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Representing power sector variability and the integration of variable renewables in long-term energy-economy models using residual load duration curves

Falko Ueckerdt^{#*}, Robert Brecha^{#+}, Gunnar Luderer[#], Patrick Sullivan¹, Eva Schmid[#], Nico Bauer[#], Diana Böttger², Robert Pietzcker[#]

[#]*Potsdam Institute of Climate Impact Research PO Box 601203, 14412 Potsdam, Germany*

⁺*Also with Dept. of Physics and Renewable and Clean Energy Program, University of Dayton, Dayton, OH 45469-2314, USA*

¹*National Renewable Energy Laboratory, 1617 Cole Boulevard, Golden, CO 80401, USA*

²*Institute for Infrastructure and Resource Management, Universität Leipzig, Grimmaische Straße 12, 04109 Leipzig, Germany*

**Corresponding author, E-mail: ueckerdt@pik-potsdam.de, phone: +49 (0)151 178 139 27*

Abstract – We introduce a new method for incorporating short-term temporal variability of both power demand and variable renewables (VRE) into long-term energy-economy models: the RLDC approach. The core of the implementation is a representation of residual load duration curves (RLDCs), which change endogenously depending on the share and mix of VRE. The approach captures major VRE integration challenges and the energy system’s response to growing VRE shares without a considerable increase of numerical complexity. The approach also allows for an endogenous representation of power-to-gas storage and the simultaneous optimization of long-term investment and short-term dispatch decisions of non-VRE plants. As an example, we apply the RLDC approach to REMIND-D, a long-term energy-economy model of Germany, which was based on the global model REMIND-R 1.2. Representing variability results in significantly more non-VRE capacity and reduces the generation of VRE in 2050 by about one-third in baseline and ambitious mitigation scenarios. Explicit modeling of variability increases mitigation costs by about one fifth, but power-to-gas storage can alleviate this increase by one third. Implementing the RLDC approach in a long-term energy-economy model would allow improving the robustness and credibility of scenarios results, such as mitigation costs estimates and the role of VRE.

1. Introduction

There is broad evidence that anthropogenic climate change is threatening the welfare and development of human societies [1]–[3]. Combustion of fossil fuels is the main driver of anthropogenic climate change, causing over 60% of global greenhouse gas emissions [4], [5], which is why climate change mitigation requires a transformation of the global energy system towards low-carbon technologies. Identifying mitigation scenarios that minimize the macroeconomic costs (so-called mitigation costs) of achieving a prescribed climate target requires long-term numerical energy-economy models that capture key interactions between the energy, economic and climate systems, as well as interactions within the energy system itself (heat, transport and power sector).

The power sector appears to be a centerpiece for climate change mitigation. Most mitigation scenarios show that the power sector decarbonizes earlier and more extensively than the non-electric energy part of the energy system [6]–[9]. Electricity can be supplied by a number of comparably low-cost mitigation options such as renewable energy sources, carbon capture and storage and nuclear power, whereas supplying non-electric energy demand with low greenhouse gas emissions relies strongly on biomass. Electrification is also an important mitigation strategy for transport and residential heating.

Future power systems will likely show a significant share of renewable energy of which a large contribution will come from the *variable*¹ renewable energy sources (VRE) wind and solar photovoltaics (PV). This is not only indicated by current high growth rates, ambitious policy targets and renewable support schemes, but also estimated in mitigation scenarios based on long-term energy-economy models [6], [10]–[14]. The recent EMF27 model comparison [14] 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 show renewables share of 59% or higher. In those scenarios with high overall renewable deployment wind and solar PV contribute the major electricity share (>40%) in the second half of the century.

However, long-term energy-economy models have a deficit that leads to inaccurate or even biased results: Typically, they only have a crude representation of power sector variability,

¹ “Variable” (or sometimes intermittent) is used to describe generators that rely on fluctuating weather conditions (wind and solar plants) and thus can hardly be controlled in their power output.

which needs to be improved in particular to give an accurate account of the economics of VRE [14], [15]. This includes both variable power demand as well as VRE like wind and solar and their integration into energy systems. Variability on temporal scales from minutes to years shapes the economics of the power sector. As demand is inherently variable and electricity cannot be stored easily, a heterogeneous mix of power-generating technologies is optimal, rather than a single technology [16]–[20]. If a model does not represent the variability of demand there is a tendency to bias the results towards more base-load technologies and to underestimate the total costs of power supply. Neglecting the variability of VRE intensifies this bias since VRE variability imposes costs on the power system as a whole. These costs are often termed integration costs and can be substantial at high VRE shares [21], [22]. Consequently, the economic value and optimal deployment of VRE strongly decrease due to their variability [23]–[27]. For wind this amounts to 25–35 €/MWh at a share of 30–40%, according to an extensive literature review [22]. For a fundamental analysis of the impacts of power sector variability (demand and VRE) on the economics of electricity see Ref. [28].

Accounting for short-term power sector variability in models that focus on long-term transformation pathways of the energy system is highly challenging, due to the trade-off between model scope and detail in the presence of numerical and complexity limits. Long-term energy-economy models have a very wide scope, i.e., coverage of multiple sectors, a centennial perspective on mitigation challenges, often a global perspective, and a representation of the major drivers of climate change and mitigation options. Inevitably, this limits the level of detail that can be represented. Many models use a temporal resolution for investment decisions of 5–10 years. Power demand and supply are aggregated and balanced in terms of annual averages, in contrast to actual electricity demand, wind speeds, and solar radiation variability time scales. Numerical constraints prohibit increasing the resolution of long-term energy-economy models to a degree that would allow for an explicit representation of variability. To keep model complexity manageable, one needs a lean, yet accurate representation of power sector variability and VRE integration that successfully bridges relevant timescales.

Most long-term energy-economy models use stylized representations covering different aspects of variability; these representations have limitations and leave room for refinement [14], [29], [30]. A review of 17 long-term energy-economy models [14] reveals a range of methods to represent VRE variability spanning from highly stylized economic approaches over constraint

and cost-penalty based methods to investment requirements in integration options. Two of these models have no dedicated representation of variability, but account for the imperfect substitutability between different power sources using constant elasticity of substitution (CES) production functions. Such an approach is highly stylized and tends to preserve power supply structures as observed today, making it difficult to explore the types of transformative changes required for low stabilization. One common approach is to limit the maximum generation share of wind and solar by means of an exogenous constraint, e.g., to 15% each. This rigid approach might be overly pessimistic as dedicated studies and real-world experience indicate that VRE integration poses no insurmountable technical barrier [31]. A less rigid approach is the imposition of an integration cost penalty per generated unit of electricity from VRE that increases with the VRE generation share (see e.g. [32]). While representing monetary integration challenges, this approach is not capable of capturing the pivotal impacts of VRE on the non-VRE part of the power system. Increasing shares of VRE result in a substantial reduction of full-load hours of dispatchable power plants, and thus alters optimal investments in the non-VRE part of the energy system [33]. Another prominent approach is to impose fixed investments in specific integration options with rising VRE shares, e.g., firm capacity from gas-fired power plants, electricity storage or transmission infrastructure. However, a single integration option is unlikely to mitigate all aspects of variability, these approaches are difficult to parameterize and the preselection of specific integration options hampers the opportunity for the model to determine a cost-effective way to cope with variability.

