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Summary

Mitigation-Process Integrated Assessment Models (MP-IAMs) are used to analyze long-term transformation pathways of the energy system required to achieve stringent climate change mitigation targets. Due to their substantial temporal and spatial aggregation, IAMs cannot explicitly represent all detailed challenges of integrating the variable renewable energies (VRE) wind and solar in power systems, but rather rely on parameterized modeling approaches. In the ADVANCE project, six international modeling teams have developed new approaches to improve the representation of power sector dynamics and VRE integration in IAMs. In this study, we qualitatively and quantitatively evaluate the last years' modeling progress and study the impact of VRE integration modeling on VRE deployment in IAM scenarios. For a comprehensive and transparent qualitative evaluation, we first develop a framework of 18 features of power sector dynamics and VRE integration. We then apply this framework to the newly-developed modeling approaches to derive a detailed map of strengths and limitations of the different approaches. For the quantitative evaluation, we compare the IAMs to the detailed hourly-resolution power sector model REMIX. We find that the new modeling approaches manage to represent a large number of features of the power sector, and the numerical results are in reasonable agreement with those derived from the detailed power sector model. Updating the power sector representation and the cost and resources of wind and solar substantially increased wind and solar shares across models: Under a carbon price of 30$/tCO2 in 2020 (increasing by 5% per year), the model-average cost-minimizing VRE share over the period 2050-2100 is 62% of electricity generation, 24%-points higher than with the old model version.

Keywords: Integrated Assessment Models (IAM), Variable Renewable Energy (VRE), Wind and Solar Power, System Integration, Power Sector Model, Flexibility Options (Storage, Transmission Grid, Demand Response), Model Evaluation, Model Validation

JEL Classification: C6, C61, Q40, Q42, Q47, Q49

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System integration of wind and solar power in Integrated Assessment Models: a cross-model evaluation of new approaches

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Glossary:

ADVANCE – Advanced Model Development and Validation for Improved Analysis of Costs and Impacts of Mitigation Policies (a collaborative project funded by the European Union's 7th Framework Program)
AR5 – Fifth Assessment Report of the IPCC
CES – Constant Elasticity of Substitution production function
CSP – Concentrating Solar Power
CF – Capacity Factor
CV – Capacity Value
IAMs – Integrated Assessment Models
IPCC – Intergovernmental Panel on Climate Change
LCOE – Levelized Cost of Electricity
MNL – Multinomial Logit
PV – Photovoltaics
RLDC – Residual Load Duration Curve
VRE – Variable Renewable Energy

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Abstract

Mitigation-Process Integrated Assessment Models (MP-IAMs) are used to analyze long-term transformation pathways of the energy system required to achieve stringent climate change mitigation targets. Due to their substantial temporal and spatial aggregation, IAMs cannot explicitly represent all detailed challenges of integrating the variable renewable energies (VRE) wind and solar in power systems, but rather rely on parameterized modeling approaches. In the ADVANCE project, six international modeling teams have developed new approaches to improve the representation of power sector dynamics and VRE integration in IAMs.

In this study, we qualitatively and quantitatively evaluate the last years' modeling progress and study the impact of VRE integration modeling on VRE deployment in IAM scenarios. For a comprehensive and transparent qualitative evaluation, we first develop a framework of 18 features of power sector dynamics and VRE integration. We then apply this framework to the newly-developed modeling approaches to derive a detailed map of strengths and limitations of the different approaches. For the quantitative evaluation, we compare the IAMs to the detailed hourly-resolution power sector model REMIX. We find that the new modeling approaches manage to represent a large number of features of the power sector, and the numerical results are in reasonable agreement with those derived from the detailed power sector model. Updating the power sector representation and the cost and resources of wind and solar substantially increased wind and solar shares across models: Under a carbon price of 30$/tCO2 in 2020 (increasing by 5% per year), the model-average cost-minimizing VRE share over the period 2050-2100 is 62% of electricity generation, 24%-points higher than with the old model version.

Highlights:

- We develop a comprehensive framework to evaluate power sector modeling in IAMs
- We evaluate 6 new modeling approaches to represent variability of wind and solar
- Most IAMs now represent key power sector dynamics, as shown by hourly model REMIX
- Previous integration modeling was in many of the analyzed IAMs too restrictive
- IAMs with new approaches show on average 24%-points higher wind/solar shares than before

Keywords:

Integrated assessment models (IAM); variable renewable energy (VRE); wind and solar power; system integration; power sector model; flexibility options (storage, transmission grid, demand response); model evaluation; model validation.

1 Introduction

Mitigation-Process Integrated Assessment Models (MP-IAMs) are the main tool to analyze the long-term energy system transformation pathways needed for stringent climate change mitigation (Clarke and Kejun, 2014; Fisher et al., 2007; Kriegler et al., 2014). One of their uses is the evaluation of the long-term role of technology classes, such as the variable renewable energy (VRE) sources wind and solar[1], for climate change mitigation (Luderer et al., 2014; Pietzcker et al., 2014b). This knowledge provides useful policy advice and can help in setting targets for technology support and deployment, such as the 2020 target for renewable energy in the EU (Bertram et al., 2015; Lehmann et al., 2012). While IAMs are crucial tools for exploring mitigation pathways, they face a considerable challenge in modeling the short-term dynamics of the power sector: On the one hand, they have to span the whole century to cover the relevant decarbonization dynamics, while on the other hand, short-term dynamics down to an hourly scale matter for investment decisions in the power sector (see (Després et al., 2015) for a typology of different energy models and their time scales).

Power systems must balance generation and demand in each moment, which is a challenge due to the variability of demand and possible outages of power plants and grid lines. When integrating VRE generation, their variability creates additional challenges, such as back-up capacity requirements (due to a low VRE capacity credit) or VRE curtailment[2] (Holttinen et al., 2011; IEA, 2014; Lew et al., 2013b; Schaber et al., 2012; Ueckerdt et al., 2015a). While these integration challenges do not pose an insurmountable technical limit to increasing VRE shares, they can increase total system costs and thereby decrease the economic value of VRE (Hirth et al., 2015; Ueckerdt et al., 2013). In addition, VRE and demand variability shape the economics of a power system as a whole, i.e. also the non-VRE part of the power system adapts in response to increasing VRE shares (IEA, 2014; Ueckerdt et al., 2015b).

IAMs need to represent[3] not only integration challenges but also options to mitigate these challenges. The most important technical options are i) adjustments in the non-VRE generation mix towards both more flexibility and less capital intensity, ii) expansion of long-distance transmission grids to reduce variability via pooling, iii) making demand response, and iv) storage technologies (suited for diurnal and seasonal time scales) (Becker et al., 2014; Haller et al., 2012; IEA, 2014; Mai et al., 2012; Rasmussen et al., 2012; Scholz et al., in this issue). Additionally, there are a number of system operation and market design options that can facilitate VRE integration, such as shortening dispatch intervals, allowing VRE to provide system services, or using up-to-date forecasting

[1] For the purpose of this paper, we define variable renewable energy (VRE) as the sum of wind and solar electricity production, since both are characterized by variability. We also include concentrating solar power (CSP) in this definition, even though CSP can be combined with large heat storage facilities to reduce variability, or even become fully dispatchable if combined with gas or hydrogen co-firing.

[2] Throughout this paper, "curtailment" always refers to "production curtailment", i.e. the reduction of output from power generators.

[3] "Representing integration challenges" means that aggregated models mimic features of the real world that inhibit or facilitate VRE integration, possibly informed by highly detailed models.

methods (IEA, 2014)[4]. All these options can reduce integration challenges and thus mitigate the economic impacts of variability.

As VRE costs have strongly decreased over the last decade, integration challenges and options to mitigate them increasingly determine the role of VRE in climate change mitigation. In addition, scenarios show that the power sector is a centerpiece for climate change mitigation as it decarbonizes earlier and more extensively than the non-electric energy sectors (Krey et al., 2014; Luderer et al., 2011, 2012). Electrification is an important mitigation strategy for transport and residential heating (Krey et al., 2014; Pietzcker et al., 2014a). Hence, an accurate representation of the power sector with its specificities is crucial for deriving robust and credible mitigation scenarios.

IAMs consist of very aggregated representations of real-world dynamics, it is therefore important to analyze the validity of their process representations and results (Parker et al., 2002; Schwanitz, 2013; Weyant, 2009). As IAMs produce scenarios about the future, it is difficult or even impossible to validate them against the real world (Craig et al., 2002; Parker et al., 2002). Concerning the topic of this paper, there are no large-area power systems in the world where wind and solar generate more than 50% of electricity, thus it is impossible to validate the modeling of integration challenges at high VRE shares against real-world data. However, other approaches to evaluate IAMs have been developed over the last decades, as discussed in detail in (Schwanitz, 2013). For the purpose of evaluating power sector modeling, we here focus on the approach "evaluation with stylized behavior patterns" (Schwanitz, 2013). Building on the idea by Kaldor to analyze how well economic models represent a number of "stylized facts" of economic growth (Jones and Romer, 2010; Kaldor, 1961), the approach can be generalized to testing how well an aggregated model reproduces a certain process or dynamic that is derived from experience or from more detailed analysis or modeling (Blanford et al., 2012; Schäfer et al., 2014; Wilson et al., 2013).

The current study presents the first coordinated undertaking to comprehensively evaluate a number of IAMs with respect to how they model VRE integration. In a collaborative effort in the context of the EU FP7 project ADVANCE, six state-of-the-art MP-IAMs used for policy advice have developed new representations of power sector dynamics, most importantly the challenges of integrating solar and wind power (see Section 2). The modeling approaches used to represent variability cover a wide range, from implicit and explicit cost markups to flexibility and capacity equations, time slices, and residual load duration curves. Many of the approaches are based on residual load duration curves (RLDCs) developed within ADVANCE for different world regions (Ueckerdt et al., in this issue). RLDCs are the temporally reordered residual load that remains after VRE generation is subtracted from load, and that thus needs to be supplied by dispatchable power plants (see (Ueckerdt et al., 2015a) for a detailed description of RLDCs). All participating IAMs have global coverage and produce scenarios for the full 21st century.

The goal of this study is to analyze and evaluate these newly-developed modeling approaches through a two-fold approach based on qualitative and quantitative analysis: We first develop a framework of fundamental principles governing power sector dynamics, and discuss how well

[4] As IAMs do not represent the existing market structures and – possibly sub-optimal – system operation procedures and regulations, representing these options is not a focus of this paper.

these principles are covered by the different modeling approaches (Section 3). We then analyze how the last years' improvement of VRE integration modeling affects the modeled VRE deployment, and compare the IAM scenarios to results from a detailed power sector model in order to test the quantitative plausibility of the different approaches (Section 4).

2 Overview of the integrated assessment models

In the following, we will briefly describe the power sector representation of the six participating IAMs as well as the power sector model REMIX. All the IAMs have full global coverage; POLES is the only model that explicitly represents 24 EU member states. All IAMs updated their wind and solar resource potential assumptions based on the country-level data in (Eurek et al., in this issue) for wind and (Pietzcker et al., 2014b) for solar. A cross-model comparison of resulting levelized costs of electricity can be found in the editorial of this special section (Luderer et al., in this issue). Sources for other technology assumptions can be found in the model-specific documentations referenced behind each model name.

