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Analyzing major challenges of wind and solar variability in power systems

Falko Ueckerdt [a, *], Robert Brecha [a, b], Gunnar Luderer [a]

[a] Potsdam Institute for Climate Impact Research, P.O. Box 601203, 14412 Potsdam, Germany
[b] Physics Dept., Renewable and Clean Energy Program, and Sustainability, Energy and the Environment (SEE) Program, University of Dayton, Dayton, OH, USA

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ABSTRACT

Ambitious policy targets together with current and projected high growth rates indicate that future power systems will likely show substantially increased generation from renewable energy sources. A large share will come from the variable renewable energy (VRE) sources wind and solar photovoltaics (PV); however, integrating wind and solar causes challenges for existing power systems. In this paper we analyze three major integration challenges related to the structural matching of demand with the supply of wind and solar power: low capacity credit, reduced utilization of dispatchable plants, and over-produced generation. Based on residual load duration curves we define corresponding challenge variables and estimate their dependence on region (US Indiana and Germany), penetration and mix of wind and solar generation. Results show that the impacts of increasing wind and solar shares can become substantial, and increase with penetration, independently of mix and region. Solar PV at low penetrations is much easier to integrate in many areas of the US than in Germany; however, some impacts (e.g. over-production) increase significantly with higher shares. For wind power, the impacts increase rather moderately and are fairly similar in US Indiana and Germany.

1. Introduction

Future power systems will likely show a substantially increased share of renewable energy of which a large share will come from the variable renewable energy (VRE) sources wind and solar PV. This is indicated by the current high growth rates, future market trends, ambitious policy targets and support schemes, and scenario results.

The expansion of variable renewable electricity is progressing rapidly, with worldwide annual growth rates for wind and solar PV of 21% and 55%, respectively, from end-2008 to 2013 [1]. In 2012 new power generating capacity from renewables exceeded that of conventional fuels (fossil and nuclear) [2]. In 2013, Denmark, Germany and Spain had renewable electricity generation shares of 56%, 25% and 42%, respectively, with more than half being from wind and solar energy in each country [1]. For the future policy makers have set renewable energy targets (in 138 countries) and adopted support schemes (in 127 countries) for a variety of reasons including climate-change mitigation targets, enhanced energy security and to reduce externalities such as air pollution [2]. For example, Denmark has a goal of 100% renewables in final energy consumption and Germany is aiming for 80% in the power sector by 2050. The European Council adopted an EU-wide binding target of at least 27% renewables in final energy in 2030 [3] and in its 'Energy Roadmap 2050' the share of renewables rises substantially in all decarbonization scenarios, achieving at least 55% in final energy in 2050 [4]. In the US, many states have introduced renewable portfolio standards that require increased renewable electricity shares. For example, California and Colorado have targets of 33% and 30% by 2030, respectively.

Many long-term integrated assessment scenarios and bottom-up resource assessment studies show that renewable energy has the potential to play an important role in achieving ambitious climate mitigation targets [5–10]. Scenario results summarized in Ref. [6] suggest that in the case of future policies to mitigate climate change in line with the globally-agreed long-term climate targets, renewable energy shares as a fraction of total primary energy consumption will increase from 13% to a range of 30%–80% by the middle of the century, with the uncertainty being mainly due to variations in assumptions as to which other low-carbon

* Corresponding author.
E-mail address: falko.ueckerdt@pik-potsdam.de (F. Ueckerdt).

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technologies will be available to complement renewables. The recent EMF27 model comparison [10] shows that for all but one model, renewables provide more than 35% of power supply in the second half of the century, and half of the models have a renewables share of 59% or higher. In those scenarios with high overall renewable deployment wind and solar PV contribute the major electricity share exceeding 40% in the second half of the century.

Achieving the high shares of wind and solar presented in many scenarios will require integration into global power systems. However, VRE differs from conventional power-generating technologies in that they exhibit characteristic properties that pose challenges to their integration. There is wide consensus that these challenges create no insurmountable technical barriers to high VRE shares, however, they cause additional costs at the system level, which are usually termed “integration costs” [6,11–15]. There are slight differences in the way many studies classify the cost-driving VRE properties, but it is possible to categorize three specific properties of VRE: uncertainty, locational specificity, and variability [12,14–18]. Integration studies often estimate the associated costs of these properties. We briefly go through the properties and elucidate their technical reason and relative importance.

First, VRE output is *uncertain* due to the limited predictability (forecast errors) of inherent natural variations of wind speeds or solar irradiation. This requires additional short-term balancing services and the provision of operating reserve capacity. Some studies review balancing costs estimates for wind and find that they are mostly below about 6 €/MWh of wind which is about 10% of their levelized costs of generation [12,19,20]. Note that with steadily improving forecast techniques these costs are likely to further decrease.

Second, VRE output is *location-specific* because the primary energy carrier of wind and solar power cannot be transported like fossil or nuclear fuels and consequently additional costs for electricity transmission occur to meet spatially distributed demand. Estimates for grid costs are scarce and there is no common methodology. It is estimated that annual transmission grid costs of € 1bn may be incurred to integrate 39% renewables in Germany's power sector by 2020 [21], translating to 10 €/MWh if the total cost is attributed to the increase in renewable generation. For the US, the National Renewable Energy Laboratory (NREL) estimates grid investment costs to integrate 80% renewable electricity (of which half are VRE) to be about 6 $ per MWh of VRE [22]. Holtinen et al. [12] review a number of European wind integration studies and shows a range of 50–200 €/kW at shares below 40%, which translates to 2–7 €/MWh.[1] In summary, grid costs might be slightly higher than balancing costs but still small compared to generation costs of wind.