Another common approach is to introduce “time slices”, as implemented, e.g., in the TIMES model class [34], the LIMES model [35], [36] or the ReEDS model [37], [38]. Time slices capture different representative situations in the power sector, such as winter vs. summer, day vs. night and weekday vs. weekend. This concept is quite successful in capturing the variability of demand with a low number of time slices, as demand follows very regular patterns. However, an adequate representation of the correlation between demand on the one hand, and the more complex patterns of wind and solar power on the other, requires a relatively large number of time slices, leading to high numerical complexity [39], [40].

Finally, the MESSAGE model [29] introduces an additional balance equation for “flexibility”, in which flexible generation from an endogenous mix of dispatchable plants and electricity storage technologies balances flexibility requirements from variable demand and VRE supply,

characterized by a single constraint. The parameterization does not build on technical parameters or have a rigorous definition, but is derived from a limited ensemble of scenarios of a generic unit-commitment model with six nodes. It is unclear to what extent the approach represents power-sector variability for a range of regions and system configurations. A refinement might entail a more comprehensive parameterization and potentially a differentiated representation of different aspects of variability, for example by finding specific “flexibility” constraints for different time scales of load balancing.

The research community using long-term energy-economy models works on consolidating different approaches and developing best practices. Explicit modeling of some aspects of variability, implicit representations of other aspects using exogenous parameters, and/or soft-coupling with high-resolution models can be part of the solution. In correspondence to the above limitations of the prevalent approaches we suggest three criteria that a sound representation of variability should fulfill. First, it should be comprehensive, i.e., it should represent the most important aspects of demand and renewable supply variability. Second, it should be robust, i.e., its parameterization should be valid for a broad range of different energy system configurations. To this end the representation should either build on a rigorous definition of economic impacts of variability or on physical constraints that capture variability such that the correct economic impacts are induced. Third, a representation should be flexible, i.e., it should allow for an endogenous choice of different integration options, including adjustments of the non-VRE part of the energy system.

This paper presents a novel modeling approach for representing variability in long-term energy-economy models that aims at meeting these criteria. It is based on a model representation of residual load duration curves² (RLDCs) that change depending on the model-endogenous share and mix of VRE. RLDCs are a purely physical concept only requiring demand and VRE supply data without using exogenous cost parameters, yet it delivers the economic impact of both the major aspects of demand and VRE supply variability. RLDCs reflect the temporal distribution of demand and residual demand³, which determines the cost-efficient mix of non-VRE power plants. Changes of the RLDC with increasing VRE shares induce potential shifts in the non-VRE

² The RLDC is derived by subtracting the time series of VRE power supply from the time series of power demand and then sorting the resulting curve in descending order. See a more detailed introduction in the appendix A.1.

³ Residual demand is the power demand after subtracting VRE supply.

capacity mix. Moreover, RLDCs capture so-called “profile costs”, which depend on the temporal matching of VRE supply profiles with (residual) power demand. While profile costs can be even negative at low shares, e.g., for solar PV in many US regions, profile costs are the largest cost impact imposed by VRE variability at higher shares of VRE (>15%) ([22], [41]), i.e., they tend to be substantially larger than costs related to additional balancing or grid requirements of VRE.⁴ Ref. [33], [41] show that RLDCs capture the three main drivers of profile costs: a low capacity credit and resulting requirements for firm capacity, reduced utilization of the capital embodied in dispatchable plants⁵, and over-produced VRE generation. There are several integration options that reduce profile costs [41]. Apart from a shift towards less capital-intensive dispatchable plants the RLDC approach covers endogenous investment in seasonal energy storage via hydrogen and methane (power-to-gas storage). This provides some flexibility to mitigate the challenges and corresponding costs of power sector variability. Other integration options such as short-term storage and demand-side management (DSM) cannot easily be modeled (as discussed in Section 2.4). In addition, the approach contains model equations that in a stylized way account for minimum load limits of dispatchable generators, ancillary services and operating reserve requirements. Note that these additional methodical elements rely on exogenous parameters that are difficult to parameterize in a rigorous way. By contrast, the parameterization of the RLDC, which is the core of the approach, can be parameterized more stringently from VRE supply and load data.

In this paper we describe the RLDC approach and demonstrate its impact on the results of REMIND-D, a long-term energy-economy model for Germany ([42], [43]). There are two reasons why we use this model. First, the German government has both adopted an ambitious climate-change mitigation target and agreed on a nuclear phase out; at the same time, the share of VRE has risen considerably in the past two decades and carbon capture and storage (CCS) as a mitigation option faces serious acceptance concerns. Hence, the potential role of renewables, in particular wind and solar PV, in climate change mitigation is crucial and its variability can be expected to have a major impact on future mitigation scenarios. Second, the model structure and equations of REMIND-D resemble those of the global integrated assessment model REMIND-R,

⁴ The reason is that the supply of additional VRE plants is correlated with the existing VRE plants and thus the matching with residual demand gets unfavorable at higher VRE shares.

⁵ In principle, the utilization is reduced for all dispatchable plants; however, for capital-intensive base-load plants this is particularly costly.

which will allow a transfer of the RLDC equations. Stylized representations of power sector variability are particularly relevant for global models because their wide scope limits the level of model details.

The paper is structured as follows. The RLDC approach is explained in Section 2, including a representation of power-to-gas storage. Impacts of this approach on model results of REMIND-D are reported in Section 3. Finally, conclusions are drawn in Section 4.

2. Method

In this section we describe the RLDC approach. In section 2.1 we present the core: a representation of load duration curves (LDCs) and RLDCs in long-term energy-economy models. In Section 2.2 we suggest two complementary elements: a constraint that accounts for minimum generation requirements of dispatchable plants, and a constraint that requires operating reserves for sufficient flexible generation (introduced in Ref. [29]). In Section 2.3 we demonstrate how the approach allows a representation of power-to-gas storage in which renewable over-production is stored as hydrogen or methane. Finally, in Section 2.4 we outline the limitations that prevail to date.

2.1. The RLDC approach

The preparatory step for the RLDC approach is implementing an approximation of the LDC. In the subsequent step, the RLDC is represented in terms of the change of the LDC induced by VRE. LDCs are already used in some long-term energy-economy models, [14]. While typically a step function is applied to approximate the shape of the LDC, here we suggest a more accurate representation that also contains a triangular part. Hereby the LDC is reduced to three parts: A base load box, an intermediate load triangle⁶, and peak capacity including a reserve margin (Figure 1). The approximation is derived from regional demand data such that the deviation between the linear pieces and the actual LDC data is minimized and the integral of the original LDC is conserved. The reserve margin provides additional firm capacity to assure reliability in case of contingency events, e.g., outages of plants or grid lines. Different values are applied in

⁶ Note that these terms are indicative and do not necessarily match other definitions of base, intermediate or peak load.

different power systems. In our application we assume a capacity margin of 20% of peak load⁷ in absence of VRE (or equivalently 20% of residual load in case of approximation of the RLDC, see below). The International Energy Agency argues that capacity margins in the order of 20% are common in liberalized electricity markets [44, p. 23], and show this figure also specifically for Germany [45, p. 163], [46, p. 8]. Note in addition that this figure corresponds to the U.S. standard [29].