To provide a quick overview, we present a list summarizing the main power sector module characteristics (see Table 1) before discussing the models in more detail. For a later analysis of the impact of different representations of VRE integration challenges in Section 4.1, we also summarize the characteristics of the previous model versions that were used in the EMF27 study. Due to the complexity of power sector modeling and the number of different approaches taken, we can here only give a brief summary – for a detailed overview of changes between the model versions, see the individual model papers of this special issue as well as the EMF27 paper on renewables (Luderer et al., 2014).

Table 1: Main characteristics of the power sector and VRE integration representations, once in the current ADVANCE model version, and once for comparison purposes in the older model version used for EMF27

Model	Current model version developed for ADVANCE (2016)	For comparison: older model version used for EMF27 (2013)
AIM/CGE	• Electricity is a uniform good, technologies compete on LCOE in a multinomial logit (MNL) • Short-term storage and curtailment exogenous functions of wind and solar share, parameterized based on ADVANCE RLDCs	Not applicable
IMAGE	• Investment based on ADVANCE RLDC (20 load bands) • Technologies compete on LCOE in a MNL • Capacity and energy backup requirements lead to LCOE markups for wind and solar • Exogenous curtailment derived from ADVANCE RLDC • Exogenous short-term storage facilitates integration	• Investment on 10 time slices, technologies compete on LCOE in a MNL • Exogenous fix backup for VRE • Exogenous curtailment and spinning reserve
MESSAGE	• Electricity is a uniform good, technologies compete linearly on LCOE basis • Capacity equation with ADVANCE RLDC-derived parameters • Flexibility equation with ADVANCE RLDC-derived parameters • Storage investments driven by capacity & flexibility equation • Exogenous curtailment derived from ADVANCE RLDC • Endogenous hydrogen storage investments	• Electricity is a uniform good, technologies compete linearly on LCOE basis • Generic capacity equation • Flexibility equation with fixed parameters • Generic exogenous curtailment

POLES	• Investment based on combinatorial RLDC formed from 54 days: 2 seasons x 3 demand levels (high/med/low) x 3 solar levels (high/med/low) x 3 wind levels (high/med/low) • Technologies compete on LCOE in MNL • Additional "technology diffusion" markups for wind/solar • Dispatch within EU calculated in dispatch model EUCAD between POLES investment calculations, on 12 hourly representative days from new cluster analysis • Endogenous within-day storage investment	• Investment on 24 2h-time slices: 2 days (winter/summer) • Investment based on LCOE, using a multinomial logit function • Hard upper bounds on wind and solar share (region-specific) • Additional cost markups for wind and solar
REMIND	• Investment based on ADVANCE RLDC, implemented via 4 load boxes with wind/solar-share-dependent heights • Technologies compete linearly on load-band LCOE • Introduced peak capacity equation based on ADVANCE RLDC • Exogenous curtailment and short-term storage capacities based on ADVANCE RLDC • Grid cost markups updated based on REMIX results • Endogenous hydrogen storage investments	• Electricity is a uniform good, technologies compete linearly on LCOE basis • Integration cost markup for wind and solar to represent curtailment and storage costs • Grid cost markups
WITCH	• Electricity is a uniform good, technologies compete on LCOE basis in a nested constant elasticity of substitution (CES) system with medium flexibility (elasticity of substitution: 5) • Capacity equation with VRE-share dependent parameters • Flexibility equation with fix parameters • Exogenous storage investment driven by capacity and flexibility equations • Grid cost markups	• Electricity is a uniform good, technologies compete on LCOE basis in a nested constant elasticity of substitution (CES) system with low flexibility (elasticity of substitution: 2) • Flexibility equation with fix parameters • Integration cost markup for wind and solar to represent curtailment and storage costs

2.1 AIM/CGE

The power generation sector in AIM/CGE (Fujimori et al., 2012) is disaggregated in great detail to reflect technological change in the power sector, and logit functions are used to determine the share of power supply technologies as a function of their generation costs. The power generation cost is determined by the cost of intermediate inputs and primary factor (capital and labor) cost. Some barriers to VRE integration, like curtailment and storage, are explicitly taken into account in the recent version of AIM/CGE model (Dai et al., in this issue). The storage service is treated as one of the intermediate inputs for the VRE production sectors, and it is produced by an explicit storage service providing sector. The required input of the storage service is calculated through an exponential function depending on VRE shares[5], parameterized to the residual load duration curves (RLDCs) developed in the ADVANCE project (Ueckerdt et al., in this issue). Curtailment is represented as an additional demand in the electricity balance, and also takes the form of an exponential function depending on VRE shares and parameterized to the Ueckerdt et al. data.

[5] Throughout this paper, "VRE share" always refers to the share of electricity generated from VRE in total electricity generation. "Net VRE share" specifies that curtailment has been deducted both from wind and solar generation and from total generation.

2.2 IMAGE

In the integrated assessment framework IMAGE (Stehfest et al., 2014), region-specific RLDCs (Ueckerdt et al., in this issue) have been combined with a load band approach to capture integration constraints of VRE resources (De Boer and Van Vuuren, this issue). These constraints include curtailment, storage requirements, backup requirements, and system load factors that decline as the VRE share increases. The constraints have been translated to cost markups, which are added to a base levelized cost of electricity (LCOE) to form an all-in LCOE. Investments are rule-based and calculated recursively for each time step: a module calculates the required capacity additions to meet demand, and a multinomial logit equation is applied to distribute market share among the available technologies based on the all-in LCOE. Dispatch of technologies occurs according to the merit order.

2.3 MESSAGE

In the MESSAGE model (Messner and Strubegger, 1995; Riahi et al., 2012), region- and share-dependent RLDCs (Ueckerdt et al., in this issue) are used to parameterize how flexibility of the residual non-VRE system, VRE curtailment, and wind and solar PV capacity values change with increasing VRE share (Johnson et al., in this issue). These equations are translated into step-wise linear functions that describe the contribution of VRE to capacity adequacy and system flexibility constraints, where increasing VRE deployment requires more firm (backup) capacity and increasing flexibility from the non-VRE portion of generation. In addition, electricity storage and hydrogen electrolysis technologies are included as options for repurposing both VRE and non-VRE production that would otherwise be curtailed. Thermoelectric technologies are represented in two modes of operation, baseload and flexible, to better account for the cost, efficiency, and availability penalties associated with flexible operation and the consequences of VRE deployment for non-VRE plant utilization. Since MESSAGE is a least-cost optimization model with perfect foresight, the additional electricity system requirements for integrating VRE endogenously influence investment decisions within the power sector.

2.4 POLES

The new POLES (Mima, 2016) power module now includes several forms of storage technologies as well as load shedding and curtailment of surplus power (Després et al., in this issue). Each region has an endogenous RLDC of 648 time-slices built from demand, wind and solar variations. They are used to define the seven load bands in which the production technologies compete. Investments for each load band are rule-based and calculated recursively for each time step: a module calculates the required capacity additions to meet demand, and a multinomial logit equation is applied to distribute market share among the available technologies based on the curtailment-adjusted LCOE plus a multiplier representing technology maturity and other non-cost effects on investment. A storage investment mechanism is also implemented based on a computation of its expected economic value. In this way, each region takes into account the integration challenges linked to the gradual development of VRE sources.

POLES is the only IAM that follows a model-coupling route and combines a long-term investment planning model with a dispatch model (EUCAD, European Unit Commitment And Dispatch) based on twelve representative days with hourly resolution (Després et al., in this issue; Després, 2015;

Nahmmacher et al., 2016). Such a model-coupling brings the advantage that it enables representation and analysis of short-term effects, but it also creates the challenges of a) creating a reliable interface to ensure that the results from one model influence the other model (e.g., investment decisions should be influenced by the revenues realized in the dispatch), and b) gathering sufficiently detailed data for the individual regions. Due to lack of data, the current version of POLES only uses the detailed model coupling for the European countries, while the other world regions rely on an aggregated RLDC-based investment and dispatch procedure.

2.5 REMIND

The energy-economy-climate model REMIND (Luderer et al., 2013, 2015) is a Ramsey-type general equilibrium growth model of the macro-economy in which inter-temporal global welfare is maximized, combined with a technology-rich representation of the energy system. Its power sector implementation is based on the region-specific RLDCs developed in (Ueckerdt et al., in this issue), which capture the effects of adding wind and solar power to the power sector on a) capacity adequacy, b) dispatch, c) storage and d) curtailment. The RLDCs are represented by four load bands plus a capacity adequacy equation. The height of these load bands is a polynomial function of wind and solar share, so their height endogenously adjusts with changing VRE shares. Investments into the different power technologies are optimized with perfect foresight over the full time horizon of the model. Dispatch is represented through the residual load bands. Short-term storage deployment and curtailment are prescribed by polynomial fits of the VRE-share-dependent RLDCs. As the model uses an optimization framework for investments into dispatchable and VRE technologies, the share-dependent polynomial RLDC formulation enables the model to fully account for the changing marginal value of VRE in the investment procedure.

2.6 WITCH

WITCH (Bosetti et al., 2006; Emmerling et al., 2016) is a hybrid model that combines an aggregated, top-down inter-temporal optimal growth Ramsey-type model (with perfect foresight) with a detailed description of the energy sector. Energy technologies – divided between the electric and the non-electric sectors - are nested in a Constant Elasticity of Substitution (CES) framework, which represents the many economic and non-economic drivers leading to limited technology substitution in a stylized way. Energy demand is modeled in average terms over the year. System integration of variable renewable energies is explicitly modeled through two constraints, related to the flexibility and the capacity adequacy of the power generation fleet. A simple modeling of the electric infrastructure and a generic storage technology are implemented as well (Carrara and Marangoni, in this issue).

2.7 REMIX

REMIX is an energy system model with high spatial and temporal resolution developed at DLR to investigate cost-efficient integration of renewable energy into the energy system with a focus on power supply (Scholz et al., in this issue; Scholz, 2012). It can be used to either validate existing power sector scenarios, or to calculate cost-optimal power sector configurations from greenfield. In this second application, it simultaneously optimizes both investments into new power plants and their dispatch with hourly resolution over the full 8760 hours of a year in order to minimize total system costs. REMIX represents Europe in 15 regions with individual electricity demand and renewable resources. Besides conventional and renewable power technologies, the model also represents a number of different short- and long-term storage technologies, and can invest into HVDC transmission lines to improve the connection between the different regions and thereby pool the variability from demand and VRE.

Wind, solar and demand fluctuate on even shorter time scales than hours. As REMIX has an hourly resolution and does not additionally represent sub-hourly phenomena, it cannot cover the very-short-term effects of managing a power system. However, the representation of hourly variability already results in substantial deployment of flexible technologies like gas turbines, hydro power and battery storage at higher VRE shares. These technologies can also provide flexibility on a sub-hourly scale. Additionally, advanced VRE generators can increasingly supply active power control (Ela et al., 2014). We therefore do not expect that including sub-hourly details would have a large effect on the results at the aggregation level used for the current analysis. This view is supported by a power sector study that varied the modeling resolution between 1 hour and 5 minutes. It found that modeling sub-hourly features has an impact on cycling/ramping values, but is of low importance to the aggregated investment behaviour (Deane et al., 2014).

