table 3
System values of storage considered in the analyses.

Authors	Reference	Arbitrage value ^a	Capacity value ^b	Reserve value ^b	Network-related value ^b	Remarks
Dispatch and investment models						
Pleßmann et al. (2014)	[12]	x	x			
MacDonald et al. (2016)	[13]	[x]	[x]	[x]	[x]	Storage excluded in final runs
de Sisternes et al. (2016)	[4]	x	[x]	x		No optimization of storage capacity
Safaei & Keith (2015)	[14]	x	x			
Budischak et al. (2013)	[15]	x	x			
Hart & Jacobson (2011)	[16]	x	x	[x]		Limited information on reserves model
Ludig et al. (2011)	[17]	x	x			Time slices
Haller et al. (2012)	[18]	x	x		[x]	Time slices, stylized interconnection
Haller et al. (2012)	[20]	[x]	[x]		[x]	Time slices, stylized application
Fürsch et al. (2013)	[22]	x	x		x	Time slices
Jägemann et al. (2013)	[23]	x	x		[x]	Time slices, stylized interconnection
Bussar et al. (2014, 2015, 2016)	[24–26]	x	x		[x]	24 h storage foresight, stylized interconnection
Nagl et al. (2013)	[27]	x	x			Time slices, limited information
Pfenninger & Keirstead (2015)	[29]	x	x		[x]	Time slices, batteries only modeled for 90% RES case
Egerer & Schill (2014)	[30]	x	[x]		x	Time slices, brownfield portfolio
Babrowski et al. (2015)	[31]	x	[x]		[x]	Time slices, exogenous transmission
Steffen & Weber (2013)	[32]	x	x			Storage has no energy dimension
Genoese & Genoese (2014)	[33]	x	[x]	[x]		System value not in the focus
Pape et al. (2014)	[34]	x	[x]	x	[x]	Exogenous portfolio, soft-linked models
Belderbos et al. (2016a, 2016b)	[42,43]	x	x			Stylized application
Dispatch models with exogenous generation portfolios						
Denholm & Hand (2011)	[35]	[x]				No cost optimization
de Boer et al. (2014)	[36]	x		[x]		Limited details on reserves model
Edmunds et al. (2014)	[37]	x			[x]	Stylized interconnection
Jentsch et al. (2014)	[38]	x				
Schill (2014)	[39]	x				Forced integration of surpluses
VDE (2012)	[40]	x		[x]	x	No optimization of storage capacity
AGORA (2014)	[41]	x		x	x	
Time series-based models^c						
Heide et al. (2010)	[44]	[x]	[x]			
Heide et al. (2011)	[45]	[x]	[x]			
Rasmussen et al. (2012)	[46]	[x]	[x]			
Steinke et al. (2013)	[47]	[x]	[x]		[x]	Stylized application
Hedegaard & Meibom (2012)	[48]	[x]	[x]	[x]		Descriptive analysis
Alexander et al. (2015)	[49]	[x]	[x]			
Weitemeyer et al. (2015)	[50]	[x]	[x]			
Sinn (2016)	[51]	[x]	[x]			Strong assumptions
Models focusing on sector coupling and soft-linked approaches						
Jacobson et al. (2015)	[56]	x	x			Optimality not ensured
Després et al. (2016)	[5]	x	x	[x]		Time slices, limited details on reserves
Poncelet et al. (2016)	[53]	[x]	[x]			Time slices, limited information
Krakowski et al. (2016)	[58]	x	x	[x]		Time slices, stylized reserves model
Palzer & Henning (2015)	[60,59]	x	x			
Koch et al. (2015)	[61]	x	x	[x]	x	Stylized reserve model
DIETER						
Zerrahn & Schill (2017)		x	x	x		Network-related value not in focus because of greenfield application

Note: ^aSquare brackets indicate that no optimization with respect to storage arbitrage is carried out. ^bSquare brackets indicate no explicit analysis of the respective system value. ^cThe reviewed time-series models only partly analyze optimized dispatch with respect to storage.

2.2. Dispatch and investment models

A large variety of dispatch and investment models for long-term planning is documented in the international literature [cf. the broad overview by Després et al.,] [11]. In the following, we review contributions distinctly encompassing a focus on the role of storage

for incorporating high shares of electricity generation by variable renewable energy sources. Our ordering follows the geographical scope of the model application. While other criteria, such as model features, could also be used for categorization, we aim at structuring the literature according to applications and findings for different regions.

Global

On a global scale, the MRESOM model is used in [12] to determine world-wide power storage requirements for a 100% renewable electricity supply. With a capacity of 73.6 TWh, thermal energy storage is found to be a major short-term storage option which out-competes batteries (1.5 TWh). Thermal storage is found to be largely located in regions close to the equator. An even higher capacity is required for power-to-methane storage with subsequent reconversion to electricity (2.36 TW / 1690 TWh). This technology, which is more evenly distributed around the globe, is found to be the major long-term storage option. Model outcomes are put into perspective by rather opaque modeling details and relatively strong assumptions on the availability of variable renewables, storage technologies, and transmission restrictions.

North America

Several more detailed studies address North American power systems. In [13], the NEWS model is used to investigate 2030 wind and solar power expansion scenarios in the contiguous U.S. The model co-optimizes dispatch, transmission and investment decisions while also considering planning and load following reserves. Renewable feed-in patterns are derived from historic weather data with a high spatial resolution. The authors find that large-scale, low-cost renewable deployment could be achieved without any power storage. Instead, renewable variability could be mitigated by pan-U.S. geographical balancing, facilitated by extensive high-voltage direct current transmission investments. Assuming further cost reductions of renewable generation technologies, no storage would be required up to a renewable share of 63% (38% wind, 17% solar PV and 8% hydro power), while leveled costs of electricity would be comparable to today's levels. In the context of this review, one drawback is that the full model does not any include storage at all – the authors eliminated storage after preliminary model runs in order to reduce model complexity and solution time.

In an application of the IMRES model, impacts of increasing storage capacity on power system operations and investments is studied for 2035 scenarios of the Texas power system with renewable shares of up to 70% [4]. Exogenously varying the installed levels of two stylized storage technologies, the authors show that storage generally delivers system values related to renewable energy integration and a better utilization of thermal generators. Yet these benefits may be smaller than technology costs for assumed 2-h battery storage, depending on scenario assumptions. In contrast, 10-h pumped-hydro storage is generally more cost-effective. It is also shown that the system value of storage increases with tighter emission constraints, but the marginal value of storage decreases with growing storage capacity.

Also leaning on input data from Texas, but focusing on wind power, the economics of different types of bulk electricity storage systems under carbon constraints are assessed in [14]. Even for a case with substantial emission reductions (150 kgCO₂e/MWh, as compared to around 448 kgCO₂e/MWh in a baseline scenario), optimal power capacity of storage is found to be smaller than 30% of the system's peak load for mechanical and smaller than 10% for electrochemical storage, respectively. In addition, no case for seasonal storage is found. Storage requirements increase substantially only in case of very high shares of wind power.

Related findings are derived in [15], where the enumerative model RREEOM is used to determine cost-minimizing combinations of wind, solar and storage capacity for the PJM interconnection in the U.S. Analyzing different scenarios with renewable shares of up to 99.9%, it is found that load can be met in 99.9% of all hours with only 9–72 h of storage. In the least-cost solution, around 52 GW of storage in the form of electric vehicle batteries are required; this compares to an average load of 31.5 GW and installed generation capacity of 258 GW. Storage requirements do not grow further even under such extremely high shares of variable wind and solar power because of substantial renew-

able excess capacity, which leads to overall (potential) renewable generation of up to three times the electric load. Still, it is found that load could be met at generation costs comparable to today's levels.

In a 2011 analysis [16], a range of scenarios with renewable shares between 18.8% and 82.2% is simulated for the California ISO. Yet storage is only marginally considered in the form of existing pumped hydro capacity as well as three-hour thermal energy storage attached to solar thermal power generators. Although details are not provided in the article, it can be derived that storage needs grow to around 330 GWh solar thermal storage capacity in a 2050 low-carbon scenario.