Third, the temporal *variability* of wind and solar has two impacts. The first one is increased ramping and cycling requirements of conventional plants because they need to adjust their output more often, with steeper ramps and in a wider range of installed capacity. This seems to be of minor importance. Studies estimate very low costs [20–22] or find that ramping and cycling requirements are easily met even at high shares of VRE [23–25]. However, even if power plants could perfectly ramp and cycle, variability would still impose an important second impact. Because electricity demand is fairly price-inelastic and electricity cannot easily be stored, demand needs to be covered at the time it arises. Thus, the temporal matching of VRE supply profiles with demand is crucial to their integration. Designated integration studies tend to neglect this impact and focus on balancing, grid, ramping and cycling, while other less technical and more economic studies implicitly account for it. They find a significant economic consequence: variability reduces the marginal value of wind from about 110% of the average electricity price to about 50–80% as wind increases from zero to 30% of annual electricity consumption [18,26–28]. It is this aspect of variability that is the focus of this paper.

This paper contributes to understanding the impact of wind and solar variability on power systems, specifically, the impact of the temporal matching of VRE supply and demand profiles. The tool we use is the residual load duration curve (RLDC), which is usually applied for illustration purposes. RLDC is a purely physical concept, which only requires demand and VRE supply data, yet it captures the relation of the different temporal profiles of wind and solar supply and demand and delivers the relevant economic aspects of major integration challenges. We define three challenge variables that represent fairly independent impacts of variability on the structure of the RLDC. We aim to analyze and compare integration challenges by estimating these variables in a comprehensive analysis for different shares of wind and solar and for two regions, Germany and for a US region in Indiana. Only based on demand and VRE supply data, we derive essential insights that are independent of model assumptions and scenario framings. Our analysis is not meant to be a surrogate for a model analysis. Instead, the results can help in understanding and framing model analyses. In addition, this study can aid in parameterizing integrated assessment models (IAMs) that cannot explicitly represent the short-term variability of wind and solar.

And to be clear, although this study addresses challenges of integrating VRE into current and future power systems, it should be emphasized that these challenges are not inherently a characteristic of VRE itself. Instead, these challenges depend on both VRE properties and the ability of the system to accommodate VRE. This means that the costs associated with VRE integration should not entirely be attributed to VRE generators. As future systems are likely to adapt in response to VRE deployment, the challenges described in this paper will reduce. One example of such a system adjustment is the changing role of the demand side. Power demand will presumably go from being variable and requiring flexibility to a source of flexibility in the future. Hereby, demand and supply will become more integrated, i.e., demand-side options will be able to shift demand in response to variations of renewable supply. As a results, the challenges of integrating VRE decrease.

The paper is structured as follows. The next section introduces the methodology for defining integration challenges using RLDCs. Section 3 provides results of our analysis and Section 4 provides a discussion of our results and conclusions.

2. Methodology – capturing major integration challenges

An intuitively appealing technique for representing the load-matching properties of VRE and the induced challenges is provided by load duration curves (LDCs) and residual load duration curves (RLDCs). These curves are mostly used for illustrative purposes and sometimes indirectly used as a model input [29–33]. We present here for the first time the application of RLDCs as a direct quantitative tool for analyzing systems with arbitrary levels of penetration of both wind and solar PV, and demonstrate the intuitive clarity of this approach to thinking about VRE challenges.

We start by explaining the concept of RLDCs. As a first preparatory step, we introduce the well-known concept of a load duration curve LDC, which is derived by sorting the load curve i.e. the time series of power demand for one year or longer (Fig. 1) from highest to lowest values. The y-axis of an LDC indicates the minimum capacity required to cover total annual electricity demand, which is reflected by the area below the curve.

[1] Assuming a 7% discount rate and 2000 wind annual full load hours.

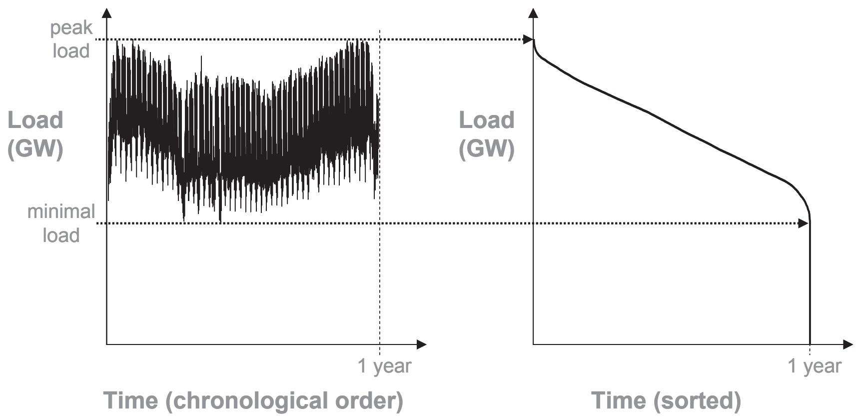

Fig. 1. (Schematic): The LDC (right) is derived by sorting the load curve (left) in descending order.

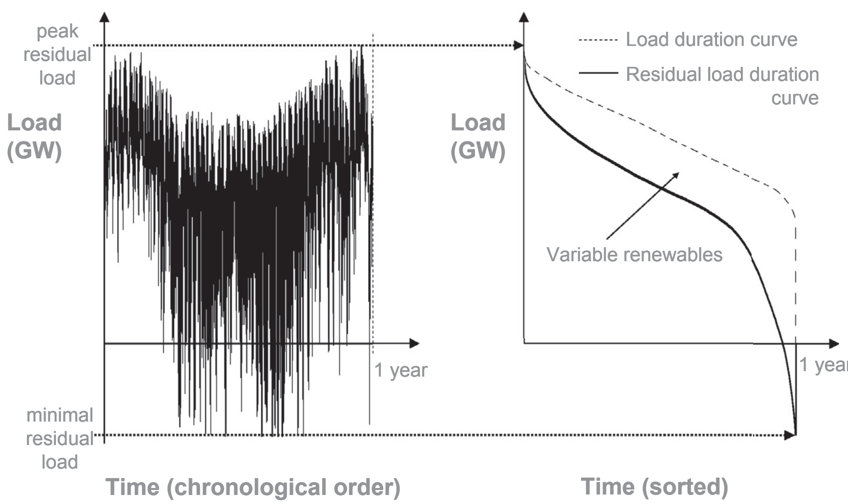

Fig. 2. (Schematic): The residual load curve (a time series) is derived by subtracting the time series of VRE from the time series of power demand (left). The RLDC (right) is derived by sorting the residual load curve in descending order. The area in between the RLDC and the LDC equals the potential contribution of VRE.