3 Qualitative evaluation framework for the power sector representations

In order to evaluate the suitability of the variety of different modeling approaches, this project follows a two-fold approach based on qualitative and quantitative analysis. The qualitative approach postulates 18 features of the fundamental dynamics and drivers of both the power sector in general as well as the effect of integrating VRE (see Table 2 for an overview of the framework). After describing each stylized power sector characteristic in detail, we evaluate the capability of the various IAM modeling approaches to represent this characteristic. The evaluation is based on the equation formulation, relevant model characteristics, as well as the adequacy of the used data. We thereby can determine strengths and limitations of different approaches, and prioritize areas with need for future improvements. To provide for better comparability and overview across models, we display the aggregated evaluation in table form (Table 3 - Table 5). For each category, a short text describes how the model represents this characteristic, as well as an estimation of how realistically this characteristic is covered, ranging from 0 to +++.

Table 2: Evaluation framework: 18 features of power sector dynamics clustered into five themes

Investment dynamics	Investment into dispatchable technologies differentiated by load band
	Investment into VRE (incl. feedback on the system)
	Expansion dynamics
	Capital stock inertia and vintaging
	Structural shift of generation capacity mix
	Love of variety
Power system operation	Dispatch
	Flexibility and ramping
	Capacity adequacy
	Curtailment
Temporal matching of VRE and demand	Wind/solar complementarity
	Demand profile evolution
Storage	Short-term storage
	Seasonal storage
	Demand response (incl. electric vehicles & V2G)
Grid	General transmission and distribution grid
	Grid expansion linked to VRE
	Pooling effect from grid expansion

3.1 Investment dynamics

Investment into dispatchable power plants differentiated by load band: Choice of technology depends on the expected capacity factor. Load is not constant, so one can distinguish base load (the load level required throughout the year), mid- and peak load (higher load levels only required in some hours of the year). The LCOE of power plants depends on their number of full-load hours per year. A given conventional power plant is usually built for a certain load-band (corresponding to a certain number of full-load hours per year). Power plants operating as base-load have low variable and high capital costs. Peak-load plants, in contrast, have low capital costs, because they have to recover their capital costs during only a few hours of the year.

For revenue calculation in energy-only markets, the expected production is weighted with the prices expected for the hours that the plant produces. Accordingly, peaking plants usually have much higher LCOE than base load plants, and still both might be profitable investments pursued in parallel, because electricity prices in times of peak demand are higher (Hirth, 2013).

As VREs have very low marginal costs, they usually get dispatched first and thus reduce the residual load that needs to be covered by dispatchable plants. As VRE plants do not run throughout the year, adding large shares of VRE can reduce or completely remove baseload, while keeping or increasing the share of mid- and peak-load. Accordingly, the total capacity factor of the dispatchable system decreases with high VRE shares (Hirth et al., 2015; Nicolosi, 2012; Scholz et al., in this issue; Ueckerdt et al., 2015a). In the short term, this leads to underutilization of existing base-load capacities, while in the long run the baseload capacities will be replaced by less capital-intensive technologies.

Model representation of "Investment into dispatchable power plants differentiated by load band":

- AIM/CGE, MESSAGE and WITCH treat electricity as a homogeneous good, so there is no differentiation between high and low load.
- To force the model to invest into mid- and peak load plants, MESSAGE and WITCH add a flexibility constraint and a capacity constraint, which represent the increasing demand for flexibility and possible backup requirements as VRE shares increase. In WITCH, each technology has a fixed flexibility parameter, and the capacity value of wind and solar decreases through the same function of wind/solar share in each region, therefore the accuracy of the representation of the actual region-specific RLDC is limited. In MESSAGE, both flexibility and capacity constraint consist of step-wise linear functions fitted to the region-specific ADVANCE RLDCs, thus the model more accurately represents the effect of VRE on the RLDC, and therefore on investments into dispatchable power plants.
- POLES implements RLDCs with seven different investment blocks, which would allow for an accurate representation of the region-specific RLDCs. However, the current model version uses an RLDC that is derived in a very specific way that does not fully capture the regional correlation between demand, wind, and solar:
  a) It uses a combinatorial RLDC, which means that the RLDC is not based on the actual time series and the actual correlation between wind/solar/load, but rather takes a combinatorial approach of using every single combination of (summer/winter) x (low/medium/high wind) x (low/medium/high solar) x (low/medium/high load) to generate 2x3x3x3 = 54 representative days, from which the RLDC is formed.
  b) It uses "region-mixed data", meaning that POLES uses data from France and Spain for the summer/winter day profile for wind and sectoral demand. This profile is then scaled up/down with the capacity factor of wind production and the sectoral decomposition of load for each region. The RLDC is derived from this data together with the summer/winter solar profiles for each region.
- IMAGE and REMIND directly implement the region-specific ADVANCE RLDCs using 4 (REMIND) or 20 (IMAGE) load bands, thereby capturing the regional correlation between demand, wind, and solar and its effect on investments into dispatchable power plants.

Investment into VRE (incl. feedback on the system) : The marginal value of electricity produced by VRE sources depends on the temporal correlation of the newly-added VRE plant with the existing load and VRE plants. If the new plant is well-correlated with load and anti-correlated with the existing VRE production, then it produces electricity of high marginal value, such as the first solar power plants in California, which contribute to meeting peak demand. If, in contrast, a new VRE plant is perfectly correlated with a large amount of existing VRE plants, the production from these VRE plants will already have decreased the residual demand during the time that the new VRE plant produces. Accordingly, the marginal value of the added unit of VRE electricity will be low (Hirth, 2013; Mills and Wiser, 2012; Ueckerdt et al., in this issue, 2013). To represent a well-coordinated system, this effect has to be taken into account when determining the profitability of investment into VRE on a cost/LCOE-basis.

A subtopic of the high/low marginal value is the contribution to capacity adequacy (Holttinen et al., 2011; Ueckerdt et al., 2015a). If a VRE plant (possibly in combination with short-term storage) can contribute to meeting peak demand, it also contributes to capacity adequacy and is therefore beneficial for the system operator. If its temporal correlation with load is less favorable and it does not contribute to peak demand (e.g., solar systems in regions with pronounced winter evening peaks in load), the system operator deciding on a VRE investment has to consider that additional costs may occur in order to guarantee capacity adequacy (e.g., building a backup gas turbine or contracting additional demand response (Hirth et al., 2015; Ueckerdt et al., 2013)). This would reduce the economic incentive to invest into VRE.

Finally, if a model aims at calculating the long-term optimal investment into VRE, it also needs to take into account the effect that adding VRE has on the residual system. As mentioned before, increasing the VRE share will reduce the utilization of the conventional power plants, thus shifting to more mid/peak load plants, which have higher electricity costs. To arrive at a cost-optimal system, the VRE investment algorithm therefore needs to reflect this feedback on the residual system.

Model representation of "Investment into VRE":

- In general, it is challenging to capture the effect that increasing deployment of one VRE type will decrease the market value of this VRE type due to the decreasing temporal correlation between generation from this VRE type and residual load, as it requires that the full information on the impact of VRE on residual load is reflected in the investment decision.
- If investment decisions are embedded within an optimization framework using VRE-share-dependent RLDCs, as in REMIND, the model automatically considers the marginal effect of adding new PV or wind on all other technologies when deciding upon investments into VRE. The VRE-share-dependent formulation of the flexibility and capacity equations within an optimization framework allows MESSAGE to also capture a large part of this effect. The lower detail of the flexibility and capacity constraints in the optimization framework of WITCH accordingly reduces the accuracy of representing this effect.
- Models that do not optimize but rather invest based on decision rules face larger challenges to represent this characteristic, as the investment process does not automatically account for the impact of wind-solar-demand correlation on the VRE-share-dependent economic value of VRE electricity. To capture the effects in stylized form, these models have to calculate explicit cost markups to add them to VRE LCOE in the investment decision. All three rule-based models (AIM/CGE, IMAGE, POLES) have cost markups for curtailment; AIM/CGE also includes cost markups for storage costs, while IMAGE also represents generalized backup costs.

Expansion dynamics: Technology diffusion is a complex process that often takes the shape of an s-curve: it starts very slow, then builds momentum until it reaches a level close to the saturation level, and then slows down (Grübler, 1996). Relevant for accurate power sector modeling, and thus a realistic description of transformation scenarios, is the slow beginning of the s-curve: it represents that a new technology cannot be scaled up infinitely fast, but rather requires a continual market growth.

Model representation of "Expansion dynamics":

- AIM/CGE, IMAGE and POLES have no limits how fast a new technology can be upscaled.
- WITCH uses hard constraints on the expansion rate, thereby limiting the relative growth of capacity additions from one time step to the next. It includes an offset to allow deployment of technologies that have never before been deployed.
- MESSAGE and REMIND use soft constraints and non-linear adjustment costs that increase with the relative growth of new capacity additions from one time step to the next. They thereby represent the fact that it is possible to deploy technologies faster if one is willing to pay cost markups.

Capital stock inertia and vintaging: The power sector features expensive, long-lived capital stocks, which limits the short-term adaptability of the system. Real-world depreciation tends to be concave, i.e. it accelerates with age: New power plants have very high utilization rates and lower failure rates, while aging power plants need to spend more time in maintenance. In addition to the technical lifetime restrictions, there is also the aspect of early retirement: if a power plant makes less revenue than its variable costs over a longer period of time, it will be shut down. While many models represent this aspect, models that at the same time a) assume fixed capacity factors for power plants and b) have no additional equations for representing early retirements will produce scenarios in which each technology is used until its technical lifetime is over, even if it does not recover its variable costs.

Model representation of "Capital stock inertia and vintaging":

- Some models (AIM/CGE, WITCH) use exponential vintaging, in which the build year of a power plant is not tracked, but the model rather reduces the total amount of capacity of one technology by the same share in each time step (usually by 1/lifetime). While better than not tracking capacities at all, it has some drawbacks: In exponential vintaging, the total reduction of capacity is largest immediately after the capacity was built, and slows down as time progresses, while the engineering reality is exactly the opposite. This can create unrealistic effects in scenarios that analyze the effect of delaying climate policies.
- The other four models use non-exponential vintaging: they track the build year for all capacities and decommission them after their lifetime, thus more realistically representing capital stock dynamics.

All six analyzed IAMs represent possibilities for early retirement.

Structural shift of generation capacity mix: On a time scale of decades, the power sector can undergo a paradigm shift and change substantially. For example, under a persistent inversion of the price differential between coal and gas (strongly reduced gas prices so that gas LCOE are below coal LCOE), the power system would evolve over 20-30 years into a "mainly gas" state, with almost no coal left in the system. The same would happen when introducing carbon prices – at ~50$/tCO2 and unchanged coal and gas prices, freely-emitting coal power plants would be completely replaced in the long term.