Overall Europe

Several other studies focus on European model applications. The dispatch and investment model LIMES is used to assess the power system implications of long-term decarbonization paths in Europe [17,18].⁵ In a stylized application for Eastern Germany [17], it is shown that additional power storage reduces wind curtailment, but also increases the utilization of inflexible thermal generators. In a European application including the Middle East/Northern Africa (MENA) region [18], storage requirements increase substantially after 2030 in case of tight carbon emission constraints, along with decreased renewable curtailment. While absolute numbers are not provided, more storage is required in case of sub-optimal interconnection. The temporal resolution of the LIMES model is based on different time slice configurations. This rather coarse approach may hamper correctly assessing the role of power storage for mitigating the variability of renewable energy sources. In addition, other flexibility options are not included.

In a related, but more generic, dispatch and investment framework, storage, as well as transmission, investment is found to play a crucial role in balancing variable renewables, thus enabling a higher and earlier deployment of wind and solar PV [20]. Although only a stylized application is presented, it is shown that indirect system effects of delaying storage investments can be substantial due to sub-optimal renewable expansion paths. Short-term variability is, however, again only captured by time slices of two type days. Storage is loosely calibrated to resemble pumped-hydro storage, shifting load within a type day.

In applications of the electricity market model DIMENSION, which is presented in more detail in [21], paths toward a decarbonization of Europe's power sector are analyzed [22,23]. The model features cost-minimal investment and dispatch decisions. In [22], transmission upgrades are generally found to be preferable compared to storage investments, which only increase if transmission expansion is constrained. A complementary analysis [23] indicates that storage requirements increase substantially only in case of very high shares of variable renewables, yet without providing details on absolute capacity. It should be noted that the temporal resolution in [22,23] is based on selected time slices of specific type days. Consequentially, the findings are based on a sample of renewable variability, which puts the conclusions on storage requirements—particularly on long-term storage—into perspective.

Other large-scale dispatch and investment models explore the role of power storage in fully renewable pan-European power systems. In a series of papers, Bussar et al. [24–26] apply the GENESYS⁶ model to analyze storage and transmission requirements for a 100% renewable power systems in Europe and the MENA region. In [24], extensive storage requirements of around 6% of annual energy demand are determined, particularly regarding long-term storage: 50 GW / 300 GWh of NaS (sodium sulfur batteries), 160 GW / 2300 GWh of pumped hydro, and 360/320 GW (charge/discharge) / 245,000 GWh

⁵ A more detailed description of the model is provided in [19].

⁶ GENESYS is one of the very few open-source models discussed here. It can be downloaded after registration. Running the model requires C++.

of hydrogen storage. These findings are—amongst other parameter choices—driven by the assumption that each modeled region faces a political requirement of 100% regional self-supply with respect to total yearly energy demand.

In two similar articles [25,26], the same geographical application is considered, yet overall energy demand is assumed to increase by around 50% compared to [24] because of an increasing standard of living in less developed regions. Here, storage requirements are much larger with 320 GW / 1600 GWh of NaS, 190 GW / 2700 GWh of pumped hydro, and 900/550 GW (charge/discharge) / 800,000 GWh of hydrogen storage. The substantial deviations between the outcomes of [24] on the one hand and [25,26] on the other may also be driven by a lower self-supply requirement (80%) in the latter cases. Additional sensitivities illustrate that storage demand grows in case of limited interconnector expansion options and under the assumption of lower costs of PV or storage technologies. While the evolutionary strategy developed to solve the model is innovative, it is not clear if the problem can be solved to optimality, or how large numerical gap is. Moreover, a myopic 24-h time horizon for storage operation is assumed, which may have an impact particularly on long-term storage operations.

When introducing stochasticity concerning the realization of RES feed-in patterns, variable renewables are generally found to be less valuable while system costs are higher compared to a deterministic treatment [27,28]. In [27], a deterministic and a stochastic modeling approach lead to different outcomes with respect to long-run European power plant portfolios and system costs. Here, stochasticity refers to good or bad wind and solar years, while foresight on RES feed-in is perfect within a realized year.⁷ Storage requirements seem to increase only moderately for growing RES shares up to 95% in Europe. Storage needs moreover tend to be slightly lower in a stochastic setting compared to a deterministic one. Unfortunately, only a graphical representation of these results is provided instead of specific numbers. Furthermore, no intuition is provided how the consideration of stochastic renewable feed-in impacts storage requirements in the model, and the role of different storage options may be underestimated because of a limited number of type days considered.

Europe: country studies

In [29], the open-source model Calliope is used to investigate numerous scenarios with varying shares of renewables up to 100%, nuclear, and fossil fuels in the UK. First, a set of scenarios is investigated in which only pumped-hydro storage is considered, which is restricted to its currently installed capacity of 2.74 GW. It is shown that this storage capacity would not suffice to enable a fully renewable power system. Afterwards, the effects of introducing an additional grid-scale storage technology (generic battery) are studied for a set of scenarios with a RES share of 90%. It is shown that system costs would decrease for sensitivities with lower battery costs; such cost reductions are particularly pronounced if battery costs decrease below 75 GBP/kWh. Unfortunately, only cost data is provided, but no information on storage capacity. As in many other analyses, storage-related findings may be skewed by the model's low time resolution. Other modeled scenarios indicate that, instead of storage deployment, high RES shares could also be achieved at relatively low costs if dispatchable tidal technologies or large-scale solar imports were available.

Several studies focus on the analysis of power storage requirements in Germany. Using a dedicated version of the ELMOD model family, medium-term storage requirements in Germany are studied in [30]. Interactions between investments in pumped-hydro storage, gas-fired power plants, and pumped storage plants as well as their spatial allocation is explicitly modeled. In a reference scenario, only 0.7 GW additional storage is required by 2034, as the other investment options

are more cost-effective. The authors still argue that a moderate expansion of storage may be considered a no-regret strategy because the full system value of such capacity expansion is not captured in the analysis and system costs increase only slightly with higher storage investments. It is also shown that storage requirements increase strongly if renewable curtailment is penalized.

In a related study, storage requirements and their spatial distribution in Germany are analyzed with the PERSEUS-NET-ESS model [31]. Hardly any additional storage capacity is found to be required up to 2040, when the renewable share exceeds 60%. Only in a scenario where uncontrolled charging of electric vehicles is assumed, additional 3.2 GW battery storage are deployed, largely in north western Germany. Yet these batteries are substituted by flexibly charging electric vehicles in a respective scenario. Drawbacks of the analysis include the use of selected type-days, which implicitly excludes all storage options except for short-term storage from the analysis, and the assumption of a fixed transmission network, which contrast with substantial changes in the generation portfolio and its spatial distribution.

From a different methodological angle, storage investments in a high-RES system can be analyzed within a theoretical peak-load pricing model. For a dispatch and investment study for Germany, storage was found to fulfill its classical role as arbitrageur between base and peak plants with low CO₂ prices [32]. For lower clean spreads between technologies, storage investments become efficient only for high RES shares. Beyond 60% renewable penetration, negative residual load triggers the additional role of storage to accommodate variable renewable generation. As such analysis is based on residual load duration curves, information on cyclicity and according issues of storage energy are disregarded.

In an agent-based setting, annual investment decisions and an hourly dispatch are simulated for selected years in Germany [33]. A potential for 5 GW of eight-hour pumped-hydro storage plants in a 58% RES system is identified, where the inertia of conventional plants plus a merit order-like effect drive results. Investment in renewable energy sources and storage is implemented exogenously via scenarios, and an optimization horizon of one day precludes the analysis of longer-term storage.

Turning to some gray—but nonetheless policy-relevant—literature, the so-called “Roadmap Storage” [34] determines German long-term power storage requirements in a European context. In the second part of the study, a model that partially includes investment decisions is used.⁸ In a 2050 case with a renewable share of 88% in Germany, and 82% in overall Europe, additional short-term storage capacity between 0 and around 19 GW is needed in Germany, depending on the availability of solar thermal power imports, DSM potentials, and other flexibility options. Larger storage investments are required in Spain and Italy because interconnection is weaker in these countries. Among modeled power storage technologies, lead acid batteries dominate. A case for long-term storage cannot be found for the renewable shares considered. Results are largely driven by extensive power exchange with neighboring countries, which are assumed to have somewhat lower shares of renewables in all scenarios, and by the assumption of a very flexible demand side.