If a new source is added to the system, in our case wind and solar, the power generated from that source at each point in time can be subtracted from the load at that same time to arrive at a time series describing the residual load that must be supplied by the rest of the system (Fig. 2, left). This residual load curve is based on the unsorted and thus fully temporally matched time series of load and VRE supply. In a second step, the RLDC is then derived by sorting this residual load curve in descending order. The area between the LDC and the RLDC is the electricity generation from variable renewables (wind and solar). Note that the shape of the area between the LDC and RLDC is not able to indicate the temporal distribution of VRE supply, due to different sorting of load and residual load in the respective duration curves, yet this information is not relevant for our current purpose. This is in contrast to the temporal distribution of residual load, which is accurately represented. As we argue in the following, the RLDC represents the major challenges of renewable integration.

RLDCs contain crucial information about the variability of wind and solar supply, as well as correlations with demand, thereby capturing three major challenges of integrating VRE into power systems, as shown in Fig. 3,[2] namely (i) low capacity credit, (ii) reduced full-load hours of dispatchable plants, and (iii) overproduction of VRE. At the same time, it is important to note that the RLDC does not capture ramping and cycling requirements, since that would require the chronological order of the residual load, which is lost in a duration curve. However, as discussed earlier, the effect of ramping and cycling requirement on VRE integration costs is relatively modest compared to the three major challenges analyzed here [15].

The RLDCs not only *illustrate* the challenges of VRE but also allow for *quantifying* three "challenge variables" that represent the different and fairly independent integration aspects. We explain the challenges and their quantification used in the analysis:

1) *Low capacity credit*: Wind and solar contribute energy while only slightly reducing the need for total generation capacity, especially at high shares, due to a relatively low capacity value; consequently some firm capacity is required complementing VRE (including electricity storage or demand response mechanisms). In other words, the long-term capacity cost savings in a system are lower when adding VRE compared to adding a dispatchable plant. There are several similar qualitative definitions of capacity credit in the literature [34–36] that are in line with the following: The capacity value of a generator can be defined as the amount of perfect reliable capacity (firm capacity) that can be removed from the system due to the addition of the

[2] For wind and solar generation we use quarter hourly feed-in data from German TSOs for 2011. For power demand of Germany hourly data for 2011 is used from ENTSO-E.

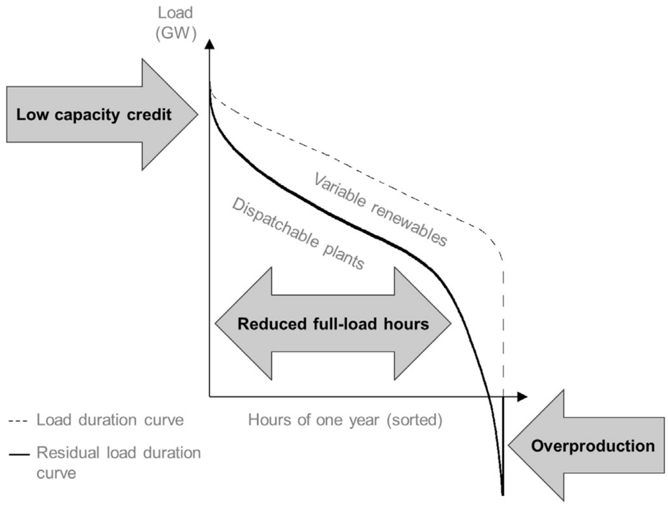

Fig. 3. Residual load duration curves capture three main challenges of integrating VRE (illustrative). The utilization of conventional plants is reduced, while hardly any generation capacity can be replaced. At higher shares VRE supply exceeds load and thus cannot directly be used. Load and renewable feed-in data for Germany is used to derive the curves.

generator, while maintaining the existing level of reliability. The capacity credit is the ratio of capacity value and the added capacity. Moreover there are different formal definitions, i.e. different methods of actually estimating the capacity credit [36–40]. Because we only want to rely on load and VRE supply data and to provide full transparency we follow an approximation method that was introduced by Garver [41] and has been shown to well-represent actual system performance. The method is based on the concept of Effective Load Carrying Capability (ELCC). The ELCC of a power plant represents its ability to increase the total generation capacity without increasing the existing level of reliability often measured in terms of *loss of load probability* (LOLP). In Ref. [41] an approximation for the ELCC is given, which has been used in many analyses to express the capacity value or capacity credit (see for example equation (13) in Ref. [40], or the appendix in Ref. [42]):

$$a = m \ln\left(\sum_i e^{LDC_i/m} \Big/ \sum_i e^{RLDC_i/m} \right) \Big/ C_{VRE} \quad (1)$$

where a is the capacity credit of the total VRE capacity C_{VRE}, LDC_i and $RLDC_i$ are the values of the (residual) load duration curve at a given instant i. The Garver capacity factor m was chosen for both regions to have a typical value of 4% of peak load [37,42]. By considering the ratio of exponentials, the capacity credit as defined in Eq. (1) is to a large part determined by the difference between the peaks of the LDC and the RLDC, although there are contributions from the rest of the curves. Our work represents a first thorough treatment of capacity credit for a wide range of combinations of solar PV and wind power.