Table 3: Evaluation of IAM approaches to represent VRE integration challenges – Investment dynamics

	Investment dynamics											
Model	Investment into dispatch. technol. differentiated by load band		Investment into VRE (incl. feedback on the system)		Expansion dynamics		Capital stock inertia & vintaging		Structural shift of generation capacity mix		Love of variety	
AIM/CGE	0	homogeneous good	+	Curtailment and storage increase LCOE	0	na	++	exponential vintaging (+); early retirement (+)	++	possible	++	logit
IMAGE	+++	region-specific RLDCs with 20 load bands	++	Curtailment and storage increase LCOE (+); backup cost markups partially emulate additional VRE interaction (+)	0	na	+++	non-exponential (+) vintaging (+) of capacities; early retirement (+)	++	possible	++	logit
MESSAGE	++	homogeneous good; share dependent flex&cap constraint partially reproduce RLDC shape (++)	++	Optimization provides feedback on effects of VRE on VRE-share-dependent (+) flex. & cap. equation (+)	++	constraints on expansion rate that can be weakened at additional cost	+++	non-exponential (+) vintaging (+) of capacities; early retirement (+)	++	possible	+	intertemporal optimization & expansion constraints ensure variety
POLES	+	RLDC load bands (+++); but combinatorial RLDC[1] (-) with region-mixed data[2] (-);	+	Curtailment increases investment LCOE	0	na	+++	non-exponential (+) vintaging (+) of capacities; early retirement (+)	+	possible, but limited by slow convergence of non-cost logit parameters [3]	++	logit
REMIND	+++	region-specific RLDCs with 4 load bands	+++	Optimization provides full feedback of VRE investment on RLDC	++	adjustment costs that increase non-linearly with fast expansion	+++	non-exponential (+) vintaging (+) of capacities; early retirement (+)	++	possible	+	intertemporal optimization & adjustment costs ensure variety
WITCH	+	homogeneous good; flex&cap constraints with fixed parameters creates demand for peak-load technologies (+)	+	Optimization accounts for feedback of VRE on flexibility constraint and capacity equation (+)	+	hard constraints on expansion rate	++	exponential vintaging (+); early retirement (+)	+	possible, but limited by CES[4] with elasticity 5	+	CES[4]

[1] combinatorial RLDC means that the RLDC is not based on the actual time series and the actual correlation between wind/solar/load in a region, but rather takes a combinatorial approach of mixing every single combination of (summer/winter) x (low/medium/high wind) x (low/medium/high solar) x (low/medium/high load) days to generate 54 representative days (2x3x3x3), from which the RLDC is formed

[2] "region-mixed data": POLES uses data from France and Spain for the summer/winter day profile for wind and sectoral demand. This profile is then scaled up/down with the capacity factor of wind production and the sectoral decomposition of load for each region. The RLDC is derived from this data together with the summer/winter solar profiles for each region. Accordingly, the RLDC does not fully capture the regional correlation between demand, wind, and solar.

[3] non-cost parameters for renewables decrease investments into RE compared to conventional technologies until 2050/2060, although already the current market (2013&2014) showed higher global investments into RE than into other power technologies

[4] CES (constant elasticity of substitution) functions result in love of variety, but also create a preference for base-year calibration shares (with low elasticities of substitution, this can result in lock-in), and can lead to physically implausible aggregation

Abbreviations: CES – constant elasticity of substitution; flex&cap – flexibility and capacity; LCOE – levelized cost of electricity; RLDC – residual load duration curve;

Model representation of "Potential for a structural shift":

- AIM/CGE, IMAGE, MESSAGE and REMIND have linear formulations that allow for a full structural shift.
- Some IAMs use a constant elasticity of substitution function in the power sector, which can limit the substitution between different technologies and thus create an unrealistically strong tendency to reproduce the calibration year technology shares if the elasticity of substitution is too low (<3-4). WITCH uses a CES function, but as the new WITCH version

employs a medium elasticity of substitution of 5, the model allows for substantial structural shifts (Carrara and Marangoni, in this issue).
- Similarly, "technology-readiness"-premiums on LCOE in logit formulations can slow or even prevent a fundamental structural shift. In the current version of the POLES model, the technology-readiness premiums create a large valuation difference between VRE and conventional power plants, and only fully converge after 2050. These premiums reduce the investments into VRE over the next decades, even if VRE are cost-competitive on an LCOE basis in stringent climate policy scenarios. Given that investments into VRE are on par or have surpassed investments into fossil and nuclear power plants in 2014 and 2015, such a decade-long persistence of investor skepticism against VRE in the future seems highly unlikely.

Love of variety: The revenues from a power plant are influenced by many factors that are unknown during time of construction, such as fuel prices, climate policies, demand evolution or competing technologies. As a result, investors may strategically invest into a portfolio of several different technologies, if the fundamentals are not so one-sided that all other technologies seem very unfavorable.

Model representation of "Love of variety":

- Although MESSAGE and REMIND have a linear power system, the intertemporal optimization in combination with expansion rate constraints or adjustment costs leads to a certain love of variety in both of the models. The non-linear CES structure in WITCH additionally enhances these aspects.
- AIM/CGE, IMAGE and POLES use a logit investment formulation, which automatically represents the "love of variety" aspect.

3.2 Power system operation

Dispatch: When determining which of the installed plants is used to meet the residual load in a given moment, a "cheapest variable cost takes all" logic is used – the merit order. Only ramping constraints and the variety of plant age and technology (leading to different efficiencies and variable costs) will lead to the effect that the resulting dispatch is not fully monotonous in fuel choice.

Model representation of "Dispatch":

- AIM/CGE does not model dispatch at all. As AIM/CGE uses a fixed capacity factor per technology, the installed capacities fully determine electricity generation. Accordingly, electricity production is dictated by the logit formulation of the investment equation.
- WITCH also does not explicitly model dispatch, but as the technology capacity factors are implemented as an upper limit, the model can choose to not use standing capacities. The flexibility and capacity constraints can force the model to decrease generation as the share of VRE increases, which reproduces dispatch-like behavior in a rudimentary way.
- MESSAGE implements two modes of operation for each technology, a baseload mode and a flexible mode with lower capacity factor, so capacities do not fully determine electricity

generation. However, MESSAGE does not explicitly model dispatch into load bands. Instead, the flexibility and capacity constraints can force the model to use technologies in flexible mode as the share of VRE increases, which leads to a dispatch-like behavior.

- IMAGE and REMIND dispatch into bins derived from the region-specific RLDCs, with IMAGE having a much higher granularity (156 time slices in IMAGE vs. 4 load bands in REMIND)
- For the EU, the dispatch is best represented in POLES, as it is coupled to an explicit dispatch model that calculates hourly dispatch for each EU member state on 12 representative days. The representative days were derived with the help of a sophisticated clustering algorithm and contain the full correlation between wind, solar and load (Nahmmacher et al., 2016). Outside the EU, however, POLES uses a simpler RLDC-based dispatch over two days, relying on mixed-region data.

Flexibility and ramping:

We refer to flexibility as the ability of a power system to adjust supply or demand on short notice in order to balance the two. Traditionally, flexibility is provided by dispatchable power plants within the limits of ramping and cycling constraints, minimum electric load, minimum heat load (in case of CHP), minimum up and down times, part-load efficiency, operating reserve requirements, and corresponding costs.

While it is clear that flexibility requirements increase with VRE, the size of the effect is debated, with a range of studies finding reserve requirement increases of 2-9% of added VRE capacity (Hirth and Ziegenhagen, 2015). The regulation of balancing power markets can also have a substantial impact on the size of reserve requirements: although the VRE share in Germany almost tripled from 2008 to 2015, reserves were reduced by 15%, with possible reasons including the establishment of a balancing power cooperation by the four German TSOs, and the fact that 15-minute trading on power exchanges has become more common (Hirth and Ziegenhagen, 2015). Additional sources of flexibility are currently in development, and include storage (batteries, flywheels), demand-response, or the concerted control of wind and solar power plants (Ela et al., 2014; Van Hulle et al., 2014).

Model representation of "Flexibility and ramping":

- AIM/CGE has no representation of flexibility.
- In IMAGE and REMIND, the explicit RLDC representation leads to increasing deployment of low-capital peaking technologies and storage with increasing VRE shares. As these technologies are more flexible than baseload plants, the deployment of flexibility-providing technologies increases with increasing VRE share, even if both models do not include explicit flexibility equations.
- MESSAGE and WITCH include a so-called flexibility constraint (Sullivan et al., 2013), which represents the requirement for flexibility in a stylized way. As WITCH uses only a fixed parameter for each technology, the accuracy of the representation is necessarily limited. The more sophisticated step-wise linear formulation in MESSAGE allows a better representation, although still in an aggregated parameterized form.
- POLES explicitly represents ramping constraints in hourly detail over the representative days for the EU. For all other regions, there is no explicit flexibility modeling, but the

scenarios were ex-post checked to ensure that sufficient flexibility is available in the power system.

Capacity adequacy: For a stable functioning of a power system, load has to be met at all times. In order to ensure this even in the face of plant outages and forecast errors, the sum of reliable generation, storage output, demand reductions and imports has to exceed the sum of initial demand, storage input and exports by a non-negligible margin ("reserve margin").

Model representation of "Capacity adequacy":

- All models except for AIM/CGE include a capacity adequacy constraint, which ensures that peak demand can be met by the installed power system.
- While WITCH uses a generic formulation for the decrease of the capacity value of wind and solar, IMAGE, MESSAGE and REMIND use the actual RLDC values that take into account the region-specific contribution from wind and solar to meeting peak demand.
- POLES also implements an RLDC, but the above-described combinatorial formulation of the RLDC has the effect that the correlation of wind and solar with load is not fully captured, thus leading to an overly high demand for firm capacity. While this has the advantage of providing a particularly resilient system with high reserve margins, it also leads to higher system costs, thereby possibly penalizing the deployment of VRE.

Curtailment: As the share of VRE increases, there will be times when VRE production is higher than load, thus there will be curtailment, which increases the per-energy cost of VRE (Lew et al., 2013a).

Model representation of "Curtailment":

- WITCH is the only model that represents curtailment in an implicit way through the CES function: When the model uses more of a technology that was not used much in the calibration year, e.g., wind, the economic output of the CES function increases less than linearly with increasing wind generation input. However, this is a rough representation that cannot take into account the regional differences and the dependence of curtailment on the correlation between demand and VRE.
- For the EU, POLES has the best representation of curtailment, as it calculates curtailment endogenously in the dispatch model based on 12 representative days and can thus fully take into account the exact system design. However, it relies on the combinatorial RLDC with region-mixed data for all other regions, which is a much less accurate representation.
- All other models implement the region-specific curtailment values contained in the ADVANCE RLDCs.

3.3 Temporal matching of VRE and demand

Wind-Solar complementarity: In most places of the world, the temporal profile of solar and wind is either uncorrelated or even anti-correlated. This is true both for short-term variability as well as for regular daily or seasonal time patterns. Using both sources therefore in most cases smooths total variability and results in a better matching to load. Put differently, the integration challenges of different technologies are not additive: Combining different VRE types (wind, solar) reduces the integration challenges compared to a case where only one type is used (Heide et al., 2010; Ueckerdt et al., in this issue).