Without focusing on an actual country application, Belderbos et al. investigate optimal sizing of different storage technologies. They study how power and energy ratings depend on the shape of load and RES profiles. To do so, they develop both a stylized analytical approach and a numerical model. In [42], the method is applied to a stylized fully renewable setting, drawing on synthetic wind power profiles and two generic types of power storage. In [43], the application is extended to

⁷ A stochastic approach that explicitly addresses short-term uncertainty of RES feed-in is presented in [28]. Yet the application presented does not focus in storage.

⁸ In the first part, the study also contains an analysis of short- and medium-term storage requirements, which is carried out with a pure dispatch model. Given specific portfolio assumptions, it is shown that hardly any additional storage investments are needed up to a renewable share of 69% in Germany and 37% in overall Europe.

include solar PV as well as more realistic renewable feed-in profiles. It is shown that daily to weekly balancing of demand and supply requires such storage technologies that have relatively low specific investment costs with respect to power rating, while technologies with low-cost energy ratings are preferred in case of longer-term balancing needs.

2.3. Dispatch models with exogenous generation portfolios

This stream of the literature evaluates the role of storage within a short-term dispatch framework. Capacities are exogenously set through scenario assumptions. While the endogenous interplay between storage and variable renewable capacity deployment cannot be addressed, this approach allows for insights into the operational aspects of storage facilities.

North America

In a case study on the integration of up to 80% variable renewable energy sources in Texas [35], the stylized dispatch model REFLEX is used. For moderate RES penetration levels, it is shown that relatively small amounts of storage suffice to substantially reduce renewable curtailment. Yet for a renewable share of 80%, a storage or load shifting capacity of about one day of average demand, corresponding to around 69 GW, 826 GWh, is needed to keep RES curtailment below 10%.

Europe: country studies

In a case study for the Netherlands, exogenously introduced additional storage capacity is found to reduce operational costs because of lower wind curtailment and lower start-up costs of thermal plants [36]. These cost savings increase with larger wind penetration. In this framework, pumped-hydro storage—which is assumed to be located in Norway and connected by transmission infrastructure—proves most cost-effective. Yet a proper interpretation of results is somewhat of a challenge because of exogenous capacity choices, a focus on operational costs only, and the fact that storage optimization is based on a rolling time horizon of twelve hours, rendering longer-term benefits of storage difficult.

An analysis based on the EnergyPLAN simulation model aims to quantify the benefits of additional storage (and interconnection) capacity in Great Britain [37]. By exogenously varying additional storage capacity between 0 and 8 GW in a 2030 scenario, it is shown that wind curtailment decreases and wind penetration accordingly increases by a few percentage points beyond 30%. Yet the analysis neither distinguishes between different storage technologies, nor does it draw conclusions on cost-optimal storage portfolios.

With a unit commitment dispatch model, storage requirements in a scenario with a 85% renewables penetration in Germany are studied in [38]. While the analysis focuses on power-to-gas, other sources of flexibility such as power-to-heat are also considered. At medium cost projections, around 12 GW of power-to-heat are found to be cost-optimal. This value decreases to 5–6 GW in case of higher technology costs or additional power-to-heat options in the system. With respect to the spatial dimension, power-to-gas facilities would be largely deployed in northern Germany because of large wind power potentials in this region. While [38] provides a rare example of a study where a case for (moderate) long-term storage deployment can be established, it should be noted that the analysis abstracts from both medium-term storage technologies and European interconnection. The latter has been found to render long-term storage obsolete in a comparable setting with European interconnection in [34].

In another case study on Germany [39], hypothetical storage requirements for integrating increasing amounts of renewable surplus generation are analyzed. In a 2032 setting with a RES share of around 58%, no additional storage would be required under the assumption that 1% of potential renewable feed-in is curtailed and thermal power plants are flexibilized. By 2050, this value grows to 16 GW, or 37 GW if only 0.1% RES curtailment were tolerated. Full integration of all

renewable surpluses would require even larger power storage capacities if no other flexibility options were available.

Other policy-relevant studies dealing with long-term power storage requirements in Germany have been published as gray literature. For example, within a pure dispatch model the requirement of two stylized short- and long-term storage options is studied [40]. For a renewable share of 80%, 14 GW / 70 GWh of short-term storage and 18 GW / 7.5 TWh of long-term storage are considered economically advantageous. In a 100% renewable scenario, these values strongly increase to 36 GW / 184 GWh and 68 GW / 26 TWh, respectively. Yet the analysis abstracts from most other flexibility options, including DSM and cross-border exchange, and may thus overestimate storage requirements. In a related study [41], it is found that up to a renewable share of 60%, a moderate extension of existing German storage capacities would be beneficial; however, this is true only in case of optimistic assumptions on storage cost developments, combined with pessimistic assumptions on system flexibility. For a share of 90%, additional installations of 7 and 16 GW short- and long-term storage would be preferable.

2.4. Time series-based models

Another modeling stream employs stylized time series models to analyze storage requirements to satisfy large shares of demand by variable renewables. Assuming perfect flexibility for conventional power plants, stylized storage technologies serve to shift RES oversupply to periods with positive residual demand.⁹

Overall Europe

Based on monthly weather data and accordingly scaled load and variable renewables feed-in time series, Heide et al. [44] derive results for seasonal long-term arbitrage of excess PV generation in summer and excess wind generation in winter. For Europe, storage energy needs of 1.5–1.8 times the average monthly load are determined, amounting to 400–480 TWh, to integrate 100% variable renewables supply. Importantly, this large-scale spatial and temporal balancing depends on assumptions of a copperplate-like transmission system and the availability of appropriate long-term storage technologies.

Taking a slightly different perspective, Heide et al. [45] assess the effect of excess wind and solar PV deployment on storage needs for different types. For the European case, the tolerance of 50% excess renewables generation would reduce the required storage energy to about 5% compared to a full RES integration case [45]. In this respect, a single idealized storage technology with perfect roundtrip efficiency is assumed. Likewise, the need for gas-fired or hydro reservoir backup capacities is sharply reduced through excess RES deployment. Numerical findings, however, strongly depend on the wind/solar PV mix, for which, as for storage, no economic considerations are regarded.

Finally, when addressing both short-term and long-term variability, a mix of efficient short-term storage and long-term hydrogen storage, with an energy capacity amounting to less than 1% of annual energy demand is identified as sufficient to almost completely integrate variable RES in Europe [46]. Also here, energy transport across Europe is assumed not to be restricted by transmission congestion.

Specifically, the tradeoff between spatial flexibility, provided by expanding interconnections between regions, and temporal flexibility, provided by storage, is analyzed in [47]. Based on time series of load and bottom-up weather data, the authors define copperplate regions of varying size and assess the backup energy demand for different levels of available storage energy. In all scenarios, variable renewables supply 100% or 130% of annual electricity demand, however not necessarily spatially and temporally coinciding with demand. While both regarded

⁹ Note that the discussed references do not apply econometric time series analysis methods.

flexibility options are, as such, substitutes, backup needs can be substantially reduced toward zero by means of large-scale long-term storage, however at significant costs.

Europe: country studies

Based on time series of variable renewables feed-in data for western Denmark, Hedegaard et al. [48] qualitatively discuss the value of implementing different storage technologies to accommodate fluctuations of varying time-scales. In this respect, wind power patterns predominantly trigger the need for storages with E/P ratios up to one day, whereas long-term storage has the potential to enable a fully renewable system.

Using a simulation model based on time series, storage requirements for a 100% renewable UK electricity grid are investigated in [49]. It is found that 14 GW / 3 TWh pumped storage, or 11 GW / 2.3 TWh liquid air storage, or 65 GW / 13.6 TWh hydrogen storage would be required in a baseline scenario. More storage would be necessary in case of additional power consumption related to electric heating and (seemingly inflexible) electric vehicles.

For the German case, storage is found to be not required to almost fully integrate wind and solar PV up to a renewable share of 50% in annual electricity demand [50]; however given that the backup power plant park is fully flexible. Between 50% and 80%, short-term storage is best suited to enhance integration, and for higher RES shares long-term storage is most adequate.