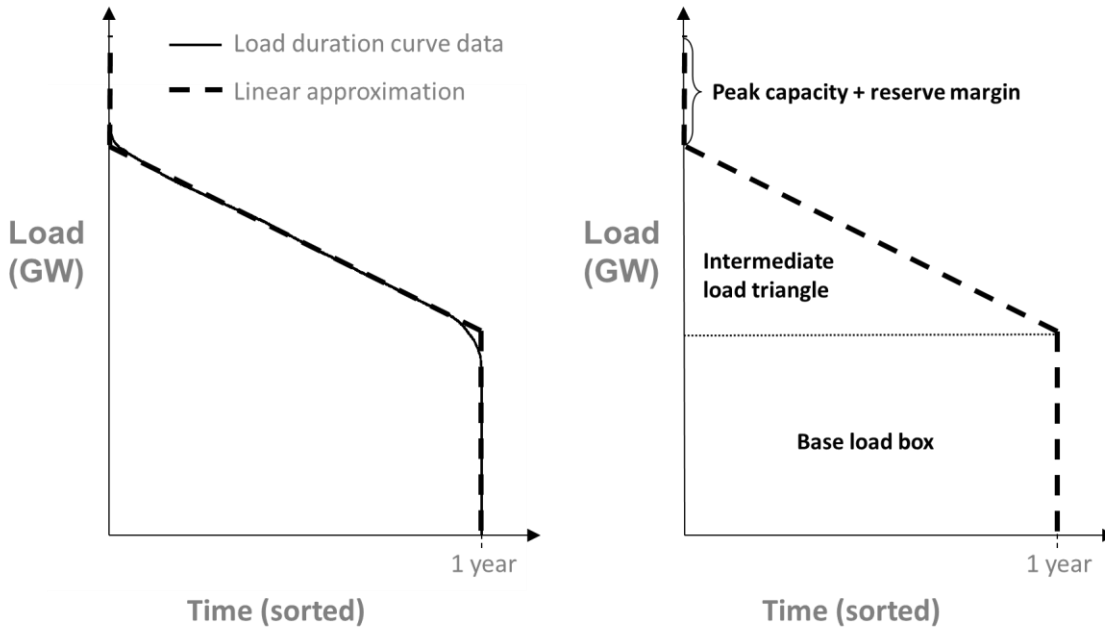


Figure 1: The LDC is approximated by a linear function (left). Three different parts build up the load: A base load box, an intermediate load triangle, and a capacity margin. (schematic illustration)

With growing VRE shares, dispatchable power plants merely cover residual load: The RLDC depends on the share and mix of wind power and solar PV, and the linear approximation in the model changes accordingly (Figure 2). The change in the RLDC induced by VRE is controlled in terms of four parameters (C_{box} , C_{Δ} , C_{peak} , v_{box}), which are functions⁸ of the generation shares of wind power and solar PV. Prior to model optimization, the function parameters are derived from a data analysis based on VRE supply and power demand data. More precisely, each parameter has been first estimated for a broad range of wind and solar shares and then fitted with a polynomial of the two variables wind and solar share. While increasing the degree of the

⁷ Peak load refers to the highest load hour of a specific year.

⁸ Note that VRE over-production could be regarded as a fifth parameter. However, this parameter does not need to be estimated, because it can be calculated from the other four parameter and the given solar and wind share.

polynomial allows for an increased fit accuracy, it also increases model complexity and run time. Considering this tradeoff we chose a third-degree polynomial (with mixed terms), which allowed for a coefficient of determination R^2 of about 0.8.

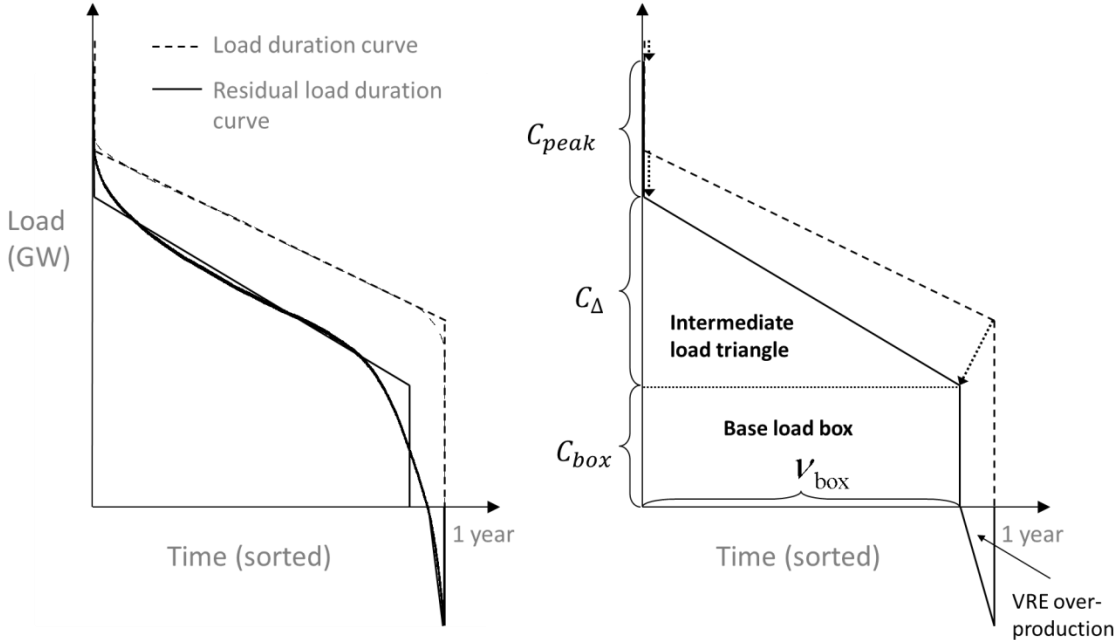


Figure 2: The RLDC is approximated by a box and a triangle (left). This is implemented into the model as a transformation of the original LDC (right). The transformation is controlled by the change of four parameters (C_{box} , C_{Δ} , C_{peak} , v_{box}) that are functions of the VRE generation share and mix of VRE power. (schematic illustration)

By endogenizing the RLDC changes we enable the model to anticipate the resulting long-term effects, i.e., VRE contribution to total capacity, the reduced utilization of dispatchable plants and the over-produced VRE generation. Analogously, when investing in dispatchable power plants, the model considers the long-term capacity requirements for covering base load, intermediate load and the capacity margin, as well as the long-term development of annual full load hours (FLH) (i.e. capacity factors⁹) over the lifetime of the dispatchable plants. Note that as a part of this also the total peak capacity requirements are fulfilled, which has been formulated in a single model equation in Ref. [29].