Table 4: Evaluation of IAM approaches to represent VRE integration challenges: Power system operation and temporal matching of VRE and demand

	Power system operation								Temporal matching of VRE and demand			
Model	Dispatch		Flexibility and ramping		Capacity adequacy		Curtailment		Wind/solar complementarity		Demand profile evolution	
AIM/CGE	0	na	0	na	0	na	++	based on region-specific RLDC	+	wind-solarRLDC (+++); no cross-product interation[1] (-); no effect on capacity/dispatch (-)	0	na
IMAGE	+++	dispatch on RLDC with 156 time slices	+	indirectly through RLDC-driven switch to low-capital technologies	++	RLDC-derived CV for VRE	++	based on region-specific RLDC	++	wind-solar RLDC (+++); backup requirements don't fully emulate wind/solar correlation (-)	0	na
MESSAGE	+	technologies can be used in flexible or baseload mode	++	flexibility constraint in combination with two modes of operation for dispatchable technologies	++	RLDC-derived CV for VRE	++	based on region-specific RLDC	++	uses wind-solar RLDC (+++); relies on single wind-solar mix per region to parameterize flex. & cap. equations (-)	+	basic representation of changing importance of different sectors
POLES	++	EU: hourly dispatch on 12 representative days (+++); Non-EU: dispatch on 2 days (-)	++	EU: explicit ramping on hourly representative days (+++); Non-EU: only ex-post check of ramping/flexibility (-)	+	RLDC(++); combinatorial RLDC[2] can lead to overcapacity in regions where VRE match peak demand (-)	+	EU: based on dispatch model (+++); Non-EU: based on combinatorial RLDC[2] (-) with region-mixed data[3] (-)	+	EU: explicit W&S interaction in representative days for dispatch (+++); Non-EU: combinatorial RLDC[2] (-) with region-mixed data[3] (-)	+	basic representation of changing importance of different sectors
REMIND	++	dispatch according to RLDC with 4 loadbands	+	indirectly through RLDC-driven switch to low-capital technologies	++	RLDC-derived CV for VRE	++	based on region-specific RLDC	+++	explicit wind-solar interaction from RLDC	0	na
WITCH	+	capacity factor as upper limit allows output reduction	+	flexibility constraint with fixed parameters	+	CV for each VRE type decreases with VRE share	+	implicitly contained in the CES function	+	non-linear CES function favours mix of wind and solar	0	na

[1] AIM/CGE uses fits of storage and curtailment based on VRE shares that have the form g(wind) + f(solar). Accordingly, there are no cross-product terms h(wind * solar) which could better represent the interaction

[2] "combinatorial" RLDC: see footnotes for Table 3

[3] "region-mixed" data: see footnotes of Table 3

Abbreviations: CV –capacity value; CES –constant elasticity of substitution; RLDC – residual load duration curve;

Model representation of "Wind-Solar complementarity":

- AIM/CGE uses the ADVANCE RLDCs, which contain the full wind-solar complementarity, but represents the resulting storage and curtailment through functions that depends only on the separate wind and solar terms (g(wind) + f(solar)) and does not contain a cross-term (h(wind * solar)). Accordingly, the functional form cannot fully account for the complementarity, but simply has a general preference for an even mix of wind and solar.
- Similarly, the CES function in WITCH does not allow explicit accounting of complementarity, but only has a general preference for an even mix of wind and solar.
- For the EU, the representative days in the POLES dispatch model contain the full temporal and regional wind-solar complementarity. Investment in POLES relies on the combinatorial RLDCs, which do not fully account for region-specific complementarity due to their design.
- IMAGE implements the ADVANCE RLDC, thus incorporating the interaction of wind and solar on curtailment and capacity values. It however does not fully reflect the wind-solar complementarity when calculating cost markups due to backup requirements for VRE.
- MESSAGE also relies on the ADVANCE RLDC. However, it does not represent the full RLDC, but first determines a region-typical mix of wind and solar to derive the parameters of the flexibility and capacity equation that are later used in the actual scenario runs.
- REMIND replicates the ADVANCE RLDC through a third-order polynomial with three cross-terms, thus managing to represent wind-solar complementarity to a large extent.

Demand profile evolution: Demand profiles are not fixed, but rather depend on economic development, climate change, and the relative importance of different demand groups and technologies. Accordingly, they will change in the future, as some industries grow and others decline. Deployment of technologies can also influence the temporal pattern of demand and therefore the matching with different VRE sources: For example, as rising incomes lead to increased deployment of air conditioning in hot countries, the temporal matching between electricity demand and solar power will improve.

Model representation of "Demand profile evolution":

- Only MESSAGE and POLES include a basic representation of demand profile evolution. Both track the ratio between industrial and residential electricity demand, and accordingly change peak demand (MESSAGE) or load profile (POLES).

3.4 Storage

Short-term storage: Short-term storage can reduce the challenge of short-term variability of VRE generation and help to align diurnal supply with diurnal demand profiles (Denholm and Hand, 2011; Després et al., in this issue; Rasmussen et al., 2012; Ueckerdt et al., in this issue). Most short-term storage in use today consists of pumped hydro storage, but there is limited geographic potential for a large up-scaling of existing capacities. Batteries such as lithium-ion or redox-flow batteries might become cost-competitive if cost reductions experienced in the recent past continue.

Model representation of "Short-term storage":

- In AIM, IMAGE, REMIND, short-term storage is an exogenous requirement driven by VRE share, and the positive effect as calculated by the hourly-resolution dispatch and investment model DIMES (Ueckerdt et al., in this issue) is already included in the RLDCs used to parameterize the IAM. Depending on the detail of power sector representation, the represented effect of storage can either be limited to reducing curtailment (AIM/CGE), or also include capacity adequacy and RLDC shape (IMAGE, REMIND).
- WITCH and MESSAGE endogenously calculate investments into storage, but due to the limited temporal resolution of IAMs, the effect needs to be parameterized. This parameterizations happens either in a simplified manner based on a fixed contribution of storage to the flexibility and capacity equations (WITCH) or in a more sophisticated manner based on a mix of a fixed contribution to flexibility and capacity equations with the capability to absorb curtailment parameterized on the regional RLDCs (MESSAGE).
- POLES endogenously calculates investments into storage in a very sophisticated process. However, as it only models within-day storage, it underestimates the peak-reducing effect of storage. Outside the EU, the effect of within-day storage on the investment RLDC is implemented through less accurate heuristic rules.

Seasonal storage: When VRE generation and load are anti-correlated on a seasonal scale (e.g., in Europe solar production is highest in summer and load is highest in winter), seasonal storage can become cost-efficient to accommodate high shares of VRE. Due to the large reservoir need, seasonal storage is usually envisioned as power-to-gas, either in the form of hydrogen or further converted to methane (Ueckerdt et al., 2015b).

Model representation of "Seasonal storage":

- MESSAGE models the conversion of electricity to hydrogen for seasonal storage, but assumes a constant capacity factor for the electrolysis technology, independent of curtailment. Moreover, seasonal storage can only address seasonal curtailment, which is parameterized for all regions using US-specific data.
- Within the EU, POLES also models hydrogen electrolysis. As the usage is modeled in the dispatch model, it directly reacts to the different economic value of electricity at different hours and different VRE contributions. Outside the EU, POLES does not model seasonal storage.
- REMIND models hydrogen electrolysis with a stylized representation of increasing capacity factor with increasing curtailment.

Demand response (incl. electric vehicles and vehicle-to-grid): Demand that flexibly reacts to short-term changes electricity prices can help balance generation and demand (Gils, 2014). Due to transaction costs, short-term demand response was until now mostly restricted to large industrial consumers. However, with increasing communication capabilities and a potential increase in end-user loads that can be shifted in time (electromobility), end-user demand response could become a relevant integration option in the future.

Model representation of "Demand response (incl. electric vehicles and vehicle-to-grid)"

- POLES is the only model that contains an explicit representation of demand response as well as vehicle-to-grid storage. Outside the EU, these flexibility options are represented less accurately through heuristic rules on the investment RLDC.
- WITCH represents demand response from vehicle-to-grid in a simplified manner by reducing the flexibility and capacity requirements when electric vehicles are deployed.

3.5 Grid

General transmission and distribution grid: Due to the large scale of power plants, the benefit of pooling load variability over large areas, and the locational difference in availability of fuels and fuel transport infrastructure, most places of the world are connected to a large-area electricity grid. This long-lived capital-intensive infrastructure contributes to the price differential between wholesale and retail electricity prices.

Model representation of "General transmission and distribution grid"

- IMAGE and WITCH implement a requirement for transmission and distribution capital that is linearly proportional to total electricity-generating capacity.
- MESSAGE and REMIND implement a requirement for transmission and distribution capacity that is linearly proportional to total final energy electricity demand.
- The dispatch model EUCAD that is coupled to POLES endogenously represents net transfer capacities between EU member states. However, the grid deployment mechanism depends

heuristically on use, not economic value, and does not include possible peak-reducing effects from grid expansion. Outside the EU, no grid and no grid costs are modeled.

Grid expansion linked to VRE: Generation from wind and solar is very heterogeneous in space: for VRE, the capacity factor and the matching with load can vary strongly in different locations. Pooling VRE generation over large geographical scales can mitigate much of the weather-related variability (IEA, 2014). However, such pooling requires additional investments to expand transmission grids. From an economic point of view, transmission grid expansion has been found to be a no-regret option for smoothing variability and thus reducing VRE integration challenges (Becker et al., 2014; Fürsch et al., 2013; Haller et al., 2012; Scholz et al., in this issue), making it a likely part of cost-optimal climate mitigation scenarios. Although the costs for such a transmission expansion are much smaller than the costs for transforming the generation part of the energy system in a low-carbon scenario, these additional costs should be reflected in IAMs (Scholz et al., in this issue).

Model representation of "Grid expansion linked to VRE"

- REMIND and WITCH include an aggregated representation of how grid costs increase with increasing VRE share.
- As IMAGE and WITCH calculate their grid requirements based on capacity, VRE with usually low capacity factors automatically require more grid capital per produced kWh than the average electricity produced. Therefore, these models implicitly include additional grid costs for VRE.
- The changing residual demand from VRE deployment will have an impact on the EUCAD grid representation for the EU. Outside the EU, no grid and no grid costs are modeled.

Pooling effect from grid expansion: As mentioned in the previous category, improving the grid connection over large areas leads to much lower gradients and smoother VRE generation due to pooling, and can therefore substantially reduce the integration challenges (Becker et al., 2014; IEA, 2014; Scholz et al., in this issue). To our knowledge, aggregated energy-economy-models have often parameterized integration challenges using small-scale wind and solar time series on the level of existing balancing regions or even individual measuring stations, mostly because of limited data availability on a larger scale. As with any statement about the future, it is impossible to foresee if balancing areas will continue to expand in the future, or if they will fragment. However, as economic arguments speak in favor of expanding transmission grids to accommodate VRE, and as the ongoing deployment of ICT technologies facilitates national and international cooperation on balancing, it seems reasonable to expect a continued improvement of transmission grid infrastructure in the long-term scenarios developed by IAMs.

To portray an equal level of long-term coordination and development across the different resources and markets represented in IAMs, it is thus advisable to include this pooling effect in the used wind, solar and demand time series: taking only time series from a small spatial area would project the fragmentation of the electricity grid, ignore the benefit of transmission grids and therefore overestimate integration challenges of VRE.

Model representation of "Pooling effect from grid expansion"

- All models except for POLES and WITCH use the ADVANCE RLDC as parameterization basis, which assumes full region-wide pooling, e.g., through an overlay transmission grid.
- POLES is more detailed when modeling the effect of pooling on dispatch, as the pooling effect of grid expansion between the EU member states is explicitly represented. For investment decisions, however, it only contains country-level pooling and does not allow for region-wide pooling through an overlay transmission grid.