Drawing on historic time series of wind and solar power feed-in, Sinn [51] aims to derive the storage capacity necessary to perfectly smooth wind and solar power volatility in Germany. Assuming that the variable wind and solar generation of 2014 must be transformed to a constant average yearly level, a storage capacity of 6.89 TWh would be required (compared to around 0.04 TWh installed in Germany in 2014). It should be noted that this concept of renewable smoothing is very different from the economic criterion of least-cost system integration, and the relevance of such approach is thus questionable. Further, it is demonstrated that temporary surplus generation of wind and solar power increases with growing shares of these technologies in overall power consumption. Accordingly, the storage capacity that would be hypothetically required to fully integrate these growing surpluses would also increase. While this finding is not new—for instance, it has been studied in more detail in [39]—it would not be cost-efficient to fully integrate renewable surpluses by means of power storage. Assuming full integration of surpluses, that is, implicitly neglecting alternatives to renewable curtailment such as cross-border exchange [44,45,47], demand response [49,56] or flexible sector-coupling measures [38,31], a storage capacity of 3.6 TWh would be required for reaching a share of 50% of wind and solar power in Germany. Alternatively, this share could also be reached without any storage if renewable curtailment of 6% was tolerated. Somewhat detached from the literature, Sinn identifies an allegedly “unavoidable” expansion of expensive and inefficient storage devices as a barrier toward further expansion of variable renewables.

2.5. Models focusing on sector coupling and soft-linked approaches

Mathiesen et al. [52] argue that a focus on power storage technologies is too narrow with respect to least-cost 100% renewable energy scenarios. In their vision of “Smart Energy Systems”, power system flexibility is derived from extensive sector coupling. Power, heat, and transport sectors could be linked by means of CHP, heat pumps, and electro-fuels. It is argued that in such settings, electricity storage technologies, which take up electricity and feed it back to the grid at later points in time, should be avoided because of their roundtrip losses. Instead, system flexibility could be better provided by other forms of energy storage; for example solid, gaseous, or liquid fuel storage, thermal storage or flexible system integration of battery electric vehicles.

On a methodological note, any analyses of storage requirements carried out with energy system model applications may warrant caution, as the temporal resolution of such models may be too low. In [53], the long-term planning model TIMES¹⁰ is soft-linked with the unit commitment dispatch model LUSYM.¹¹ Aiming to close the gap between long-term planning and short-term operational models, the authors study the effects of different modeling features with respect to (i) time resolution and (ii) how detailed operational constraints are considered. With respect to both domains, the authors find that lower-detail modeling overestimates the deployment of variable renewables and underestimates the requirements of flexible technologies, including power storage. Under growing shares of variable renewables, this particularly hold for simplifications of the temporal resolution; the impact of simplifying dispatch rigidities is found to be of lesser importance.

North America

In [56], the energy system model LOADMATCH is applied to the U.S. for the years 2050–2055 in order to study scenarios where all energy end uses are fully supplied by wind, water and solar energy. This model, which has a very high time resolution, follows a heuristic trial-and error approach and derives non-unique, non-optimal, but feasible solutions. Without providing concrete numbers, underground thermal storage is found to be most relevant, followed by electricity storage in the form of phase-change materials connected with solar thermal power generation, pumped hydro, and hydrogen. Stationary batteries are not required in the system studied.

Overall Europe

In an article conceptually related to [53], a linkage of the long-term planning model POLES and the dispatch model EUCAD¹² is described [5]. These linked models are used to explore the role of power storage for renewable integration in Europe until 2100. In a 2 degree Celsius policy scenario, which leads to a variable RES share of around 50% in 2100, storage plays a substantial role. According to a graphical illustration provided in the article, overall European power storage requirements increase to around 560 GW, consisting of 70 GW pumped hydro, 240 GW batteries, and 250 GW of electric vehicle storage.

This finding, which strongly contrasts the outcomes of most other articles reviewed here, may be related to specific parameter assumptions, for instance, regarding exogenously fixed E/P-ratios of storage (for example 3.75 for pumped-hydro storage), the particular definition of time slices with high and low renewable availability and demand, as well as a rather styled approach of modeling wind variability. As can be inferred from the supplementary material, wind patterns for all countries seem to be calibrated according to French 2013 data, that is, they are perfectly correlated over all countries. Moreover, the flexibility potentials of electric vehicles and demand response are modeled in a rather simplified way, which may likewise lead to somewhat skewed results.

Europe: country studies

In [58], a variant of the TIMES model family is used to investigate the long-term power system effects of variable renewable energy sources and the requirements for flexibility options in France, up to a renewable share of 100% by 2050. It is found that substantial investments in flexibility options are required, but these largely consist in demand response and interconnection. Power storage technologies only play a small role with around 5 GW, largely consisting of pumped hydro, for RES shares up to 90%. This value increases up to 8.9 GW in

¹⁰ The Integrated MARKAL-EFOM System, [54]

¹¹ For a general description of the LUSYM model, see [55].

¹² A description of the EUCAD model is provided in [57].

one of the 100% RES cases modeled. These findings are largely driven by assumptions on demand-side flexibility and interconnection, which may be considered rather optimistic, and which almost perfectly substitute power storage technologies in the model. Moreover, the low temporal resolution of only 84 time slices per year may not suffice to approximate operational patterns of storage technologies that would arise from, for example, hourly-resolution models.

For the German case of 100% renewables, large-scale deployment of variable wind and solar PV together with extensive capacities of batteries and power-to-gas storage are found as cost-optimal configurations to ensure stable energy supply [59,60]. In this respect, in a medium scenario as much as 55 GWh of batteries, but only 60 GWh of pumped-hydro storage are deployed in a cost-minimal system configuration. Both papers feature a greenfield setting based on one year with full hourly resolution and a representation of different sources of flexibility in the heat sector.

In another holistic approach for Germany—including the district heating system, flexibility from different levels of exchange with neighboring countries, DSM, storage as well as power-to-heat and power-to-gas—a mix of flexibility options is found to facilitate the integration of high shares of variable renewables up to 75% [61]. These foremost comprise European exchange, as well as pumped-hydro storage and DSM. In this respect, pumped-hydro storage reduces the need for additional backup capacities by about 25%. Only for renewables shares close to 100% would additional long-term storage be necessary.

2.6. Synthesis

The literature survey shows that model-based analyses do not lead to unanimous conclusions with respect to the role of power storage in electricity systems with high shares of variable renewable energy sources. Rather, storage requirements are generally context-dependent. They depend not only on specific geographical applications, but also on a range of parameter assumptions and model features. Nonetheless, some broader common findings emerge.

To begin with, different types of power storage are generally found to be valuable to accommodate increasing generation of variable renewables. In this respect, up to around 50–70% RES penetration, no or only moderate storage deployment is necessary in most power systems studied in the literature. Second, for higher RES shares, mostly short- and medium-term storage, roughly up to twelve hours, proves economical. In many studies, long-term storage enters optimal system configurations only for very high RES shares approaching 100%, or under rather strong assumptions on the availability of other flexibility options. Any particular assessment, naturally, also depends on parameter assumptions such as specific cost, availability, and efficiency projections of the technologies considered. Moreover, for very high shares of renewables, the coupling of the electricity sector with other energy sectors such as heat or mobility is likely, driven by efforts to mitigate climate change. Depending on the flexibility potential of this new demand, power storage requirements can be expected to vary significantly.

Addressing the relevant modeling dimensions to soundly assess the role of storage in renewable dominated electricity systems, several distinct domains emerge from the literature review. First, in several models, the time resolution is rather coarse, for example based on multi-hourly time slices and aggregated type days. This can impede a proper representation of both short- and long-term variability, and accordingly renders a more in-depth assessment especially of longer-term storage deployment difficult. Second, it is important to include competing flexibility options. This is particularly true for demand-side flexibility resources, which are often represented in a stylized way, if modeled at all. Third, it is relevant to consider the full system value of storage. While all analyses at least partly capture the arbitrage value of storage, system values related to capacity or balancing reserves are

often reflected only partially.

In addition, many complex and computationally demanding models tend to be silent about sensitivities toward parameter assumptions, of which numerous usually have to be made. This appears to be particularly important with respect to substantial uncertainties on the future development of many storage technologies. Finally, for transparency, details of analytical model formulations should be provided, ideally the model's source codes and a full set of input parameters. Otherwise, a lack of traceability and transparency may render the interpretation of results somewhat opaque.

Based on these conclusions from the literature review, we aim to tackle many of the identified issues and thus complement previous research with a new open-source dispatch and investment model that is particularly suited to the exploration of power storage requirements in systems with high shares of variable renewable energy sources. We present the model formulation in the following. A first application of the model to a long-term greenfield scenario is presented in a companion paper [1].