2) *Reduced full-load hours*: The higher the penetration of wind and solar PV, the more the annual full-load hours (FLH) of the dispatchable power plants required to serve the residual load will be reduced. The average utilization and therefore the life-cycle generation per capacity of non-VRE plants is smaller than in the absence of VRE, and thus specific generation costs (per MWh) of supplying the residual load is higher. In fact, if new generation plants (such as VRE) are added to an existing system with sufficient capacity any new generation plant would decrease the FLH of incumbent generators and the impact is therefore not VRE-specific in a short-term perspective. However, on a longer time horizon, for which all uncompetitive incumbent generators would be decommissioned, the impact remains only for VRE generators. While new dispatchable plants would replace other generation capacity in a specific load band (e.g. intermediate load) and do thus not reduce the FLH of other plants, VRE generators replace very little capacity and contribute to different parts of load (from peak load to baseload) due to their variability (Fig. 3). We operationalize this challenge by measuring the decrease in full-load hours of the RLDC at two heights as indicated in Fig. 4. To capture the effect on intermediate load we chose a height equal to half of the peak load and to account for the reduction of baseload FLH we measure at the intersection with the x-axis. When T_{RLDC} and T_{LDC} are the inverse (residual) load duration curves the relative reduction at the two heights can be expressed as follows:

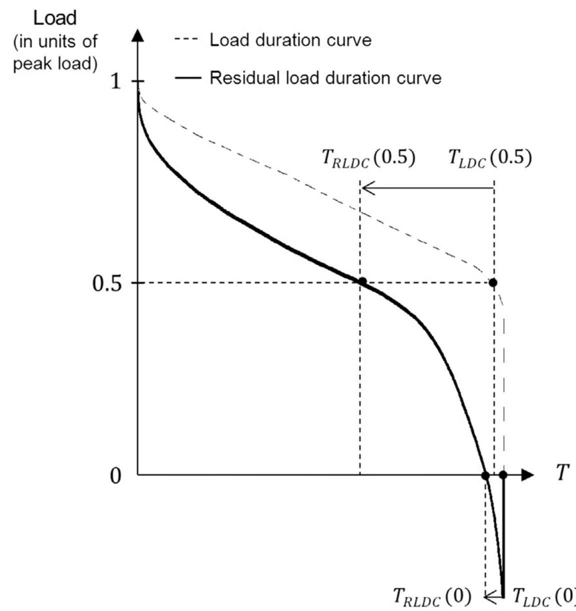

Fig. 4. With VRE deployment the width of the RLDC is decreasing. We measure this effect at two heights relative to peak load: at half height and at the x-axis.

$$b = T_{RLDC}(0.5)/T_{LDC}(0.5) \quad (2)$$

$$c = T_{RLDC}(0)/T_{LDC}(0) \quad (3)$$

3) *Over-production of VRE*: At high generation shares there are hours in which combined wind and solar PV generation exceeds load, and thus production must be curtailed if it cannot be stored or transmitted. Hence, the effective capacity factor[3] of VRE decreases and specific per-energy costs of VRE increase. We measure over-production as the share of potential total generation of wind and solar that exceeds domestic load. This equals the ratio of the negative part of the RLDC between the x-

[3] The capacity factor describes the average power production per installed nameplate capacity of a generating technology.

intercept T_0 and the maximum T_{max} of the data series (e.g. one year) to total potential variable renewable generation (G_{VRE}).

$$d = \int_{T_0}^{T_{max}} RLDC(T)\mathrm{d}T / G_{VRE} \tag{4}$$

Note that our approach provides a simplified estimate of curtailment that can be derived from a pure data analysis without requiring detailed power system modeling. It may underestimate curtailment occurring in the real-world, because grid or minimum-load constraints of dispatchable power plants are neglected, or overestimate curtailment, because it does not account for the possibility of long-distance transmission or storage. Some studies focus on over-production. Ref. [43] uses a similar RLDC methodology and analyze curtailment for New York State. For Germany, Ref. [44] estimates storage requirements to limit over-production to various levels and uses RLDC to illustrate the model results.

These three challenges impose costly redundancy on the system. We will show that the magnitude of these challenges depends on the renewable source (wind or solar), on the region and becomes more severe at higher shares. Note that all “challenge variables” are measured in average and not marginal terms *i.e.* the impacts are distributed across the total wind and solar penetration, rather than quantifying them for the last added unit of wind or solar. Marginal impacts can be much higher, for example the average capacity credit of all wind and solar plants is higher than that of the last unit, because the capacity credit always decreases with increasing penetration.

Furthermore, in this work we concentrate on the direct impact of variable renewable generation from solar PV and wind on the electrical system. In introducing the quantitative use of RLDCs, we assume no possibility for long-distance transmission, and that there is no potential for demand-side management (DSM), storage, or other integration options. Hence, the results we present are effectively upper limits of the challenges to integration. The challenges are not to be seen as insurmountable barriers, but give insights as to how wind and solar PV might be efficiently deployed, and emphasizes the need for an integrated perspective on the integration challenge.

We look at two specific regions, Germany and the Midwestern United States, in some detail to illustrate the RLDC technique and show the regional diversity in results.

For Germany we use wind and solar generation from actual quarter-hourly feed-in data from German Transmission System Operators (TSOs) for 2011, which is publicly available on the respective websites.[4] To simulate higher penetrations we scale up the time series linearly. Hourly data for power demand in Germany in 2011 were downloaded from the ENTSO-E website.[5] The data were interpolated linearly to match the quarter hourly resolution of VRE generation. By spatially aggregating over the four different TSO zones in Germany we implicitly assume perfect domestic transmission (“copper plate assumption”). This is reasonable because Germany is already well interconnected and will be even better so after governmental plans are implemented [45]. Even though the data we analyze comes from Germany, it is to some extent representative for other European power systems due to typical load, solar and partly also wind patterns.

Hourly demand data for the US region (near Evansville, Indiana) are taken from documents filed with the Federal Energy Regulatory Commission.[6] This region was chosen as it is representative of total overall load patterns for much of the US, which in turn differ significantly from those in Europe. In much of the US, peak loads occur in the summer months at irregular intervals due to heavy use of air conditioning. Typically, lower secondary peaks in load are seen in December and January, with lower demand during about two weeks around the Christmas and New Year's holidays. Average demand in the chosen region was 750 MW during the year 2005, with average demand higher in the summer months, reaching a peak of 1291 MW. Demand data were interpolated to a ten-minute-interval basis to match the available solar data for the same region.

Solar data for the region are taken from the National Solar Radiation Database [46] and are based on both satellite measurements and ground-based meteorological data having the same long-term statistical properties as the measured radiation data sets with which they are validated for a relatively small number of sites. The data used for our analysis is the average global radiation (direct plus diffuse) on a horizontal surface, given in units of Wh/m^2. Using these data is equivalent to averaging over a large number of arrays that may not all be optimally sited, tilted, or oriented – total solar output for the region will be given by a multiplicative scaling factor of the global insolation for each hour.