Table 5: Evaluation of IAM approaches to represent VRE integration challenges – Storage and grid

	Storage						Grid					
Model		Short-term storage		Seasonal storage		Demand response (incl. electric vehicles & V2G)		General transmission and distribution grid		Grid expansion linked to VRE		Pooling effect from grid expansion
AIM/CGE	+	Exog. storage investm. based on VRE-shares; effect on curtailment based on DIMES	0	na	0	na	0	na	0	na	+	Region-wide pooling contained ex ante in the RLDC
IMAGE	++	Exog. storage investm. based on VRE-shares(+), effect on curtailment & capacity based on DIMES	0	na	0	na	+	grid capital (trans. & distr.) linearly proportional to total electricity capacity	+	implicitly included as grid capital requirement is based on capacity, not energy	+	Region-wide pooling contained ex ante in the RLDC
MESSAGE	++	Endog. storage investments driven by capacity & flexibility equation with fixed coeffcients (+) and by VRE-share-dependent effect on curtailment (+)	+	Endogenous (+) investment into hydrogen electrolysis (+), but relies on US data to model the effect (-)	0	na	0	grid capacity (trans. & distr.) linearly proportional to FE electricity use	0	na	+	Region-wide pooling contained ex ante in the RLDC
POLES	+	EU: Endogenous storage on representative days (+++), but only within-day storage (-); Non-EU: exogenous within-day storage on RLDC basis (-)	++	EU: Endog. (+) H2 electrolysis (+), CF reacts to curtailment (+); Non-EU: no seasonal storage (-)	+	EU: explicit V2G & DR modeling (++); Non-EU: heuristic modeling on comb. RLDC[1] with region-mixed data[2] (-)	0	EU: endog. grid in EUCAD (++); investment heuristic from use (not value), peak reduction not modeled (-); Non-EU: no grid (-)	0	EU: endog. grid in EUCAD (++); investment heuristic based on use (not value), peak reduction not modeled (-); Non-EU: no grid (-)	+	EU-wide pooling for dispatch explicitly modeled (++); Investment RLDC only has country-level pooling (-)
REMIND	++	Exog. investm. into storage based on VRE-shares (+); region-specific effect on curtailment, capacity and RLDC shape from DIMES (+)	+++	Endog. (+) H2 electrolysis (+) using curtailments; CF depends on curtailment (+)	0	na	+	grid capacity (trans. & distr.) linearly proportional to FE electricity use	+	aggregated grid costs depending on VRE share	+	Region-wide pooling contained ex ante in the RLDC
WITCH	+	Endogenous storage investm. driven by capacity & flexibility equation with fixed coeffcients	0	na	+	basic representation: reduction of cap. & flex. requirements from V2G	+	grid capital linearly proportional to total electricity-producing capacity	+	aggregated grid cost markups depending on VRE share; also included implicitly as grid capacity is calculated from capacity, not energy	0	na

[1] combinatorial RLDC: see footnotes for Table 3

[2] "region-mixed data: see footnotes for Table 3

Abbreviations: CF – capacity factor; DR – demand response; endog. – endogenous; exog. – exogenous; FE – final energy; RLDC – residual load duration curve; trans. & distr. – transmission & distribution; V2G – vehicle to grid;

To summarize, the approaches span a wide range of model types and have different strengths and limitations. The difference in basic model typology (optimizing or rule-based) influences which parts of the integration challenges are easier to represent: optimizing models can more easily incorporate the effects on VRE investment decisions, while they are at the same time more computationally restricted than rule-based models, which usually can implement more technologies and more complicated functional forms. While AIM/CGE and WITCH use rather reduced-form approaches and have less technological detail, they still manage to incorporate several aspects of the influence of VRE on power sector dynamics. More explicit representations in models with higher technology detail, like those in IMAGE, MESSAGE, POLES or REMIND, come with higher computational challenges and data requirements, but represent the integration of wind and solar in a more comprehensive way.

The developed framework helps to identify those aspects among the 18 power sector characteristics where future research is most needed. Demand profile evolution, transmission grid modeling (both the effect of pooling and the grid expansion requirements), and demand response / vehicle-to-grid modeling are areas that are represented in few models, and have only basic representations, thus in-depth research is most needed. In contrast, some other aspects that are not well covered by a few models, e.g. expansion dynamics, have more advanced representations in other models, so a knowledge transfer might be easier.

4 Quantitative approach

While a specific modeling approach is targeted at representing a certain dynamic, in a large-scale IAM it interacts with many other equations, possibly leading to non-intuitive results. It is therefore crucially important to not only discuss the equation structure and used data (as was the focus in the qualitative evaluation framework), but to also analyze the quantitative model results and validate them against the benchmark of a more detailed power sector model. The quantitative part of this study thus uses the results from the hourly-detail power sector model REMIX to check how well the IAM scenario results respect fundamental power sector characteristics and reproduce integration challenges.

The sixty scenarios produced with REMIX for the ADVANCE project provide a detailed map of the impact of VRE on power system economics, featuring the following key aspects (Scholz et al., in this issue):

a) hourly detail over a full year,
b) national demand and VRE generation profiles for the 15 modeled EU regions,
c) a green-field power system optimized to accommodate a given VRE share,
d) coverage of VRE shares up to 100%,
e) the inclusion of short- and long-term storage,
f) endogenous representation of the benefits and costs from expanding the transmission grid between the modeled EU regions.

To analyze the quantitative capability of the different modeling approaches to reproduce changes in the power sector in reaction to increasing VRE shares, we use five IAM scenarios (see Table 6). Two of these scenarios use the newly developed ADVANCE model versions and explore the policy dimension: The **2°C Policy** scenario implements a constraint of 1550 GtCO2 on the cumulative 2000-2100 budget of CO2 emissions from fossil fuels, industry, and land use. As discussed in the IPCC's Fifth Assessment Report, this budget is broadly consistent with a long-term CO2e-concentration of 480-530 ppm, limiting global warming below 2°C with a medium likelihood (Clarke and Kejun, 2014). In the **Tax30** scenario, a fixed trajectory for the CO2-Price is prescribed, starting at 30$/tCO2 in 2020 and increasing exponentially at 5% per year. We use these two scenarios as they ensure that the results for each model cover a wide range of VRE shares, and thus provide a good testing range for the power sector modules. Also, the 2°C Policy scenario has the advantage of representing a policy-relevant target, while the Tax30 scenario is better suited for comparing power sector decarbonization: A prescribed carbon tax creates a similar decarbonization pressure in the power sector of each IAM, whereas the different modeling of decarbonization of land use and other energy use in the various IAMs can lead to very different price signals in the power sector for 2°C Policy.

To explore the question how important VRE integration modeling is for the resulting VRE deployment in IAMs, we use three scenarios that are all subject to the same carbon tax as the Tax30 scenario but employ different model versions: The **EMF27** scenario uses older versions of the IAMs that were used for the 2013 EMF27 study (Kriegler et al., 2014; Luderer et al., 2014)[6]. The **EMF27 NewCostRes/Old Integration** scenarios use a mixed model version that combines the VRE integration modeling from the EMF27 models with the updated VRE cost and resource assumptions developed in ADVANCE. Finally, the counter-factual **Full Integration** scenario is based on the ADVANCE model version but treats wind and solar as dispatchable, thereby allowing to discern the effect of the currently implemented integration challenges.

The results are compared across different IAMs and to REMIX results to test the plausibility of the IAM results. We use the following power sector indicators:

- Capacity adequacy
- Capacity factor of dispatchable power plants
- Curtailment
- Storage

Table 6: Overview of IAM scenario definitions

Scenario name	Short name	Climate policy	Model version
2°C Climate Policy	2°C	2000-2100 CO_2 budget limited to 1550 $GtCO_2$	ADVANCE
Tax30	Tax30	30$/$tCO_2$ tax in 2020, increasing by 5%/year	ADVANCE
EMF27	EMF27	30$/$tCO_2$ tax in 2020, increasing by 5%/year	EMF27
EM27 NewCostRes / Old Integration	NuCoRes	30$/$tCO_2$ tax in 2020, increasing by 5%/year	VRE integration modeling: EMF27; VRE costs and Resources: ADVANCE
Full Integration	Full	30$/$tCO_2$ tax in 2020, increasing by 5%/year	ADVANCE; wind and solar treated as dispatchable technologies

4.1 Aggregated effect of the model update for participating IAMs

When subject to a carbon price in the Tax30 scenario, all of the participating IAMs show a strong deployment of wind and solar in the ADVANCE model version, with net shares[7] of VRE in global electricity generation ranging from 33-80% in 2050 and further increasing until 2100 (see Figure 1 left). The residual electricity is produced mostly from gas, nuclear, biomass or hydro, with each model showing different preferences. In all models except POLES, the biomass share stays below 12%, as biomass is in strong demand from the other energy sectors, e.g. for the production of liquid transport fuels. All models increase their deployment of hydro power, but the share of hydro in

[6] As AIM/CGE was not part of the EMF27 study, it could not be included in the analysis of changes between EMF27 and ADVANCE.

[7] "Net share" refers to the share calculated after curtailment has be deducted both from the wind and solar generation and from the total generation.

total electricity nevertheless decreases, as most world regions have limited potential for hydro power expansion.

The comparison of the aggregated results from the IAMs with improved power sector modeling to a scenario with the same carbon policy but produced with older versions of these models show that the methodological advances (a more detailed representation of VRE integration challenges, updated VRE resource and VRE cost assumptions) lead to strongly increased VRE deployment and less variation across the various IAMs (Figure 1 left).

To separate the effect of updating the representation of the power sector and integration challenges from the effect of updating costs and resources, we employ the four scenarios using the same carbon tax but four different model versions: Tax30, EMF27, NuCoRes, and Full (Figure 1 right).

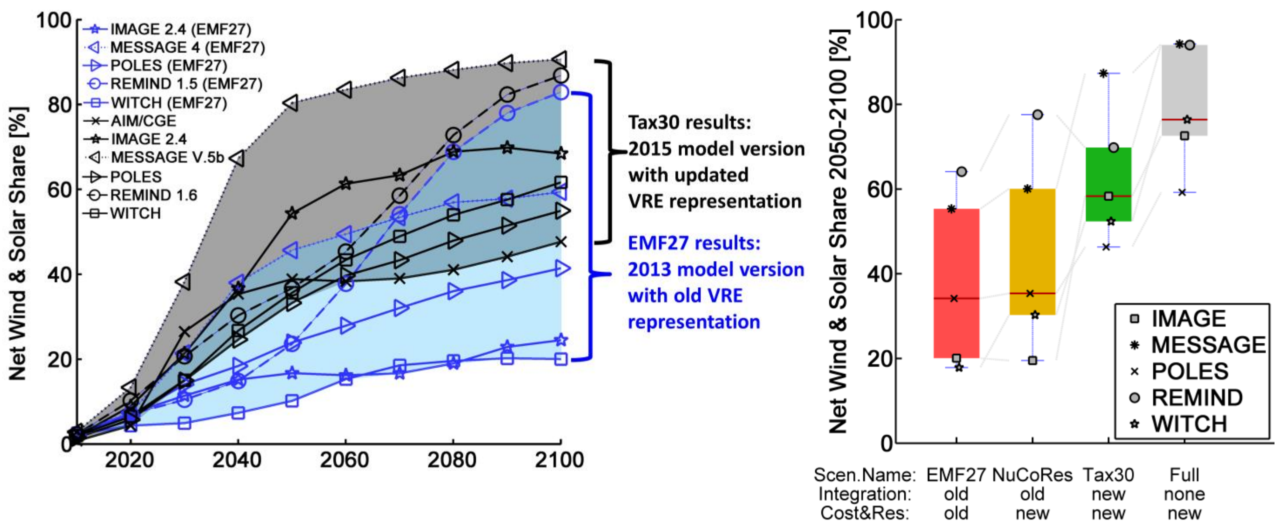

Figure 1: Net share of electricity produced from wind & solar in global net electricity generation for a Tax30 carbon policy. Left: VRE shares over time. The colors denote the model version: blue is the 2013 model version used for the EMF27 study, black the newly developed implementations with updated costs, resources, and modeling of integration challenges. The model update has substantially shifted the range of VRE shares upwards and reduced the variation between models. Right: Influence of model versions on the average 2050-2100 VRE shares under a Tax30 carbon policy. The largest effect comes from the updating of integration modeling between *NuCoRes* and *Tax30*. In the diagnostic scenario *Full*, integration challenges are removed completely and wind and solar are treated as dispatchable technologies.