3. A new model

We introduce a new open-source model, the Dispatch and Investment Evaluation Tool with Endogenous Renewables (DIETER), which addresses the domains distilled from the literature review: an hourly resolution for a full year, and the incorporation of balancing energy and demand-side management while being traceable to perform multiple sensitivity analyses on various parameters.

DIETER minimizes total system costs over 8760 h of a full year. System costs comprise annualized investment costs and fixed costs as well as variable costs of conventional generators, renewables, power storage, and DSM. For storage, separate investment decisions regarding power and energy capacities are made. The model ensures that power generation equals price-inelastic demand at all times, while also accounting for the provision and activation of balancing reserves. The full analytical formulation is provided in the following. Capital letters denote variables, and lowercase letters denote parameters. Tables 4, 5, 6 provide an overview of the sets, variables, and parameters.

The objective function is given as

$$\begin{aligned}
 C = & \sum_h \left[\sum_{con} (c_{con}^m G_{con,h}^l + c_{con}^+ G_{con,h}^+ + c_{con}^- G_{con,h}^-) + \sum_{res} c_{res}^{cu} C U_{res,h} \right. \\
 & + \sum_{sto} c_{sto}^m (STO_{sto,h}^{out} + STO_{sto,h}^{in}) + \sum_{ls} c_{ls}^m (DSM_{ls,h}^{d+} + DSM_{ls,h}^{d-}) \\
 & + \sum_{lc} c_{lc}^m DSM_{lc,h}^{cu} + \sum_{con} [(c_{con}^i + c_{con}^{fix}) N_{con}] + \sum_{res} [(c_{res}^i + c_{res}^{fix}) N_{res}] \\
 & + \sum_{sto} \left[\left(c_{sto}^p + \frac{1}{2} c_{sto}^{fix} \right) N_{sto}^p + \left(c_{sto}^E + \frac{1}{2} c_{sto}^{fix} \right) N_{sto}^E \right] \\
 & + \sum_{lc} [(c_{lc}^i + c_{lc}^{fix}) N_{lc}] + \sum_{ls} [(c_{ls}^i + c_{ls}^{fix}) N_{ls}] \\
 & + \sum_h \left[\sum_{sto} \left(\sum_{r \in \mathcal{R}^+} \phi_{r,h}^{call} c_{sto}^m (RP_{r+,sto,h}^{out} - RP_{r+,sto,h}^{in}) \right. \right. \\
 & \left. \left. + \sum_r \phi_{r,h}^{call} c_{sto}^m (RP_{r-,sto,h}^{in} - RP_{r-,sto,h}^{out}) \right) \right] \\
 & + \sum_{lc} c_{lc}^m \left(\sum_{r \in \mathcal{R}^+ \setminus pr} \phi_{r,h}^{call} RP_{r+,lc,h} \right) \\
 & \left. + \sum_{ls} c_{ls}^m \left(\sum_{r \in \mathcal{R} \setminus \{pr, pr\}} \phi_{r,h}^{call} RP_{r,ls,h} \right) \right]
 \end{aligned} \tag{1}$$

Table 4

Sets.

Set	Element	Description
\mathcal{C}	$\ni con$	Conventional generation technologies
\mathcal{H}	$\ni h, hh$	Hours
$\mathcal{L}\mathcal{C}$	$\ni lc$	DSM load curtailment technologies
$\mathcal{L}\mathcal{S}$	$\ni ls$	DSM load shifting technologies
\mathcal{R}	$\ni r$	Reserve energy qualities (pr^+ , pr^- , sr^+ , sr^- , mr^+ , mr^-)
\mathcal{R}^+	$\ni r^+$	Positive reserve energy qualities (pr^+ , sr^+ , mr^+)
\mathcal{R}^-	$\ni r^-$	Negative reserve energy qualities (pr^- , sr^- , mr^-)
$\mathcal{R}\mathcal{E}$	$\ni res$	Renewable generation technologies
\mathcal{S}	$\ni sto$	Storage technologies

Specifically, capacity investments N occur per technology without addressing discrete units. A fixed exogenous capacity limit for conventionals, renewables, storage, and DSM can be given by m . Thus, constraints (2a–2f) enable fitting the model to the conditions of a specific geographical setting or scenario, for instance by restricting investments into nuclear power or run-of-river.

$$N_{con} \leq m_{con} \quad \forall con \quad (2a)$$

$$N_{res} \leq m_{res} \quad \forall res \quad (2b)$$

$$N_{sto}^P \leq m_{sto}^P \quad \forall sto \quad (2c)$$

$$N_{sto}^E \leq m_{sto}^E \quad \forall sto \quad (2d)$$

Table 5

Variables.

Variables	Unit	Description
BCF_h	[MW]	Balancing Correction Factor in hour h
$CU_{res,h}$	[MW]	Curtailment renewable technology res in hour h
D_r	[MW]	Reserves demand of quality r
$DSM_{lc,h}^{cu}$	[MW]	Load curtailment technology lc in hour h
$DSM_{ls,h}^{+}$	[MW]	Net load increase shifting technology ls in hour h
$DSM_{ls,h,hh}^{-}$	[MW]	Net load decrease shifting technology ls in hour hh accounting for increases in hour h
$DSM_{ls,h}^{d+}$	[MW]	Load increase taking effect in the wholesale segment shifting technology ls in hour h
$DSM_{ls,h}^{d-}$	[MW]	Load decrease taking effect in the wholesale segment shifting technology ls in hour h
$G_{con,h}^l$	[MW]	Generation level conventional technology con in hour h
$G_{con,h}^{+}$	[MW]	Generation increase conventional technology con in hour h
$G_{con,h}^{-}$	[MW]	Generation decrease conventional technology con in hour h
$G_{res,h}$	[MW]	Generation renewable technology res in hour h
$RP_{r,con,h}$	[MW]	Reserves provision quality r in hour h by conventional technology con ; analogous for renewable and DSM technologies
$RP_{r,sto,h}^{in}$	[MW]	Reserves provision quality r in hour h by storage technology sto while storing in
$RP_{r,sto,h}^{out}$	[MW]	Reserves provision quality r in hour h by storage technology sto while storing out
$STO_{sto,h}^{in}$	[MW]	Storage inflow technology sto in hour h
$STO_{sto,h}^{out}$	[MW]	Storage outflow technology sto in hour h
$STO_{sto,h}^l$	[MWh]	Storage level technology sto in hour h
N_{con}	[MW]	Installed capacity conventionals
N_{res}	[MW]	Installed capacity renewables
N_{sto}^E	[MWh]	Installed capacity storage energy
N_{sto}^P	[MW]	Installed capacity storage power
N_{lc}	[MW]	Installed capacity DSM load curtailment
N_{ls}	[MW]	Installed capacity DSM load shifting

Note: The basic unit for variables is megawatts (MW). As the model has an hourly temporal resolution, variables representing energy quantities can, in this vein, be interpreted as megawatt hours per hour.

$$N_{lc} \leq m_{lc} \quad \forall lc \quad (2e)$$

$$N_{ls} \leq m_{ls} \quad \forall ls \quad (2f)$$

Yet to account for different flexibility capabilities of conventional installations in following residual demand, we model the generation level of technology con in hour h , $G_{con,h}^l$, which can be altered by costly increases $G_{con,h}^{+}$ and $G_{con,h}^{-}$. The attached load change costs c_{con}^{+} , c_{con}^{-} vary by technology and reflect different levels of flexibility. In this way, technologies with a higher inertia in following residual load can be attached higher load change costs. Thus, the model aims at approximating realistic schedules of power plants, for instance by penalizing heavy cycling of base load technologies. The constraint for these generation dynamics is given by

$$G_{con,h}^l = G_{con,h-1}^l + G_{con,h}^{+} - G_{con,h}^{-} \quad \forall con, h > 1 \quad (3a)$$

$$G_{con,1}^l = G_{con,1}^{+} \quad \forall con \quad (3b)$$

together with an initial condition for the first model period (3b). Generation level $G_{con,h}^l$ and load changes $G_{con,h}^{+}$, $G_{con,h}^{-}$ are net in the sense that they comprise both energy actually delivered to the wholesale market and activated reserves. For the hourly energy balance (5), equalizing wholesale supply and demand, the generation level has to be corrected for the reserves share. To this end, we introduce the *Balancing Correction Factor* $BCF_{con,h}$.

Table 6

Parameters.