Wind data for the same year for the same geographical region come from the Eastern Wind Integration and Transmission Study [47]. Wind speeds at various heights corresponding to chosen models of wind turbines are used to then aggregate data to the modeled power output of a wind park in that study area. For both wind and solar data several sites were selected, centered on the city of Evansville, to effectively find a regional average for each time step.

3. Results

In this section we present the results of the detailed analysis of challenge variables. Before discussing each variable in detail, we provide an overview of the results.

Fig. 5 shows the RLDCs for all four combinations of region and technology (wind and solar PV) for increasing shares (0%–50%). For all combinations, the challenges (as illustrated in Fig. 3) become more severe at higher penetrations of final electricity consumption.[7] Although this overall tendency is the same there are some noticeable differences between wind and solar PV, and between the two regions considered. In Germany at low shares wind has a small capacity credit. The capacity credit of solar is even smaller, because solar PV contributes mostly to intermediate load (typically daytime in summer) rather than to peak load (typically winter evenings). At higher shares wind continuously tilts the RLDC while solar creates a kink in the RLDC so that at high shares most generation is overproduced. The US picture at low shares is the opposite: wind has a small capacity credit while solar contributes significantly to peak load. This is due to the more favorable correlation of peak demand occurring at summer days due the deployment of A/C systems with solar power supply. At higher shares the shapes become more similar to the results for Germany. The reason for the solar RLDC kink is that once summer day load is covered, further solar PV deployment mostly leads to over-production. The kink separates sun-intensive days (right side) from less sunny days and nights (left side).

4 www.50hertz-transmission.net, www.tennettso.de, www.amprion.net, www.enbw.com.

5 https://www.entsoe.eu/data/data-portal/.

6 http://www.ferc.gov/docs-filing/forms.asp#714.

7 Throughout the paper “penetration” is the share of VRE in electricity consumption, i.e. overproduced VRE are not contributing to penetration.

We note as well that for increasing penetrations, and this is especially true for solar PV, the RLDC crosses the abscissa at points further to the left, meaning that the number of hours of operation for capacity usually designated as baseload is decreased. The implications of this characteristic are discussed below. On the other hand, it is also clear that even at very high penetrations, there is a remanent capacity and time of generation (i.e. total electrical energy) that must be supplied by the system beyond that which can be provided by VREs. This capacity fraction of system requirements will necessarily be provided by either conventional thermal capacity, non-variable renewables (e.g. hydroelectric power) and, to some extent, demand-side management and storage of overproduced VRE.

We now present each of the challenge variables in more detail, including combinations of wind and solar PV, as well as looking in more detail at regional variations.

3.1. The capacity credit

Fig. 6 shows how the capacity credit depends on region, penetration and mix of wind and solar. The top panels in Fig. 6 show all mixes of wind and solar while the line plots in the bottom panels focus on pure solar and wind capacity credits.

For most mixes the level of capacity credit is higher in Indiana than in Germany, mainly driven by a high capacity credit of solar of up to 70% for the first solar plants in the system. Apart from the overall level the dependency on the mix of wind and (especially) solar shows opposite patterns in the two regions. While the capacity credit of solar is high in Indiana it is low in Germany (~20% at low penetrations), where wind has a slightly higher capacity credit (~25%). Independent of the mix and region the capacity credit decreases rapidly with increasing penetration. However, a sensible mix of wind and solar PV can increase the capacity credit compared to a pure deployment of only wind or solar. For Germany the maximizing mix contains mainly wind power. Note again that here average values are displayed. Marginal values, *i.e.* the capacity credit of the last unit of wind or solar added, would decrease even more.

The large difference in solar capacity credits is explained with Fig. 7, which shows average diurnal cycles for solar supply and load in both regions. More precisely it distinguishes between the average winter (December–February) and the average summer day (June–August).

The relation between the solar supply and load data is a free parameter and was chosen to best illustrate the findings. The load data are normalized such that the highest average load hour equals *one*. The solar data are normalized such that the summer supply peak equals the summer load peak.

Solar PV has a low capacity credit in Germany because annual electricity demand in Germany peaks during winter evenings. Solar PV supply is highest during summer days and thus contributes to intermediate load at low penetrations (as shown in Fig. 5). In Indiana as in most parts of the US power demand is highest during summer days due to the use of air conditioning. Consequently solar power supply is well-correlated with power demand. In particular demand peaks coincide (overlap) with significant solar supply and thus solar has a high capacity credit.

Wind generation does not show such regular patterns. It is more variable in the sense that the variance of wind output in an hour is very high compared to the mean value and compared to the variance of solar output. In other words, it is much harder to rely on wind power output. Hence, the matching of the average curves of wind and demand is not as important for wind. In US Indiana and Germany the capacity credit is similar even though seasonal demand patterns are different.