The scenarios produced with the old EMF27 model version show large differences across models, with average 2050-2100 net shares of VRE in total power generation VRE shares ranging from 18-20% (WITCH, IMAGE) over 34% (POLES) to 55-64% (MESSAGE, REMIND), and a model-average of 38%. Updating costs and resources to the ADVANCE values in *NuCoRes* increases the model-average by 6%-points to 44%. It is not surprising that updating the costs and resources had a relatively low effect on VRE shares, because no model decreased the capital costs of PV by more than a quarter, and all models kept the capital costs for wind unchanged or even increased them, with only a slight increase of wind capacity factors for most models from the new wind energy resource potentials (Eurek et al., in this issue).

However, additionally updating the representation of VRE integration challenges to the newly-developed ADVANCE version in *Tax30* increases the model-average VRE share by a much higher margin of 18%-points to 62%. REMIND is the only model that experiences a decrease in VRE share with the new integration modeling, while apparently the other models previously had more pessimistic representations of VRE integration (see Table 1 and discussion below).

While it might at first seem surprising that introducing more detailed integration challenge modeling increases the VRE share in all models except for REMIND, a closer look at the changes of the modeling approaches (as documented in Table 1) shows that the increase can well be explained. The VRE share increases most for IMAGE (40%-points) and MESSAGE (27%-points), models that already had relatively elaborate integration modeling in the EMF27 version. However, while being new and innovative when introduced in the IAMs, both previous approaches had certain weaknesses that lead the IAMs to underestimate potential VRE contributions.

- The EMF27 version of IMAGE had excessive backup requirements that interacted with the capacity expansion modeling, leading to exaggerated cost markups for VRE; also, IMAGE did not represent any options to reduce integration challenges such as storage. Adding storage and rewriting the backup requirements to make them dependent on the actual VRE share as expressed in the RLDC removed this artificial barrier.
- MESSAGE had integration equations that were calibrated to the results of a simplified unit commitment model focusing on a small area with limited integration options and little regional smoothing, resulting in a curtailment equation with 70% marginal curtailment for PV shares above 25% and wind shares above 47%, and a capacity equation with marginal capacity values of 0 above 25% wind or PV share. Given these numbers, it is of little surprise that introducing new parameters based on the regional RLDCs, which include the effect of short-term storage and transmission grid expansion, lead to a substantial increase of VRE share (Johnson et al., in this issue).
- WITCH also showed a substantial VRE increase (22%-points), but here the effect is more based on improving the previous coarse representation of integration challenges. The EMF27 WITCH version nested wind and solar generation in a CES nest with a low substitution elasticity of 2, which forced the model to stay close to the shares in the calibration year, essentially restricting VRE to a low contribution. The new implementation added explicit capacity and flexibility equations, thus making VRE integration more expensive, but at the same time increased the elasticity of substitution to 5, thus relaxing the tie to the shares in the initial year. Furthermore, the introduction of storage gave the model flexibility in choosing options to supply firm capacity and flexibility (Carrara and Marangoni, in this issue).
- POLES shows a VRE share increase of 11%-points – here the increase results mostly from an update of the time slices used for investment calculations, the introduction of storage, and the removal of previously-existing artificial upper bounds on the VRE share (Després et al., in this issue).
- REMIND is the only model that sees a decrease of VRE shares (8%-points) upon introducing the new integration modeling. In REMIND, integration challenges were formerly represented via aggregated VRE-share-dependent integration costs, and the previous

parameterization apparently underestimated the actual integration challenges that are now directly represented via RLDCs in the current version (Ueckerdt et al., in this issue).

Removing integration challenges completely in the diagnostic "Full Integration" scenario and treating wind and solar as dispatchable technologies increases the VRE share substantially, on average by 17%-points, to 79%. This shows that even though the improved representations of integration challenges are less restrictive than the barriers implemented in older model versions, they still have a strong effect on power sector development.

In summary, the *Tax30* scenario shows net VRE shares (averaged 2050-2100) between 46% and 87%. In comparison to the EMF27 model versions, the ADVANCE improvements of the VRE representations reduced the model spread by 4 percentage points, and increased the model-average net VRE share by 24 percentage points.

4.2 Capacity adequacy

Peak demand should be met by a given power system to avoid load shedding. In a system without VRE, capacity adequacy can be simply determined by dividing the sum of all dispatchable capacities by peak demand. To ensure reliable operation even if some generator experiences a failure, this value should be around 1.1-1.3, equivalent to a reserve margin of 10-30%. In a system with VRE, determining capacity adequacy is not as straight-forward: depending on the correlation between VRE incidence and load, VRE either can or cannot contribute to meeting peak demand. As an example, PV contributes to peak demand in California due to high midday peaks from air conditioning, but not to peak demand in Germany or France, where the yearly peak demand is on a winter evening.

The RLDCs derived from REMIX (Scholz et al., in this issue) and the dispatch model DIMES (see (Ueckerdt et al., in this issue)) contain the information regarding how well VREs contribute to peak demand. At low and medium VRE shares, capacity credits depend mostly on the region-specific seasonal and diurnal matching of VRE with demand, while at high VRE shares capacity credits continually decline and become more similar across regions (Ueckerdt et al., in this issue).

Here we calculate a proxy for capacity adequacy, which we call "peak demand coverage" by dividing the installed dispatchable capacity plus the part of peak load that is supplied from variable renewables[8] by the total peak load. This proxy allows us to check if a model manages to represent the demand for capacity, or largely over- or undersupplies dispatchable capacities. Figure 2 shows that for most of the models, the implied capacity adequacy is in a range that would allow stable operation of the system. Only for AIM/CGE, which at the current stage does not include a capacity adequacy equation, the covered demand drops below the level of one, which would imply that some load needs to be shed during peak hours. On the other hand, the power system modeling in POLES leads to high reserve margins, which means it is a very secure system with low risk of failure, but also with higher total system costs due to increased capacity redundancy. This result could be interpreted as a representation of a myopic world where the power sector transformation is not optimally coordinated, or a system where long-distance transmission is not optimally developed,

[8] The contribution from variable renewables and short-term storage to meeting peak demand is calculated directly from the ADVANCE RLDCs.

thus the cost-efficient potential of peak-shaving through better international cooperation is not tapped. Looking at the substantial number of new coal power plant constructions in the EU over the last decade, which will never recover their investment costs if the EU ETS and the long-term emission targets remain in place, as well as the slow progress of increasing the transfer capacities between member states to fully capitalize on their different generation and demand profiles, a “non-optimal coordination” view may be in fact quite realistic.

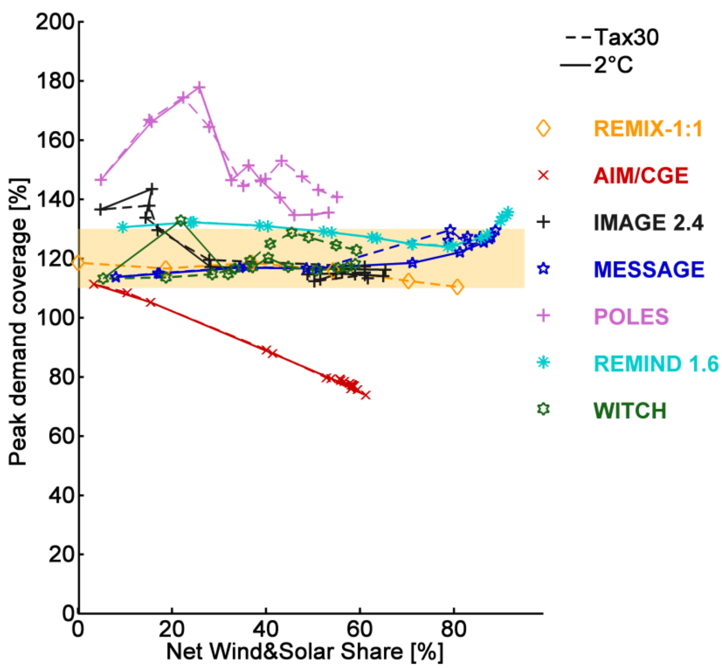

Figure 2: Proxy for capacity adequacy: peak demand coverage. The lines show model results for the EU in the Tax30 and the 2°C scenarios plotted over VRE share, spanning the period from 2010 to 2100, with each marker representing a ten-year time step. For comparison, REMIX results for an even mix of wind and solar (1:1) and different VRE-shares are also displayed. The beige rectangle represents a reserve margin of 10-30%, similar to many of today’s power systems. Lower values imply a higher chance that load cannot be covered and has to be shed; higher values imply possible overcapacities, leading to increased total system costs and difficulties for peaking plants to recover their investments. In all of the modeling approaches except AIM/CGE, peak demand is well-covered.

4.3 Capacity factor of residual non-VRE system

In a real power system, increasing the VRE share will reduce the capacity factor of the residual non-VRE system, and thereby increase the demand for power plants with low capital intensity that operate only a small fraction of the year, such as gas combustion turbines or storage (Hirth et al., 2015; Nicolosi, 2012; Scholz et al., in this issue). This effect is also called “utilization effect”, as the generating capacity is utilized less than would be possible in a system without VRE (Hirth et al., 2015). We here calculate the capacity factor of the residual non-VRE system by summing the electricity output from all installed thermal, hydro and storage power stations, and dividing by the sum of their capacities. This allows for the fact that under certain technology cost assumptions, a model may prefer to invest into a baseload technology combined with a large amount of storage, thereby still fulfilling the feature that the total capacity factor of the combination (baseload+storage) is lower than in a system without VRE, but the baseload plant itself still runs with a high capacity factor.

Figure 3 shows that the utilization effect is well-represented in most IAMs.