The RLDC approach allows for the simultaneous optimization of investment as well as operation decisions in the power system under the consideration of short-term variability: Every unit of installed capacity of a dispatchable technology can in principle operate in each part of the three

⁹ The capacity factor of a generating technology is a number between 0 and 1 given by the relation of its full-load hours compared to the total hours of one year.

parts of the RLDC (base, intermediate and capacity margin). In every time step (typically 5 to 10 years) the overall installed capacity of a technology is split cost-efficiently among the three parts of the RLDC. The FLH of each generating unit in this time step depend on the part of the RLDC where the unit is operating. While in principle every generation technology can contribute to covering each part of load, the specific economic characteristics of the heterogeneous technologies suggest typical operation decisions. For example, nuclear and coal plants (in particular lignite) have high specific investment costs and low variable costs, and thus require high operating hours, with operation predominantly as base-load. In contrast, gas turbines will mainly be dispatched to cover peak load. For each part of the RLDC model equations balance the respective electricity and capacity demand and supply (see Appendix A.2).

The above approximation uses an intermediate load triangle. Alternatively, the RLDC can also be approximated with three boxes as illustrated in Figure 3 (left). Analogously to the above formulation these boxes would change endogenously with growing VRE shares. This approximation is less accurate but might ease the implementation for two reasons. First, it avoids some equations of higher order that are needed to properly dispatch capacities in the intermediate load triangle (see Appendix A.2). Second, the boxes could be implemented similarly to a small number of representative time slices, which are already implemented in a number of models. The main novelty of our approach is the dynamic change of heights and widths of the time slices depending on VRE shares (Figure 3, right), which substantially reduces the number of time slices required to capture the variability of load, wind and solar.

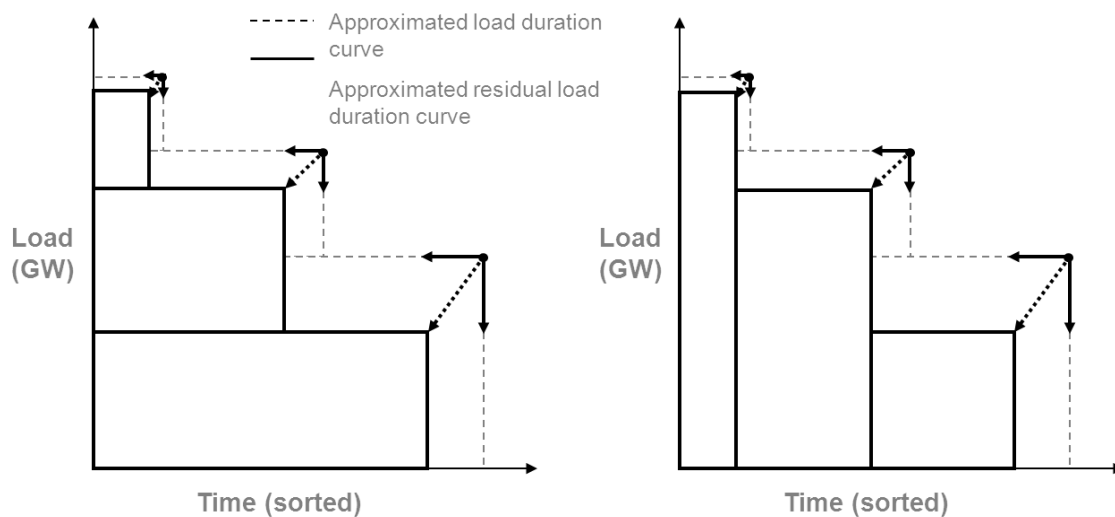


Figure 3: Using boxes as an approximation of the RLDC is less accurate than a stepwise linear approach (which results in an intermediate load triangle) but might be easier to implement. In the horizontal formulation (left), each box represents a load band, which is characterized by a specific width corresponding to a number of hours over the year. In the vertical formulation (right), each box is characterized by a specific height corresponding to load values. As the vertical formulation is similar to modeling time slices, the RLDC approach might benefit from experience made with this approach in a number of models. The main difference compared to traditional time slice approaches is the dynamic change of heights and widths depending on VRE shares.

2.2. Additional elements

There are two additional elements used to complement the RLDC approach, which account for uncertainty (i.e. stochasticity) of VRE and load as well as for power system flexibility, i.e., the ability of the non-VRE part of the system to adjust generation on short notice to balance residual load.

The first additional element of the RLDC approach is a “minimum load box”. There are three different reasons why in the next decades, VRE will not be able to cover total power demand in a single moment. First, thermal generators have a limited flexibility of reducing their output. There is a minimum load each plant unit must supply before it has to shut down, which imposes some time lag until it can supply again. Second, the provision of ancillary services like frequency control currently requires operating reserves that are necessary to maintain the security of power systems, although VRE generators can provide active power control [47]. One part of operating reserves are dispatchable capacities that run at partial load to be able to increase their output on short notice. Third, combined heat and power (CHP) plants might need to generate power even in situations of over-produced VRE because of required heat generation. As a result a minimum amount of dispatchable capacity remains supplying throughout the year even in situations when demand could actually be fully met by the VRE generators in place.

The height of this continuous band of dispatchable generation is sometimes referred to as “grid flexibility” or “system flexibility” [48], [49], [50]. We incorporate this in a “minimum load box”, which is a fourth part of the RLDC. Current estimates for minimal dispatchable electricity generation in Germany are 15 – 28 GW (13 – 20 GW for ancillary services [51] and 2 – 8 GW from CHP plants [52]), which is 15% – 27% of peak load (103 GW). An empirical estimation for Germany shows a slightly higher figure of 30% for 2012-14 [53]. The modeled height of the minimum load box (h_{min}) should be parameterized for future power system, because this constraint becomes binding only at high VRE shares (above about 25% VRE).

However, future values are uncertain and there are both drivers that increase and decrease the minimal dispatchable generation in a system. Requirements for operating reserves might increase with VRE and thus a part of the system's minimal dispatchable generation would increase. On the other hand, there are drivers that might compensate this effect. Improved VRE forecasts, more efficient power markets (e.g. shorter trading periods in intra-day markets, or later gate-closure), the capability of VRE to contribute to ancillary services, and the use of power electronics to provide ancillary services, might reduce the need for dispatchable operating reserves. In addition, must-run constraints might decrease because power plants flexibility might increase for two reasons. First, technical characteristics of power plants are likely to change, e.g., minimum load of individual thermal plants could decrease. Second, heat and power generation will be more and more decoupled leading to a flexibilization of CHP plants (e.g. by increasing the use of heat storage). However, such future developments are difficult to foresee in quantitative terms. Due to the significant potential to relax minimal dispatchable generation in the future we assume the minimum load box height to be about one third of current values, i.e., 10% of peak load (Figure 4). In principle, one could introduce an endogenous relation between this height and VRE deployment; however, we believe that this would add complexity without improving robustness of results, as the endogenous relation cannot be accurately parameterized.