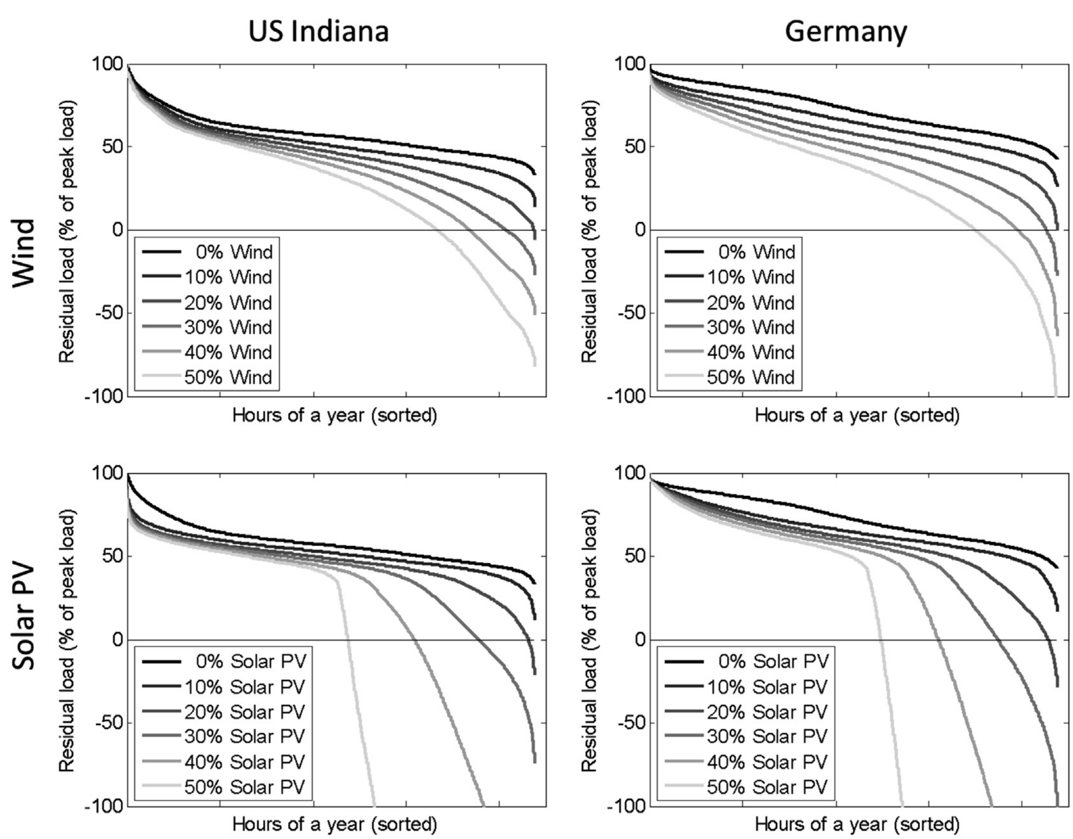

Fig. 5. RLDCs for wind and solar PV for Germany and US Indiana.

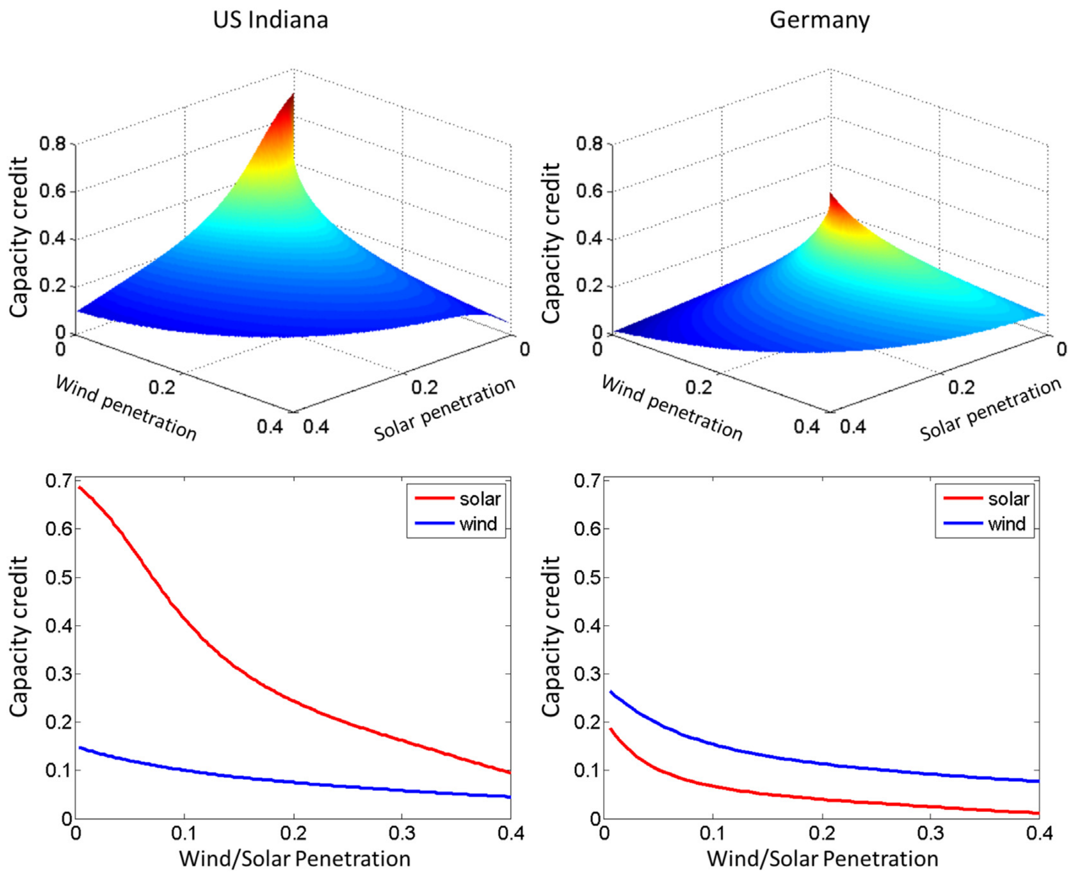

Fig. 6. The capacity credit (defined in Section 2) for different mixes and penetration of wind and solar PV for US Indiana (left) and Germany (right).

Literature results for capacity credits are in line with the above results. For wind plants there are many studies [12], typically showing a large range of capacity credit values from 10% to 35% for onshore wind plants at low penetrations that tend to decrease with higher wind shares. Literature on the capacity credit of solar PV is scarce.

Madaeni et al. show values ranging between 52% and 93% for the western US, depending on location and the plant's sun-tracking capability [40]. Perez et al. show estimations for different methodologies and diverse electric utility companies in the US [37]. In those areas where summer peak load is much higher than in winter the capacity credit is in the range of 60%–80% for low solar penetrations and decrease with higher penetrations. For the area of Portland, Oregon, for example, where summer and winter peak are about the same height, the preferred ELCC method gives a smaller capacity credit of about 33% and patterns resemble more closely those of the German data. This observation confirms that summer cooling demand drives the capacity credit of solar PV and thus its cost saving potential.