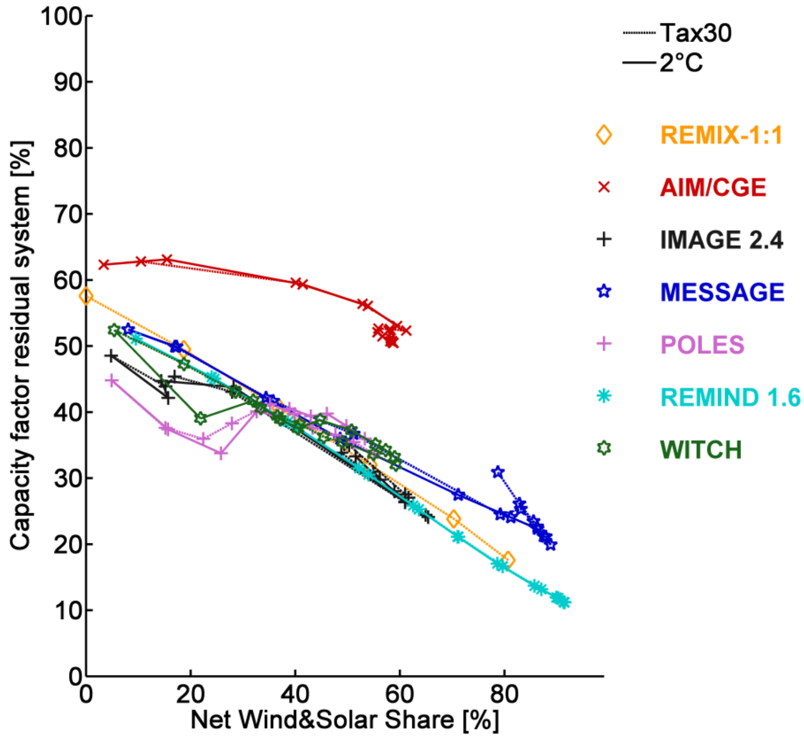

Figure 3: Capacity factor of the residual non-VRE system for the EU in the Tax30 and the 2°C scenarios plotted over VRE share of electricity consumption, spanning the period from 2010 to 2100, with each marker representing a ten-year time step. For comparison, REMIX results for an even mix of wind and solar (1:1) and different VRE-shares are also displayed. In most of the modeling approaches, the capacity factor of the residual non-VRE system follows the expected trend and decreases as the contribution from wind and solar increases, well in line with the results from detailed modeling in REMIX.

4.4 Storage and curtailment

As the share of wind and solar in a power system increases, at a certain point investing into storage becomes economic. Also, as wind and solar produce more electricity than load in certain hours, curtailment increases (see Figure 4). The two effects are partially linked – with more storage installed, curtailment can decrease, and vice versa. Also, different assumptions about costs of natural gas combustion turbines and storage as well as gas prices will influence the amount of storage that is installed. Finally, the type of VRE can have a strong influence on both storage and curtailment, as the REMIX results with different solar-to-wind ratios displayed in Figure 4 show: In Europe, wind doesn't have a strong diurnal pattern while solar does; therefore short-term storage is much less important in scenarios with high wind contributions compared to scenarios with high PV contributions. In the EU, PV is anticorrelated to aggregated demand both on the short as well as on the long term, thus curtailment increases much more than for wind (Ueckerdt et al., in this issue).

The IAMs fall into two groups: On the one side models with an almost even solar-wind mix in the second half of the century in Europe, namely AIM (50:50), REMIND (43:57) and POLES (38:62). On the other side models with very little solar contribution in Europe, namely IMAGE (12:88), MESSAGE (11:89) and WITCH (13:87) – results for these models should be compared to the results from the REMIX-Wind scenarios.

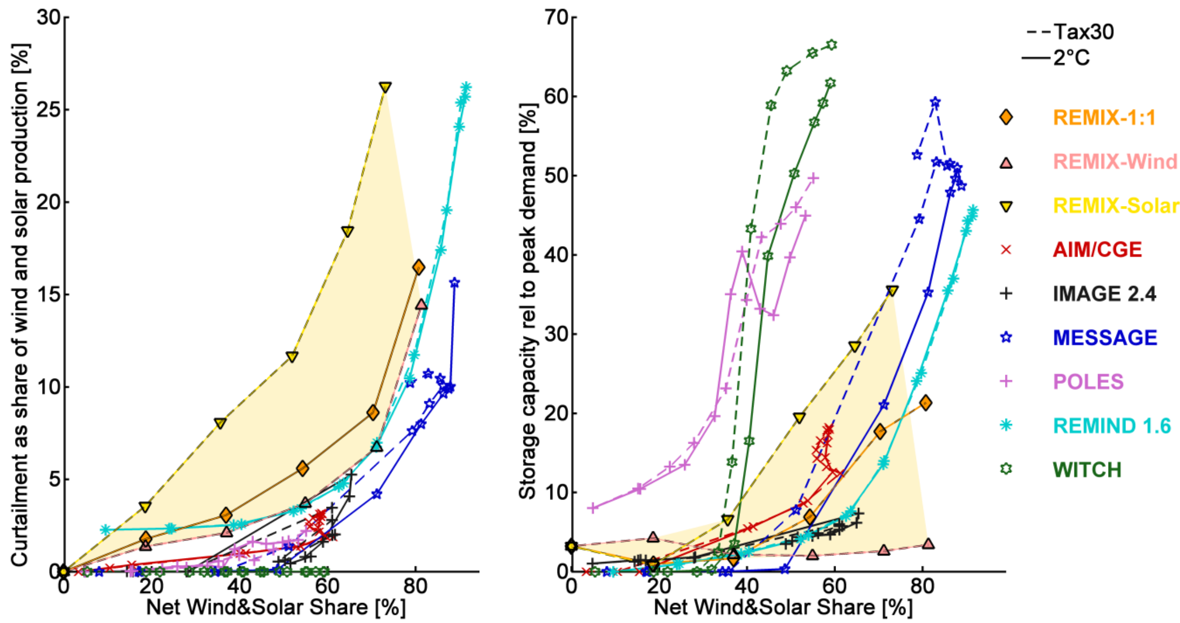

Figure 4: Curtailment (left) and storage (right) for the EU in the Tax30 and the 2°C scenarios plotted over VRE share, spanning the period from 2010 to 2100, with each marker representing a ten-year time step. For comparison, REMIX results for different VRE-shares are also displayed, both with an even solar-wind ratio ("1:1") as well as with a 20:80 ("Wind") and a 80:20 ("Solar") mix of solar to wind for each VRE-share. Curtailment here also includes the curtailment that is used for hydrogen generation in MESSAGE and REMIND. All models represent the general tendency of increasing curtailment and storage with increasing VRE shares, well in line with the results from detailed modeling in REMIX, but most of the models underestimate curtailment.

For curtailment, the comparison of results shows:

- Most IAMs reproduce the general tendency that increasing VRE shares increase curtailment.
- All models show curtailment values that are at the lower end of or even a few percentage points below the REMIX values. This may be due to the fact that REMIX explicitly models the actual losses from long-distance transmission, while most IAMs only include cost markups for transmission grid expansion. This highlights the research need to improve the representation of grids in IAMs in the future.
- WITCH does not explicitly model curtailment but rather represents the economic effect implicitly through the CES function, therefore the model values appear as 0.

For storage, the comparison of results shows:

- The IAMs express a general tendency that increasing VRE share increases storage deployment, which is similar to the solar and the 1:1 REMIX scenario.
- POLES and WITCH deviate from the green-field-optimized REMIX results by showing high storage capacities at medium VRE shares of 40-50%.
- In WITCH, this can be explained by the limited detail of the fixed-factor flexibility equation and the capacity equation, whose parameters are based on the somewhat restrictive 2013 MESSAGE parameterization of wind and solar which does not represent the finding from the RLDC analysis that wind requires less short-term storage than PV (Carrara and Marangoni, in this issue; Ueckerdt et al., in this issue).
- In POLES, the development of storage is not only based on the economic value of arbitrage, but also of ancillary services, which can bring earlier development (Després et al., in this issue). The initial fast deployment of storage in the climate policy scenario can be traced back to the deployment of gas-CCS power plants, whose capacity factor can be increased in the model by deploying storage, so the high storage values are not directly attributable to VRE deployment. Also, storage in POLES is only modeled as "within-day storage", so it cannot optimally reduce peak demand in the model investment logic, which could partially explain the overcapacity/high reserve margin seen in Figure 2.
- The initial offset at low VRE shares is due to the fact that POLES is the only model that fully accounts for pumped hydro storage.
- It should be noted that in a detailed power sector model, storage deployment depends strongly on assumptions about cost and availability of different flexibility options. In a REMIX version where no CSP with thermal storage could be installed, the deployment of short-term battery storage almost doubled.

5 Conclusion and outlook

Through the substantial cost reductions over the last decades, wind and solar power have become economically attractive options for generating low-carbon electricity. As the deployment of these technologies increases, integration challenges resulting from their variable nature become more and more relevant. To robustly analyze the long-term role of wind and solar for climate change mitigation, it is therefore of utmost importance to improve the representation of wind and solar integration challenges in IAMs. Newly-developed power sector modeling approaches need to be evaluated in order to determine how well they represent real-world dynamics.

This study makes four important contributions to the literature:

a) It develops a theoretical evaluation framework of features that describe the fundamental dynamics of the power sector and the effect of VRE. This framework enables transparent evaluation of the strengths and limitations of different modeling approaches, and helps determine the areas that are most in need of improvement.
b) It applies the developed framework to discuss and evaluate six newly-developed modeling approaches for representing power sector dynamics and VRE integration challenges in IAMs of various types.

c) It compares results from the new ADVANCE model versions to results from older model versions used in the EMF27 model comparison study, and separates the effect of updating VRE costs and resources from the effect of updating VRE integration modeling.
d) It analyzes the quantitative results of the six IAMs and tests how well they reproduce the results from a more detailed power sector model.

We find that scenario results produced with the new model versions (updated VRE resource potentials, updated VRE investment costs, improved power sector modeling) lead to a more robust view on VRE deployment in climate policy scenarios, and project higher contributions from wind and solar. While global net VRE shares, averaged over the second half of the century in scenarios with a Tax30 climate policy, ranged from 18-64% (model-average: 38%) in the 2013 model versions used for EMF27, they now increased to 46-87% (model-average: 62%) with the new model versions – an increase of the model-average by 24 percentage points. Most of this increase (18%-points) comes from the update of integration challenge modeling, while 6%-points come from the update of wind and solar costs and resources.

While AIM/CGE and WITCH use rather reduced-form approaches and have less technological detail, they still manage to incorporate several aspects of the effect of VRE on power sector dynamics. More explicit representations in models with higher technology detail, like those in IMAGE, MESSAGE, POLES or REMIND, come with higher computational challenges and data requirements, but represent the integration of wind and solar in a more comprehensive way.

Also, the model span a range of different world views: Models like MESSAGE and REMIND with intertemporal optimization, region-wide pooling and detailed representation of flexibility options best describe worlds in which all institutions and actors cooperate and coordinate their actions to achieve a cost-optimal power system transformation. At the other end of the spectrum is POLES, with its myopic rule-based investment and a rather pessimistic view on the contribution from VRE and storage to peak demand, thereby representing a world where investments are not optimally coordinated, and different countries do not fully cooperate to reduce integration challenges.

Clearly, all of the presented approaches have their limitations, and none of the models covers all aspects to the best extent possible. Further model developments both in IAMs and hourly energy system models will improve the robustness of the results and allow even more details, including the representation of various power-to-X (heat, liquids, chemical processes, etc.) technologies that link the different energy sectors, explicit modeling of demand response, and a more detailed representation of the pooling effect of grid expansion. However, the most important aspect to improve would in our view be the data basis for the region-specific implementation. Indeed, the hourly correlation between wind, solar and load is the main determinant for integration challenges, and strongly influences the results of the different modeling approaches. High-quality load data is missing for most world regions and should be a strong focus of future research to allow the creation of updated regional RLDCs (Ueckerdt et al., in this issue) – one would expect that transmission system operators and energy ministries around the world have an own interest in improved electricity sector research and should therefore be willing to make load data time series publicly available.

We conclude that a variety of different approaches to represent the integration challenges of variable renewable energies in IAMs exist, of which many manage to capture relevant non-linear feedbacks of VRE on the rest of the power sector. The analyzed approaches are a significant step towards more robust and reliable long-term scenarios useful for policy advice, as most IAM results are in decent agreement with power sector features and results from more detailed power sector models.

6 Acknowledgments

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