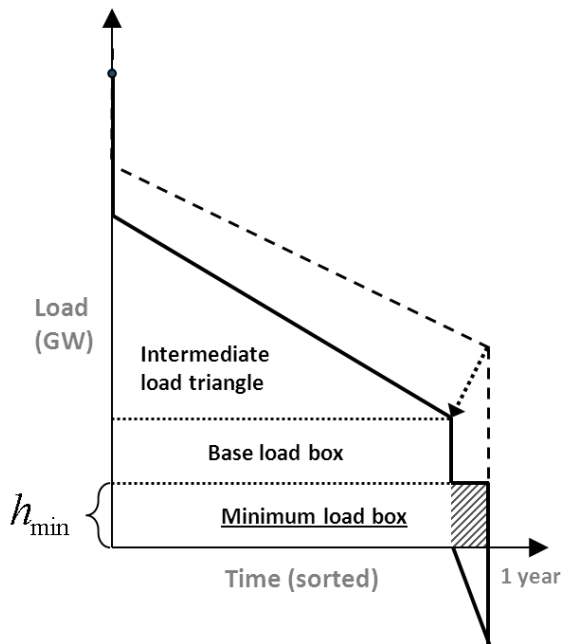


Figure 4: A minimum load box accounts for limited system flexibility, which requires some supply from dispatchable capacities throughout the year.

The “minimum load box” increases the over-produced amount of VRE (shaded area) and allows some dispatchable plants to run at a constant output throughout the year. The chosen height of the minimum load can affect the results, especially in scenarios with large shares of VRE power. Relaxing the constraint decreases the over-produced VRE generation and hereby directly increases the optimal VRE generation share. In addition, this decreases integration challenges of VRE and could induce additional investment in VRE capacity.

In addition to the implementation of RLDCs, we implemented a balance equation for “flexibility” (equation (15)), which was developed and parameterized for the MESSAGE model [29]. Flexibility coefficients α are attributed to each source of generation and load to approximate a level of flexibility that is either provided (positive coefficients for dispatchable generation) or required (negative coefficients for load and VRE generation). The coefficients α_{te} are multiplied with the respective annual generation from each technology G_{te} . The negative coefficient for load α_{load} is multiplied with total annual load G_{total} . These terms are combined in a balance equation such that positive flexibility provisions cover negative flexibility requirements.

The second additional element is the balance equation for “flexibility” described in the introduction and first presented in Ref. [29] as “operating reserve constraint”. The constraint aims at assuring sufficient operating reserves and flexible generation to cope with additional balancing, ramping and cycling requirements with growing VRE shares. The above-described model representation of RLDCs does already incentivize investments in more flexible thermal plants¹⁰ and the minimum load box also addresses some aspects of flexibility. A combination with “operating reserve constraint” is possible without double-accounting of flexibility requirements. However, the additional operating reserve constraint turns out to be not binding in the scenarios results in this paper.

2.3. Power-to-gas storage

The RLDC approach allows for modeling power-to-gas storage endogenously. The suggested model realization of power-to-gas storage consists of an electrolysis process that transforms over-production from VRE supply to hydrogen, followed by a potential second step in which

¹⁰ The reduced utilization of thermal power plants induces a shift towards less capital-intensive intermediate and peak load power plants, which are more flexible than base-load plants.

hydrogen can be further transformed to methane. A key determinant for the profitability of power-to-gas is the amount of available over-production and its frequency distribution. Both depend on the VRE share and mix and can be derived directly from geometric shape of the RLDC. This is illustrated in Figure 5. The model endogenously chooses an electrolysis capacity. The shaded area equals the resulting amount of over-production that is input to electrolysis. The width of this area is given by the frequency distribution of over-production and determines the FLH of the electrolysis. Hydrogen can be directly used, e.g., in the transport sector, fed into the natural gas grid (on a limited scale), or alternatively be transformed to methane. The latter option requires CO₂ as an input, which can be provided from biogas fermentation or synthesis. Power-to-gas storage and other seasonal storage types that are characterized by high converter costs and low reservoir costs can easily be represented within the RLDC approach by assuming that the reservoir is only filled and emptied once a year. This is equivalent to saying that the reservoir has to be as large as the total amount of electricity that is stored over one year – a somewhat conservative approach, which is however acceptable due to the low reservoir costs. By contrast, short-term storage technologies and DSM are more difficult to represent in the RLDC concept and in long-term energy-economy models in general (see next section).

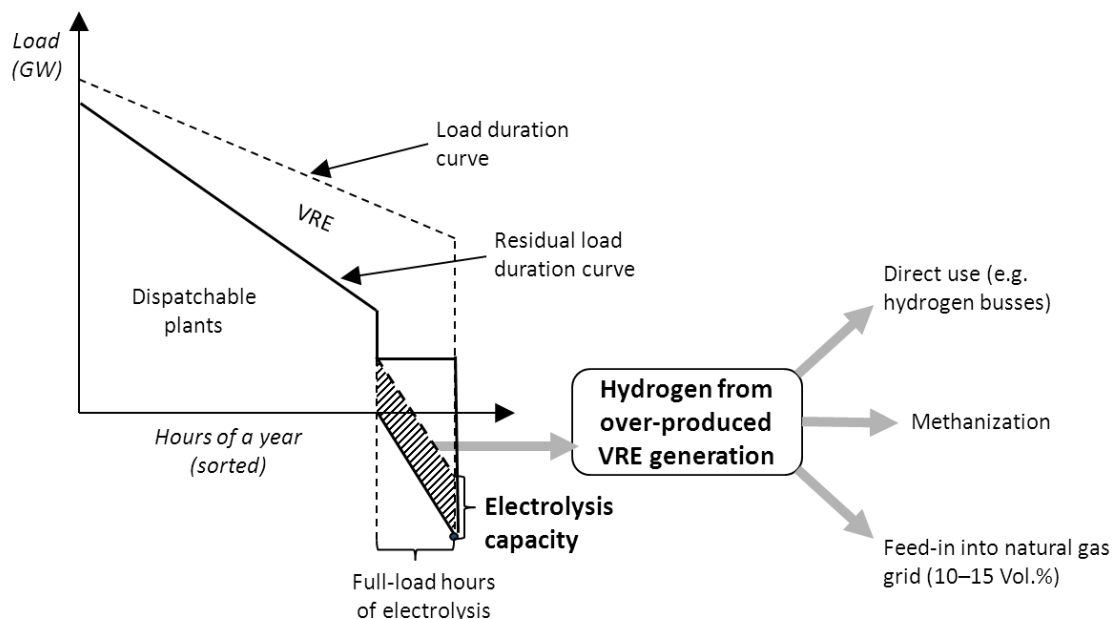


Figure 5: The representation of RLDCs allows implementing power-to-gas storage via hydrogen and methane.