3.2. Reduced utilization of dispatchable plants

Fig. 8 shows how the utilization of dispatchable plants is reduced for baseload plants (above) and intermediate load plants

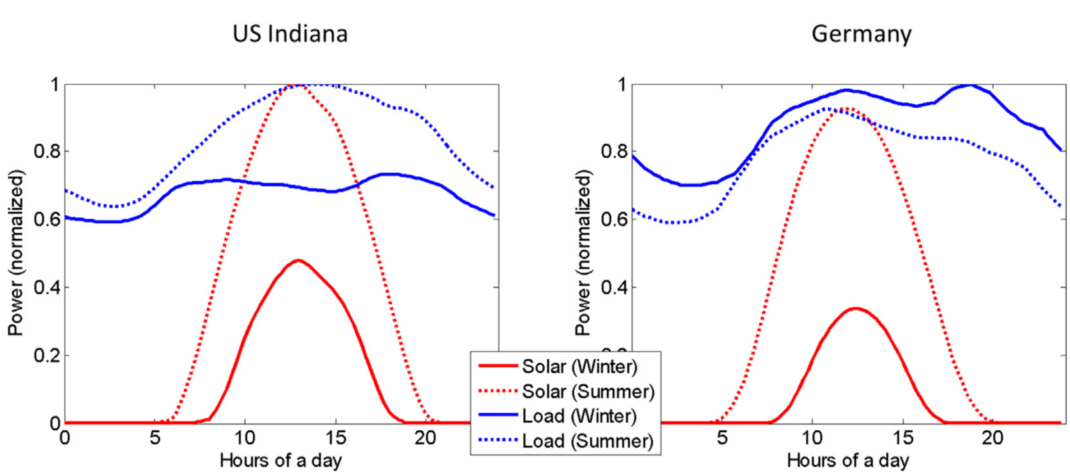

Fig. 7. Average diurnal cycles for solar supply and load in US Indiana (left) and Germany (right) in winter (December–February) and in summer (June–August). The peaks of load and solar coincide in US Indiana while in Germany the load peak is in winter evenings when no sun is shining.

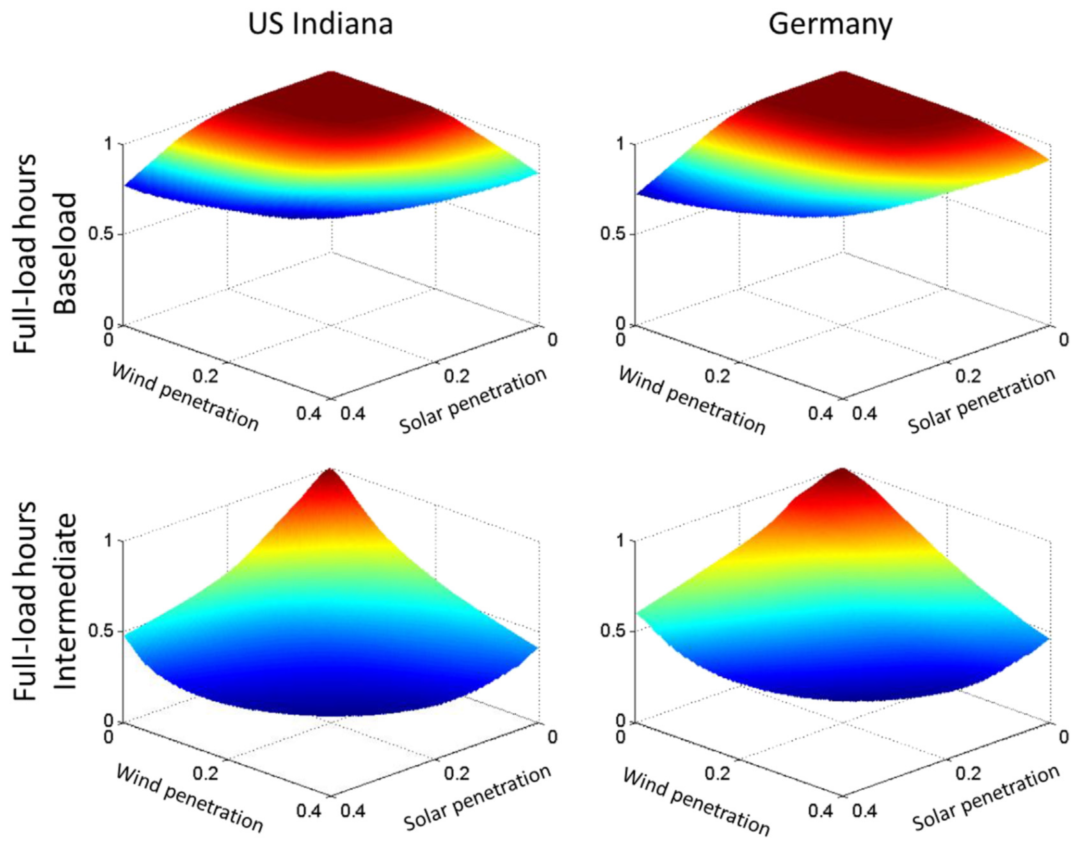

Fig. 8. Two variables (defined in Section 2) that describe the reduction of full-load hours with increasing penetration for different mixes of wind and solar PV for US Indiana (left) and Germany (right). The above variable "Baseload" shows that at moderate penetration there is no residual load that needs to be supplied constantly. The below variable "Intermediate" shows that wind and solar reduce FLH at an intermediate height of the RLDC.

(below). The FLH of intermediate load plants are reduced even at low penetrations, while baseload FLH are affected at moderate and high penetrations. The overall picture is quite similar for both regions and fairly symmetric for wind and solar. We point to a few differences. Wind and solar affect baseload and intermediate load FLH in an opposite way. While wind tends to reduce intermediate load, solar has a larger effect on baseload. This asymmetry is larger for Germany.

Note that the results for the intermediate load variable are sensitive to the chosen reference height on the RLDC. We have chosen an intermediate height of 0.5 (see Section 2) to focus on the intermediate load parts of the RLDC with high FLH. Considering the FLH reduction at higher capacity levels would tend to evaluate the peak load part that is to a large extent already covered by the first challenge variable, capacity credit.