Parameters	Unit	Description
c^{cu}	[€/MW]	Curtailment costs
c^{fix}	[€/MW]	Annual fixed costs
c^i	[€/MW]	Annualized specific investment costs
c_{sto}^{iE}	[€/MWh]	Annualized specific investments into storage energy
c_{sto}^{iP}	[€/MW]	Annualized specific investments into storage power
c^m	[€/MW]	Marginal costs
c^{+}	[€/MW]	Load change costs for increases
c^{-}	[€/MW]	Load change costs for decreases
d_h	[MW]	Hourly wholesale demand
η_{ls}	[0,1]	DSM load shifting efficiency factor
η_{sto}	[0,1]	Storage roundtrip efficiency
int'		Intercept of reserve demand regression line
m	[MW]	Maximum installable capacity conventional/renewable/DSM technologies
m_{bio}^E	[MWh]	Yearly energy cap for biomass
m_{sto}^E	[MWh]	Maximum installable storage capacity energy
m_{sto}^P	[MW]	Maximum installable storage capacity power
ϕ^{\pm}	[%/min]	Maximum load change per minute
$\phi_{res,h}^{avl}$	[0,1]	Hourly available energy from renewables as fraction of installed capacity
$\phi_{ror,h}^{avl}$	[0,1]	Hourly available energy from run-of-river plants as fraction of installed capacity
$\phi_{r,h}^{call}$	[0,1]	Hourly called fraction of provided reserves
$\overline{\phi_r^{call}}$	[0,1]	Mean activation of reserve type r
ϕ^{pr}	[0,1]	Demand for primary reserves as fraction of demand for other reserves types
ϕ_{sto}^{ini}	[0,1]	Initial storage level as fraction of storage energy installed
$\underline{\phi}^{res}$	[0,1]	Minimum fraction of annual total net load served by renewables
ϕ_r^{shr}	[0,1]	Fraction of secondary (minute) reserves among positive and negative reserves
slp^r		Slope of reserve demand regression line
t_{dur}	[h]	Duration DSM
t_{off}	[h]	Recovery time DSM
t_r^{reac}	[min]	Reaction lead time for activation of reserves of type r

Note: Parameters referring to energy quantities, usually given in megawatt hours, can be interpreted as taking effect for megawatt hours per hour.

$$BCF_{con,h} \equiv \sum_{r^-} \phi_{r^-,h}^{call} RP_{r^-,h} - \sum_{r^+} \phi_{r^+,h}^{call} RP_{r^+,h} \quad \forall con, h \quad (4)$$

where for reserves of type r , $RP_{r,con,h}$ is the capacity provided by technology con in hour h . In this respect, index r^- comprises negative reserves, index r^+ positive reserves. If a certain amount of reserve capacities is provided, fraction $\phi_{r,h}^{call} \in [0, 1]$ will be called, following actual data from the base year. Balancing correction factors are defined analogously for the other generation technologies.

The balancing correction factor, thus, captures the (negative of the) net energy activated as reserves by a technology in an hour. In the model, it is used to transform the total energy supplied by a certain technology across all segments, that is wholesale and reserves, to gross wholesale supply, and vice versa. For instance, wholesale gross supply by conventional generators is thus expressed as $G_{con,h}^L + BCF_{con,h}$.

The wholesale energy balance prescribes equality of electricity demand, consisting of inelastic consumer demand plus demand by storage and DSM load shifting units, as well as electricity supply, consisting of wholesale supply by conventional and renewable plants as well as storage and DSM facilities, in every hour. It reads

$$\begin{aligned} d_h + \sum_{sto} STO_{sto,h}^{in} + \sum_{ls} DSM_{ls,h}^{d+} \\ = \sum_{con} (G_{con,h}^L + BCF_{con,h}) + \sum_{res} G_{res,h} + \sum_{sto} STO_{sto,h}^{out} \\ + \sum_{lc} DSM_{lc,h}^{cu} + \sum_{ls} DSM_{ls,h}^{d-} \quad \forall h \end{aligned} \quad (5)$$

Equally for secondary and minute reserves r , provision must equal demand D_r in each hour. Specifically, reserves demand must be satisfied by conventional generators, storage, renewables, DSM load curtailment, or DSM load shifting. Overall, we impose three reserves qualities, each both positive and negative, resembling the setup of the German market. However, the number and types of reserves can flexibly be adjusted to other institutional settings. The formulation of reserves constraints mimics the market for short-term balancing services to level out demand and supply fluctuations, for instance caused by forecast errors of the renewables feed-in.¹³

$$\begin{aligned} \sum_{con} RP_{r,con,h} + \sum_{sto} (RP_{r,sto,h}^{in} + RP_{r,sto,h}^{out}) + \sum_{res} RP_{r,res,h} + \sum_{lc} RP_{r,lc,h} \\ + \sum_{ls} RP_{r,ls,h} = D_r \quad \forall h, r \in \mathcal{R} \setminus \{pr^+, pr^-\} \end{aligned} \quad (6a)$$

where load curtailment cannot provide negative balancing power. DSM is assumed not to be suited to satisfy primary reserves, which can only be supplied by conventional, renewable and storage technologies.

$$\begin{aligned} \sum_{con} RP_{r,con,h} + \sum_{res} RP_{r,res,h} + \sum_{sto} (RP_{r,sto,h}^{in} + RP_{r,sto,h}^{out}) \\ = D_r \quad \forall h, r \in \{pr^+, pr^-\} \end{aligned} \quad (6b)$$

Reserves demand is constant over all periods. For secondary and minute qualities, it is determined endogenously in the model as a function of installed wind and solar PV capacities according to the following equation

$$D_r = 1000 * \phi_r^{shr} * \left(int_r^r + \sum_{res} slp_{r,res}^r N_{res} / 1000 \right) \quad \forall r \in \mathcal{R} \setminus \{pr^+, pr^-\} \quad (6c)$$

Parameter ϕ_r^{shr} is the split between secondary and minute reserves, for positive and negative reserves separately.¹⁴ Intercept and slope of the reserves regression line are int_r^r , and $slp_{r,res}^r$ respectively. For the parameters we draw on [63], where a statistical convolution analysis

was carried out, determining reserves demand as a function of installed capacities of variable renewables. Demand for primary reserves is symmetric and rendered as fraction ϕ^{pr} of overall demand for the other types of reserves.¹⁵

$$D_{pr^+} = D_{pr^-} = \phi^{pr} \sum_{r \in \mathcal{R} \setminus \{pr^+, pr^-\}} D_r \quad (6d)$$

Moreover, we impose flexibility requirements on conventional generators for providing reserves, depending on the current load level of the technology.

$$RP_{r,con,h} \leq t_r^{reac} \phi_{con}^{\pm} (G_{con,h}^L + BCF_{con,h}) \quad \forall con, h, r \quad (6e)$$

Eq. (6e) restricts reserves provision to the flexibility within t_r^{reac} minutes where ϕ_{con}^{\pm} is the maximum technically possible load change per minute.

The maximum production constraint on conventional generators requires gross wholesale generation plus positive reserves provision to be no larger than installed capacity. Thus, energy held available as positive reserves may not be delivered to the wholesale segment.

$$G_{con,h}^L + BCF_{con,h} + \sum_{r^+} RP_{r^+,con,h} \leq N_{con} \quad \forall con, h \quad (7a)$$

where for run-of-river plants, $ror \in \mathcal{C}$, the gross generation limit on the right-hand side of the inequality is multiplied by an exogenous hourly availability factor $\phi_{ror,h}^{avl} \in [0, 1]$. Similarly, conventional generators may produce no less on the wholesale market than provided as negative reserves. Thus, if a conventional technology provides negative reserves, it must be running in the wholesale segment at a minimum level corresponding to the assigned reserves to enable the respective load decreases.

$$\sum_{r^-} RP_{r,con,h} \leq G_{con,h}^L + BCF_{con,h} \quad \forall con, h \quad (7b)$$

Constraints on renewables comprise the distribution of fed-in energy, (8a), between load serving $G_{res,h}$, curtailment $CU_{res,h}$, and positive reserve provision. Thus, as generation by the variable renewables wind and solar PV is not dispatchable, it must either be supplied to the wholesale or positive balancing segments, or alternatively curtailed.¹⁶ For each type of installed capacity N_{res} , $\phi_{res,h}^{avl}$ describes the hourly availability factor as a fraction of installed capacity based on exogenous actual time series from the respective base year. At the same time, parallel to conventional generators, renewables may provide no more negative reserves than their scheduled spot market dispatch (8b). Eq. (8c) caps the overall energy delivered by biomass at m_{bio}^E . This constraint captures the potential limitation of available biofuels.

$$G_{res,h} + CU_{res,h} + \sum_{r^+} RP_{r^+,res,h} = \phi_{res,h}^{avl} N_{res} \quad \forall res, h \quad (8a)$$

$$\sum_{r^-} RP_{r^-,res,h} \leq G_{res,h} \quad \forall res, h \quad (8b)$$

$$\sum_h G_{bio,h}^L \leq m_{bio}^E \quad (8c)$$

Eq. (8d) requires the share of non-renewable generation in the total yearly energy delivered to be no larger than $(1 - \phi^{res})$. Put differently, ϕ^{res} prescribes the minimum renewable share in the electricity system.¹⁷ Total yearly consumed energy, in this respect, comprises load minus load curtailment by DSM measures in the wholesale and reserves segments, as well as storage and DSM load shifting losses in both segments. For convenience, ϕ^{call} denotes the mean hourly

¹³ See [62] for a deeper discussion.