2.4. Limitations of the RLDC approach

As every simplifying method, the RLDC approach has shortcomings. Some aspects of variability require high modeling detail and can therefore hardly be captured in such an aggregated approach. Note that many of these shortcomings apply to long-term models in general and point to promising fields of further methodological research.

By using duration curves, information about the temporal sequence for generation and demand is lost. This hinders a direct and accurate representation of some aspects that are characterized by these short-term dynamics such as demand-side management, short-term storage, and flexible thermal generation¹¹.

Short-term storage and demand-side management technologies are characterized by the fact that they frequently shift small amounts of electricity in time. Sequential temporal information about residual load is necessary for modeling their operation, e.g., their number of annual cycles and the resulting optimal capacity and amount of electricity shifted in time. As a consequence these options of mitigating integration challenges are not represented in the RLDC approach. This biases the scenario results towards underestimating the deployment of VRE by overestimating back-up requirements and over-produced VRE generation. To overcome this drawback short-term storage and DSM could in principle be considered by reshaping the RLDC parameterization such that it account for the electricity-shifting impact of these technologies. However, the impact of short-term storage and DSM on the RLDC is very complex. Thus a parameterization would require using a highly-resolved production cost model for a range of wind and solar penetrations.

In addition, losing the sequential order of load and VRE supply creates a challenge for representing aspects of flexible thermal generation such as ramping and cycling constraints, minimum load, minimum up and down times, part-load efficiency, operating reserve requirements, and corresponding costs. In general, a long-term energy model cannot guarantee that there is sufficient flexibility to reliably balance supply and demand in the calculated optimal capacity expansion path. Other highly-resolved production cost models are designed for this purpose, which can be soft-coupled to a long-term model (see for example REF. [54]–[56]). The error made by using only a long-term model depends on both the general modeling of power

¹¹ Flexible thermal generation refers to the ability of thermal power plants to adjust their generation on short notice over a wide range with low associated costs.

sector variability (VRE and load) and the use of additional constraints to implicitly account for flexibility. While we did not quantify the error (which would have required a highly-resolved model coupling) we argue that it is small for models using the RLDC approach for three reasons:

1. Accounting for RLDCs alone does already incentivize investments in more flexible thermal plants. The reduced utilization of thermal power plants induces a shift towards less capital-intensive intermediate and peak load power plants, which are more flexible than base-load plants.
2. Many studies show that the costs for providing sufficient flexibility with increasing VRE shares are low, i.e., less than 6 EUR per MWh of VRE (<10% of VRE generation costs) even at high VRE shares ([57]–[59]). The substantial uncertainties of future technology costs are much larger than these small additional costs, which will therefore only have a minor effect on the findings derived from scenarios that span technology cost ranges.
3. Additional elements complement the use of RLDCs, such as the “minimum load box” and an operating reserve constraint (Section 2.2) and hereby approximately account for some aspects of flexibility such as minimum load of thermal power plants and operating reserves.

Beyond the fundamental RLDC structure that can be rigorously derived from time series, implicit representations of detailed aspects rely on parameters that mimic future system properties in a rather stylized way. These parameters are often difficult to define rigorously because a number of system-dependent small-scale aspects need to be collapsed into a single value. As this paper focuses on introducing the conceptual side of a new approach of representing power sector variability, the main effort was not on deriving the parameters. We have derived them from empirical estimates, highly resolved model analyses and qualitative arguments as described in the respective sections, but further refining the parameterization and adopting it to regionally differentiated power systems would be a valuable future improvement.

Another important limitation of using RLDCs is that modeling power exchange between multiple regions is highly challenging. Again this is because the chronological order of load and VRE supply is lost and consequently the RLDC of connected regions are not synchronous in time. The RLDC approach is most suitable to represent a single region or regions that do not transfer significant amounts of electricity between them. In addition, finding a representative RLDC

parameterization of a region requires an aggregation which will neglect some spatial heterogeneity. The aggregation of spatial aspects does also hinder an accurate accounting of additional grid costs. Implementing transmission cost penalties can help overcoming this deficit, see for example Ref. [32].

3. Application of the RLDC approach in REMIND-D

For a first application of the RLDC approach we use the REMIND-D model, which is described in Section 3.1. In Section 3.2 we investigate the impact on scenario results of modeling power sector variability with the RLDC approach.

3.1. Model and data

REMIND-D is a long-term energy-economy model for Germany; a detailed description of the model and the calibration data is available in Ref. [42]. The equations are derived from the 2010 version of the global model REMIND-R 1.2, [60], [61], which did not include any representation of variability in the power sector – this feature was only added in REMIND 1.3 and improved since then [32]. REMIND-D finds the welfare-optimal mitigation pathways until 2050, considering technological mitigation options in the power, heat and transport sector. The optimal solution is calculated by an inter-temporal, non-linear optimization algorithm, assuming perfect foresight and accounting for endogenous technological learning. Hereby, it combines a Ramsey-type growth model that reflects general macroeconomic dynamics and a detailed bottom-up energy system module. The temporal resolution is in steps of five years to keep the complexity of the numerical model manageable, which is sufficient to represent investment decisions. However, short-term power sector variability must be accounted for in a stylized way. The model REMIND-D is used as a first application of the RLDC approach.

For parameterizing the RLDC approach in REMIND-D we use wind and solar generation data from actual quarter-hourly feed-in data from German Transmission System Operators (TSOs) for 2011, which is publicly available on the respective websites¹². To simulate higher VRE shares we scale up the time series linearly. This approximation in principle tends to overestimate the correlation of VRE supply and hereby would overestimate VRE integration challenges.

¹² www.50hertz-transmission.net, www.tennetso.de, www.amprion.net, www.enbw.com

However, this is somewhat balanced by a spatial aggregation¹³ over the four different TSO zones in Germany, which implicitly assumes perfect domestic transmission (“copper plate assumption”). The geographical dispersion of wind power in 2011 is regarded as fairly representative also for future wind power expansion.

For parameterizing demand, hourly data for the German power system in 2011 were downloaded from the ENTSO-E website¹⁴. The temporal profile is assumed to remain the same for the future. The data were interpolated linearly to match the quarter-hourly resolution of VRE generation. The variability of offshore wind power supply is parameterized with wind onshore data due to a lack of offshore wind data.