As we discussed in the introduction, integration challenges of VRE depend not only on VRE variability, but on the entire power system. The impact of reduced FLH depends on the dispatchable capacity mix and cost structure of existing and new plants. A system with high must-run generation (e.g. high minimum load of baseload plants or combined-heat and power plants without thermal storage) can face a major challenge when baseload FLH decrease. Wind and solar generation that would reduce baseload FLH might not be accommodated unless the system can be made more flexible, i.e. by reducing must-run generation. Moreover system costs increase if the existing and planned plants have high fixed costs like nuclear or to some extent coal plants. These plants typically have low variable costs and rely on a high utilization to recover their investment costs. This indicates that baseload power plants are not a suitable complement to high VRE shares. In contrast a system with dispatchable plants with rather low fixed and high variable costs could better cope with reduced FLH. Combining high shares of VRE with peak and intermediate load plants can significantly reduce total costs compared to a system with high VRE shares and baseload plants.

As a consequence the "baseload" indicator shown in the upper plots in Fig. 8 tends to be more important than the "intermediate" indicator shown in the bottom. In this respect solar PV might be more of a challenge than wind.

3.3. Over-production

Fig. 9 shows how the challenge variable over-production depends on region, penetration and mix of wind and solar. Over-production occurs above penetrations of about 20%. For solar PV it increases stronger than for wind because once summer day load is covered, further solar PV deployment does mostly lead to over-production. This asymmetric effect is much stronger in Germany because of the unfavorable matching of solar supply and season load patterns (see above Fig. 7). At a solar penetration of 40%, about 50% of total solar generation would be over-produced, whereas over-production can be minimized if only wind power was deployed. For the US region curtailment is smaller for a combination of wind and solar PV than for a deployment of only wind or solar PV. When comparing all curtailment values for a VRE share of 40% there is an optimal ratio of wind and solar PV of about 2:1 (as indicated by the arrow), which minimizes curtailment. This is in line with [43], which for New York State finds a minimizing ratio of 3:2.

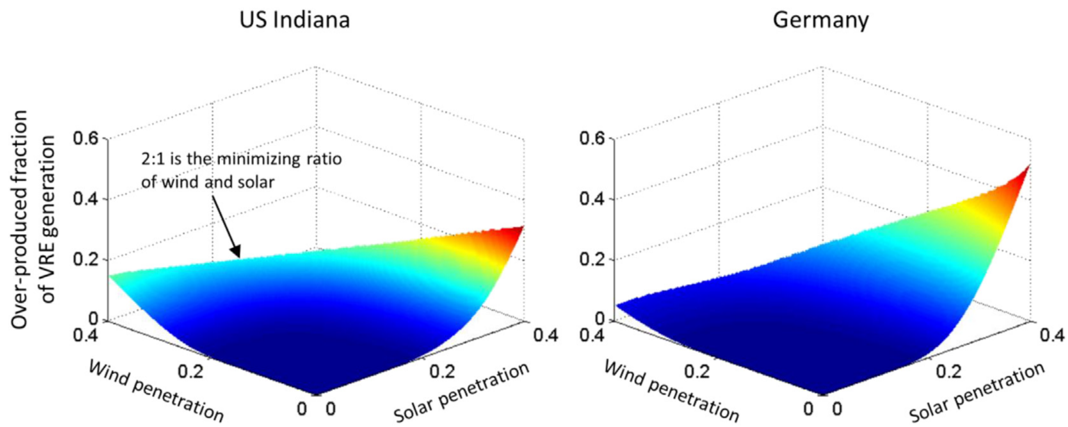

Fig. 9. Over-production (defined in Section 2) for different mixes and penetration of wind and solar PV for US Indiana (left) and Germany (right).

4. Discussion and conclusion

In this paper we analyze three major challenges of integrating variable generation from wind and solar into power systems: the low capacity credit, reduced utilization of dispatchable plants and over-production. Using RLDCs for this purpose is both a good heuristic tool and allows for quantitative analysis. We introduced corresponding challenge variables and estimate their dependence on region (US Indiana and Germany) and on penetration and mix of wind and solar. This basic, and at the same time informative, analysis provides insights into fundamental properties of the structural matching of demand with wind and solar supply.

Our results show that challenges associated with increasing wind and solar shares can become severe and consequently cannot be neglected in economic analyses and system planning. To a large extent these challenges depend on the penetration, mix of wind and solar, and regional circumstances. We summarize the results in the following six points:

1) All integration challenges increase with penetration independently of mix and region.
2) Some challenges, namely the over-production and the increasing reduction of the utilization of baseload plants, increase stronger for high shares of solar PV (>20%).
3) At low penetrations, solar PV is much easier to integrate in the US than in Germany. In particular it contributes a high capacity credit of up to 70%, while for Germany the capacity credit is low and vanishing with higher penetration.
4) For wind the challenges increase more modestly with increasing penetration than for solar. The capacity credit is relatively low even for low wind penetration.
5) The integration challenges of wind are fairly similar in US Indiana and Germany.
6) A sensible mix of wind and solar can mitigate some integration challenges such as increasing capacity credits or, for US Indiana, decreasing over-production.

These results show that the deployment and integration of VRE must be planned from a system perspective to account for the matching of wind and solar supply with demand. The challenge variables are crucial system figures that depend on various parameters. The deployment of wind and solar should not purely be based on generation costs.

This work quantifies challenge variables for a broad range of boundary conditions. The next step should be translating these estimates into economic costs. This would require some kind of energy system model that accounts for existing capacities (generation and transmission). Moreover a time frame of the analysis needs to be defined in which new capacities are built and the system adjusts to the increasing share of variable generation from wind and solar. Such an analysis should consider potential mechanisms that might reduce integration challenges like energy storage, long-distance transmission and demand side management.

Climate change mitigation policies will certainly require dramatically increased levels of electricity produced from variable renewable sources, as described at the beginning of this paper. Although the focus of this work is on the challenges to integration of VRE in the existing system, the potentially large negative externalities of anthropogenic climate change, together with the known negative externalities of current energy systems indicate that an energy system transformation will be necessary over the next few decades. The acceptance and success of this transformation will be enhanced if foreseeable consequences are examined carefully and early in the process such that options for avoiding problems can be developed in parallel with the ramp-up of VRE deployment.

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