¹⁴ Data follow the historical pattern of the years 2010–2012. Variations between years are negligible. We therefore refrain from adapting to the respective base year of the analysis. The dimensioning of the input data demands multiplication and division by the factor 1000.

¹⁵ We parameterize ϕ^{pr} resembling the actual ratio for Germany.

¹⁶ We set ϕ_{res}^{cu} to zero in the numerical application.

¹⁷ The renewable sources biomass and run-of-river are from the model's point of view categorized as a conventional technology, as we assume them dispatchable; nevertheless, both adds to the renewable share of the system.

activation of reserve type r .

$$\begin{aligned}
 & \sum_{con \in \mathcal{C} \setminus \{bio, ror\}} \sum_h G_{con,h}^l \leq \\
 & (1 - \phi_{res}^{\text{res}}) \sum_h \left[d_h + \sum_{sto} (STO_{sto,h}^{\text{in}} - STO_{sto,h}^{\text{out}}) - \sum_{lc} DSM_{lc,h}^{cu} \right. \\
 & + \sum_{ls} \left(DSM_{ls,h}^+ - \sum_{hh, h-t_{ls}^{\text{dur}} \leq hh \leq h+t_{ls}^{\text{dur}}} DSM_{ls,h,hh}^- \right) \\
 & + \sum_{r^+} \overline{\phi}_{r^+}^{\text{call}} D_{r^+} - \sum_{r^-} \overline{\phi}_{r^-}^{\text{call}} D_{r^-} \\
 & + \sum_{sto} (BCF_{sto,h}^{\text{in}} + BCF_{sto,h}^{\text{out}}) \\
 & \left. - \sum_{lc} \sum_{r^+ \in \mathcal{R}^+ \setminus pr^+} RP_{r^+,lc,h} \phi_{r^+,h}^{\text{call}} \right] \quad (8d)
 \end{aligned}$$

Eq. (8d) is central to the further analysis in this paper as it restricts the system to fulfill an exogenously pre-defined share of renewable energy among total electricity consumption. In that way, the effects within different scenarios on future renewables dominated electricity systems can be investigated.

The next set of constraints is related to storage technologies where efficiency losses in the storage dynamics Eq. (9b) are attributed equally to loading and generation. Storage technologies can provide different values to the system: an arbitrage value by transferring energy from periods with ample supply to periods with tight supply, which is represented by the intertemporal storage constraints (9a)–(9c); a balancing value, which is captured by reserves provision through storage technologies RP_{sto} ; and a capacity value, which is implicitly given by the intertemporal storage constraints: in hours of low renewables supply and high demand, energy generated by storage outflows can replace the need for additional investments into other capacities.

Note that storage can provide both negative and positive reserves by both storing in, $RP_{r^+}^{\text{in}}$, $RP_{r^+}^{\text{in}}$, and storing out, $RP_{r^+}^{\text{out}}$, $RP_{r^+}^{\text{out}}$; that is through increasing or withholding scheduled inflows or outflows. To counteract model artifacts of excessive loading in the first periods, each technology starts with a fraction ϕ_{sto}^{ini} of installed energy as initial level of energy stored (9a). Likewise, energy stored after the last period of the model horizon must equal that initial level according to (9c).

$$STO_{sto,1}^l = \phi_{sto}^{\text{ini}} * N_{sto}^E + \frac{(1 + \eta_{sto})}{2} STO_{sto,1}^{\text{in}} - \frac{2}{(1 + \eta_{sto})} STO_{sto,1}^{\text{out}} \quad \forall sto \quad (9a)$$

$$\begin{aligned}
 STO_{sto,h}^l &= STO_{sto,h-1}^l + \frac{(1 + \eta_{sto})}{2} STO_{sto,h}^{\text{in}} - \frac{2}{(1 + \eta_{sto})} STO_{sto,h}^{\text{out}} \\
 & - \sum_{r^+} \phi_{r^+,h}^{\text{call}} \left(\frac{(1 + \eta_{sto})}{2} RP_{r^+,sto,h}^{\text{in}} + \frac{2}{(1 + \eta_{sto})} RP_{r^+,sto,h}^{\text{out}} \right) \\
 & + \sum_{r^-} \phi_{r^-,h}^{\text{call}} \left(\frac{(1 + \eta_{sto})}{2} RP_{r^-,sto,h}^{\text{in}} + \frac{2}{(1 + \eta_{sto})} RP_{r^-,sto,h}^{\text{out}} \right) \quad \forall \\
 & sto, h > 1 \quad (9b)
 \end{aligned}$$

$$STO_{sto,h}^l = \phi_{sto}^{\text{ini}} * N_{sto}^E \quad \forall sto, h = |\mathcal{S}| \quad (9c)$$

Investments into energy and power are generally mutually independent—that is, we do not impose a predetermined energy-to-power (E/P) ratio—and power investments are assumed to be symmetric between inflows and outflows; (9d)–(9f). The free E/P ratio grants the model the freedom to pick storage layout most suitable to the electricity system. As the overall setup is a greenfield model taking on a very long-term perspective, it enables determining future optimal storage configurations.

Eqs. (9g)–(9h) restrict provision of reserves to installed storage power. Two additional restrictions concerning reserve provision are

required: (9i) constrains generation for satisfying wholesale demand plus positive reserve provision to last period's storage level, and (9j) restricts storage inflow plus negative reserve provision to the wedge between energy capacity and last period's level. Otherwise, for instance, an empty storage could provide reserves while anticipating never being called.

$$STO_{sto,h}^l \leq N_{sto}^E \quad \forall sto, h \quad (9d)$$

$$STO_{sto,h}^{\text{in}} + \sum_{r^-} RP_{r^-,sto,h}^{\text{in}} \leq N_{sto}^P \quad \forall sto, h \quad (9e)$$

$$STO_{sto,h}^{\text{out}} + \sum_{r^+} RP_{r^+,sto,h}^{\text{out}} \leq N_{sto}^P \quad \forall sto, h \quad (9f)$$

$$\sum_{r^+} RP_{r^+,sto,h}^{\text{in}} \leq STO_{sto,h}^{\text{in}} \quad \forall sto, h \quad (9g)$$

$$\sum_{r^-} RP_{r^-,sto,h}^{\text{out}} \leq STO_{sto,h}^{\text{out}} \quad \forall sto, h \quad (9h)$$

$$\frac{2}{(1 + \eta_{sto})} \left(STO_{sto,h}^{\text{out}} + \sum_{r^+} RP_{r^+,sto,h}^{\text{out}} \right) \leq STO_{sto,h-1}^l \quad \forall sto, h \quad (9i)$$

$$\frac{(1 + \eta_{sto})}{2} \left(STO_{sto,h}^{\text{in}} + \sum_{r^-} RP_{r^-,sto,h}^{\text{in}} \right) \leq N_{sto}^E - STO_{sto,h-1}^l \quad \forall sto, h \quad (9j)$$