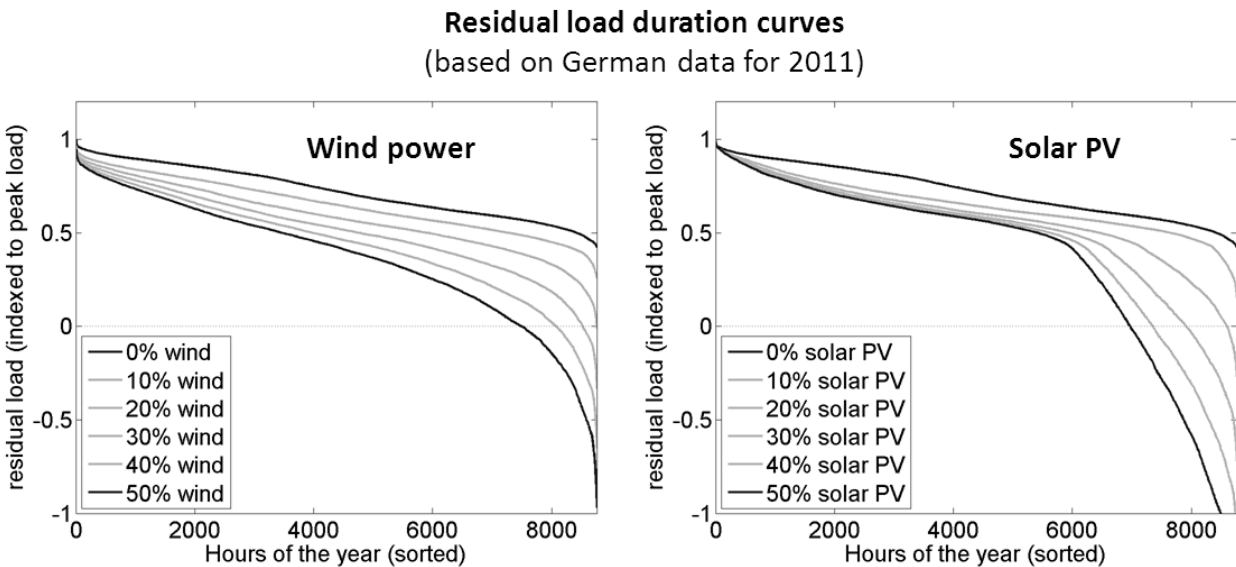


Figure 6: Residual load duration curves for different shares of wind power and solar PV based on German load and VRE feed-in data for 2011. These data are used for the RLDC parameterization in the long-term model. Note that the shares are given as potential VRE generation (including curtailment) relative to total annual load.

Figure 6 shows a part of the ensemble of RLDCs on which the parameterization in the long-term model is based. It displays the development of RLDCs for increasing shares of either wind power or solar PV (the parameterization considers a broader range of shares and mixes of wind and solar). These RLDCs retain the same shape independently of the historic year that provides the annual load and VRE supply data (in our case 2011). However, systematic changes in the future temporal distribution of load can change RLDCs. Such changes are uncertain and difficult to

¹³ The spatially aggregated times series for wind power (and solar PV) is derived by adding the 2011 feed-in data of all four TSO zones resulting in a spatial average weighted by the VRE generation in each zone.

¹⁴ <https://www.entsoe.eu/data/data-portal/>

estimate, which is why we believe that using the current distribution is the best approximation for the time being.

3.2. Results: impacts of modeling variability in REMIND-D

We compare the REMIND-D model outputs with the new RLDC approach to a REMIND-D version without any representation of variability and integration challenges. We examine both the direct impact of variability on the deployment of VRE and the indirect effect on the residual system like dispatchable generation and storage requirements. Moreover we determine broader impacts like the mitigation cost penalty due to variability and separately estimate the effect of power-to-gas storage. A comparison between model results of REMIND-D with those of other model-based scenarios looking at the future development of renewables in Germany is beyond the scope of this paper. A dedicated analysis of this kind [62] revealed that the application of the RLDC approach leads to VRE generation trajectories for Germany that are well within the range projected by detailed, bottom-up simulation models.

To maintain focus on the RLDC approach, we use a predefined scenario. All results shown here apply the boundary conditions of the ‘continuation’ scenario in [43], which enforces a set of trends in the electricity and transport sector. Nuclear power plants are phased out according to legislation and carbon capture and storage (CCS) is assumed to be unavailable because of its poor prospects in Germany [63]. Coal power plants are allowed to reduce their annual generation or serve solely as reserve power plants before the end of their technical lifetime if cost-efficient (from a system perspective), e.g., due to high CO₂ prices. We show results for the baseline scenario, where no carbon budget is applied, and for a standard ambitious mitigation scenario, i.e., achieving the German policy target of 80% emissions reduction in 2050 relative to 1990.

The RLDC approach is implemented including the additional elements of a minimum load box and the operating reserves constraint introduced in Ref. [29]. A first result is that the latter constraint, if parameterized according to Ref. [29], is not binding in any scenario, i.e., that even though the RLDC approach focuses on capturing profile costs, it tends to provide sufficiently flexible generation. The main reason is that an RLDC with high VRE shares induces a shift towards typical peak- and mid-load capacities such as gas or biomass plants, which not only reduces profile costs but also provide enough flexible generation, in contrast to base-load plants like coal plants that are characterized by supplying less flexibility.

The direct impact of the RLDC approach on modeled VRE generation levels is shown for the baseline scenario (Figure 7, left) and the standard mitigation scenario (Figure 7, right). The consideration of variability with the RLDC approach substantially reduces the power generation from VRE, by 35% in the baseline scenario and by 27% in the mitigation scenario in 2050. The shaded areas show sensitivity results for the VRE generation with 20% higher and lower VRE capital costs. In the mitigation scenario, varying the costs of VRE does only slightly change deployment levels, since there are hardly alternative mitigation options in the power sector to reach the ambitious reduction target if both nuclear and CCS are constrained. The strong effect of the RLDC approach is mainly induced by over-production. However, this can be used for producing hydrogen via electrolysis.

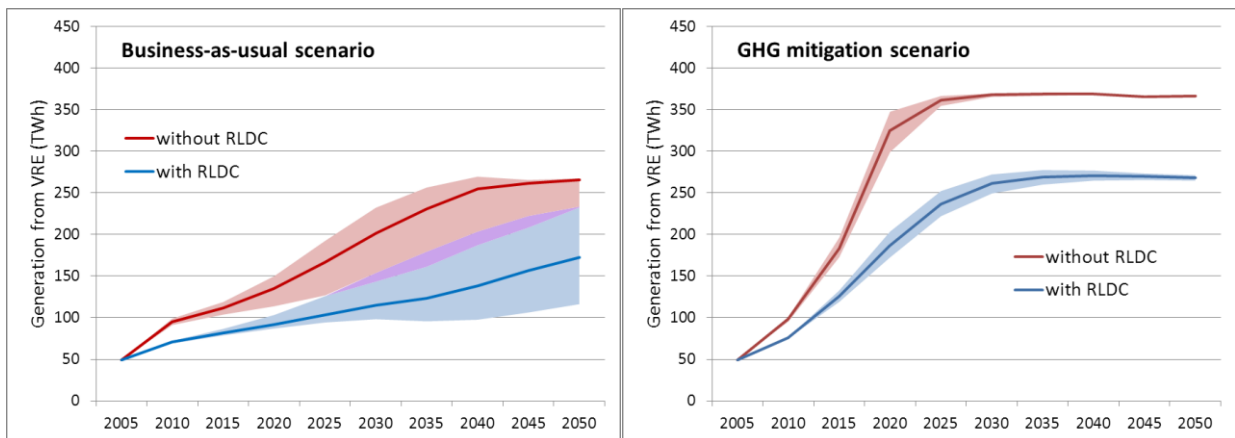


Figure 7: Representing variability with the RLDC approach substantially reduces the power generation from VRE, by 35% in the baseline scenario and by 27% in the mitigation scenario in 2050. The shaded areas show sensitivity results for the VRE generation with 20% higher and lower VRE capital costs.