System flexibility in terms of load-following capacities may not only be provided by the generation side or storage plants, but also by the demand side. The following set of constraints describes two types of demand-side management. In this respect, DSM measures are separated into load curtailment (lc) and load shifting (ls). For load curtailment, demand is reduced in one period without recovery at a later point in time. Each installed facility N_{lc} may cut load once every t_{lc}^{off} hours, the recovery period, for a duration of maximally t_{lc}^{dur} hours, implemented by Eq. (10a). Eq. (10b) ensures that maximum load curtailment capacities are also not exceeded within each single period. By reducing demand, load curtailment may also provide positive secondary and minute reserve energy.

$$\sum_{hh, h \leq hh < h+t_{lc}^{\text{off}}} \left(DSM_{lc,h,hh}^{cu} + \sum_{r^+ \in \mathcal{R}^+ \setminus pr^+} RP_{r^+,lc,h,hh} \phi_{r^+,hh}^{\text{call}} \right) \leq N_{lc} t_{lc}^{\text{dur}} \quad \forall lc, h \quad (10a)$$

$$DSM_{lc,h}^{cu} + \sum_{r^+ \in \mathcal{R}^+ \setminus pr^+} RP_{r^+,lc,h} \leq N_{lc} \quad \forall lc, h \quad (10b)$$

The implementation of DSM load shifting follows a granular interpretation: units that are shifted up in hour h , denoted by $DSM_{ls,h}^{d+}$, must be shifted down in the surrounding t_{ls}^{dur} hours, corrected by the efficiency factor η_{ls} . In this respect, $DSM_{ls,h,hh}^-$ carries two time indices, representing downshifts in hour hh to account for upshifts in hour h . Eq. (10c) employs this double-indexation to ensure that each unit of load on hold is recovered within the specified duration period t_{ls}^{dur} of the DSM technology. Both DSM upshifts and downshifts may either take effect for the wholesale or the reserves segment. Therefore, Eq. (10d) distributes the respective net upshift $DSM_{ls,h}^{d+}$ into a portion $DSM_{ls,h}^{d+}$ entering the energy balance of supply and demand on the wholesale market (5), and a portion serving negative reserves activation. The analogous distribution equation for negative shifts is given by (10e), where the left-hand side simply represents all downshifts within period h , regardless for which hour's upshifts they account for.

Interpreting each installed DSM load shifting unit N_{ls} as one granular unit which in each period can either shift up demand, shift down demand, provide reserves of one quality, or be inactive, Eq. (10f) ensures that no undue overuse takes place. Eq. (10g) specifies a recovery period t_{ls}^{off} for each DSM load shifting installation. For a more in-depth treatment of the implemented DSM representation, see [2].

$$\frac{1 + \eta_{ls}}{2} DSM_{ls,h}^+ = \frac{2}{1 + \eta_{ls}} \sum_{hh, h-t_{ls}^{dur} \leq hh \leq h+t_{ls}^{dur}} DSM_{ls,h,h}^- \quad \forall h \quad (10c)$$

$$DSM_{ls,h}^+ = DSM_{ls,h}^{d+} + \sum_{r \in \mathcal{R} \setminus \{pr^-\}} RP_{r,ls,h}^- \phi_{r,h}^{call} \quad \forall ls, h \quad (10d)$$

$$\sum_{hh, h-t_{ls}^{dur} \leq hh \leq h+t_{ls}^{dur}} DSM_{ls,h,h}^- = DSM_{ls,h}^{d-} + \sum_{r^+ \in \mathcal{R}^+ \setminus \{pr^+\}} RP_{r^+,ls,h}^+ \phi_{r^+,h}^{call} \quad \forall ls, h \quad (10e)$$

$$DSM_{ls,h}^{d+} + DSM_{ls,h}^{d-} + \sum_{r \in \mathcal{R} \setminus \{pr^+, pr^-\}} RP_{r,ls,h} \leq N_{ls} \quad \forall ls, h \quad (10f)$$

$$\sum_{hh, h \leq hh < h+t_{ls}^{off}} DSM_{ls,h}^+ \leq N_{ls} t_{ls}^{dur} \quad \forall ls, h \quad (10g)$$

4. Discussion of limitations

In the following, we briefly discuss important limitations of our model approach.

In its current setup, the model does not allow for investigating a transition from an existing power plant portfolio to a renewable-dominated one, but always assumes optimal long-run equilibria. This restricts the potential to draw policy conclusions on transformation processes. Still, the model can be used to provide, on the one hand, long-run benchmarks for the role of power storage in optimized future power systems, and, on the other, qualitative insights into interdependencies of power storage and various other flexibility options.

Next, the model focuses on the power system and neglects interactions with the heating or mobility sectors. While this simplification appears to be largely justified for most current power systems (except, for example, Denmark), it can be expected that interactions with the heat and mobility sectors substantially gain importance in future high-RES systems [52]. For example, a range of power-to-heat applications may take up temporary renewable surpluses, electric vehicles may provide system flexibility, and flexible electrolysis may be used to generate hydrogen, which could again be used for electricity generation or many other purposes. If such additional “power-to-X” flexibility options were considered, pure power storage requirements should tend to decrease. Including such cross-sector interactions would require extending the analytical framework from a partial equilibrium power sector perspective toward a larger-scale energy system model. This appears to be both a challenging and a promising avenue for future research. As regards power system interactions of electric vehicles, a respective model extension is already available (from version 1.1.0 on). It has been used to study the potential role of vehicle-to-grid and reserve provision by electric vehicles in different future scenarios for Germany [64].

Further, investment models generally require simplifications with respect to technical details of thermal generators compared to pure dispatch models. Otherwise, investment models as large as the one developed here would be hard to solve numerically. For example, our linear model setup cannot accommodate a unit-commitment formulation with start-up restrictions and costs of single thermal blocks, minimum on-times or off-times, and minimum generation levels. Instead, we aim to approximate such constraints with linearized ramping costs of aggregated technologies. This may tend to underestimate flexibility restrictions of thermal generators and, thus, lead to an undervaluation of flexibility. Yet in a future system with strongly growing renewable shares this might be of decreasing importance. Further, we keep the model solvable by abstracting from network issues and by assuming perfect foresight.

Aside from sector coupling issues mentioned above, further avenues for future extension of our framework relate to the usage of meteorological data for a bottom-up determination of feed-in patterns of variable renewable generators. Likewise, a sufficient spatial representation, for instance in a

multiple-country setting, would allow not only to consider complementary time patterns of feed in and load over larger geographic areas, but also to accommodate the network-related value of storage in the model.

Importantly, the discussed simplifications render possible a parsimonious model formulation that allows traceability of results. Even more important, this provides scope for multiple sensitivities, which are at the heart of the analysis provided in [1], as assumptions on the long-run development of cost and other relevant parameters within the power system are, naturally, highly uncertain.

5. Conclusions

We carry out a detailed review of model-based analyses on the role of power storage in electricity systems dominated by variable renewable energy sources. These analyses and their underlying models can be differentiated with respect to a range of specific features, such as the coverage of balancing reserves and demand-side management, and with respect to the potential system values of storage covered by the analysis. This includes system values related to arbitrage, capacity, and reserves, as well as network-related system values. While the arbitrage value of power storage is always covered to a certain extent, most of the studies reviewed do not capture all of these system values.

While there is no consensus in the literature, some broad common indications emerge. First, power storage can be valuable in integrating high shares of renewables, but deployment is rather moderate up to around 50–70% RES penetration levels. In this respect, second, specifically short and medium term storage, up to around 12 h, can help accommodate the variability of wind and solar PV. Third, primarily for very high RES shares approaching 100%, long-term power storage becomes economic. Yet sector coupling, for instance with the heat or mobility sector, is likely for very high shares of renewables, driven by climate change mitigation considerations. In this case, new electricity demand arises, whose flexibility can be expected to have a substantial impact on power storage requirements.

In our review, we also identify modeling features relevant to soundly assess different roles for storage: a fine temporal resolution, a large set of contiguous time periods to capture short and long-term variability, the inclusion of competing flexibility options such as demand-side management, the ability to capture different benefits to the system such as the provision of balancing reserves and firm capacity, and computational efficiency to allow for numerous sensitivity analyses.

Based on these domains, we develop the new dispatch and investment model DIETER to study the role of power storage and other flexibility options in a greenfield setting with high shares of renewables. Our model not only captures the arbitrage value of power storage, but also system values related to the provision of dispatchable capacity and reserves. DIETER is designed as an open-source tool in order to improve transparency, allow for a reproduction of results, and foster future research activities in the field. A first application of the model is described in a companion paper [1].

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