In the mitigation scenario up to 25% of VRE generation cannot directly be used in 2050 because it exceeds demand or interferes with dispatchable minimum load requirements. Figure 8 (left) shows that this amounts to up to 90TWh of potential annual curtailment, of which over 80% are then used as input to power-to-gas storage, with endogenous capacity of roughly 40GW of hydrogen electrolysis and 2GW of methanization. Due to efficiency losses the 90 TWh of curtailed electricity production is decreased by 46% to an actual stored energy of 49 TWh (35TWh hydrogen, 14TWh methane) (Figure 8, right).

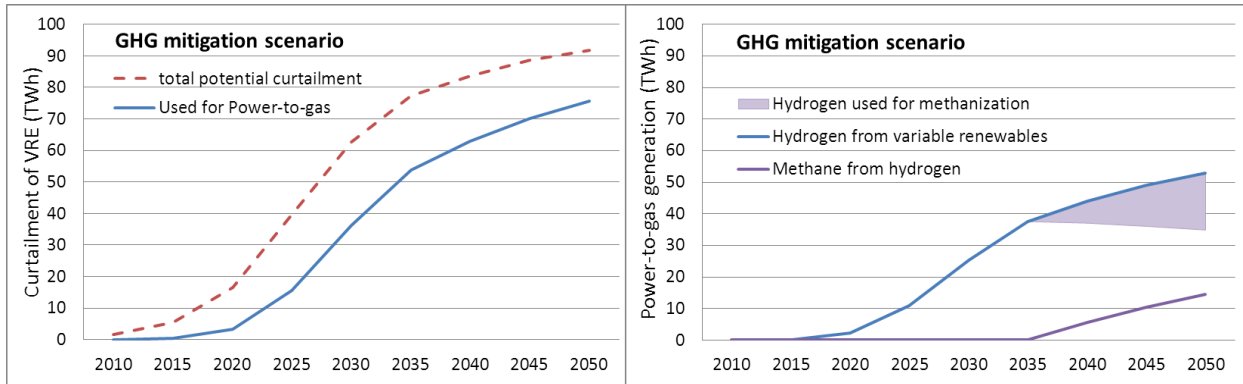


Figure 8: A high fraction of total curtailment of VRE can be used for power-to-gas storage (left). A small fraction of hydrogen is transformed into methane (right).

Comparing electricity generation and the non-VRE capacity mix for the mitigation scenario with and without the RLDC approach gives insights as to the indirect effect of variability, i.e., how the non-VRE system changes due to variability of demand and VRE. Figure 7 shows that the share of VRE generation in 2050 reduces from 72% to 55% with the RLDC approach, with the difference being made up by more dispatchable generation. Total power generation decreases because power demand is price-elastic and the costs of power generation increase with power sector variability. Dispatchable renewables like biogas, hydro-power and geothermal plants are used to a considerable extent, increasing the total share of renewables to 90% in 2050. In contrast to the case without RLDCs, a small share of fossil generation from combined-cycle gas plants remains in the power system, because in an autarkic German system the mismatch between VRE supply and residual load at high VRE shares is larger than the limited potential of dispatchable renewable energy sources. These combined-cycle gas plants replace coal power plants that are decommissioned before the end of their technical lifetime, driven by decreasing FLH for dispatchable plants and a high CO₂ price (85 €/t CO₂ in 2020). These gas plants also provide sufficient flexibility to meet the operating reserve constraint.

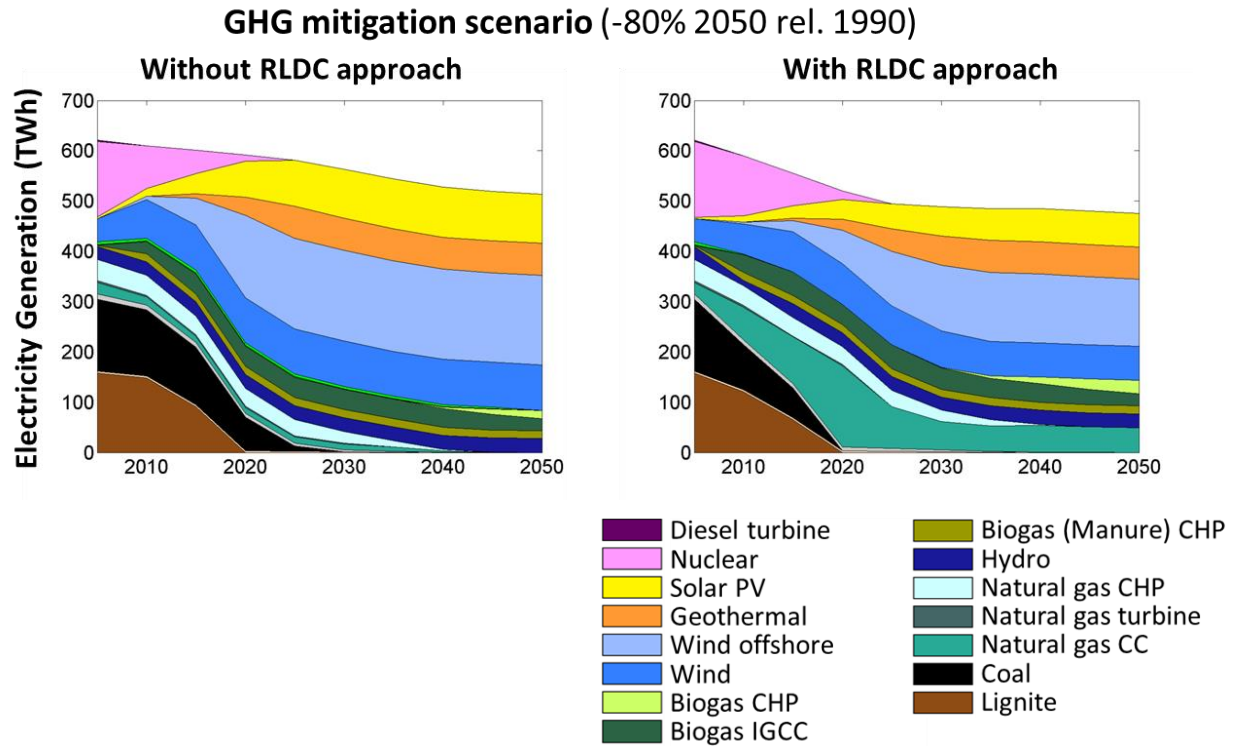


Figure 9: The development of the electricity generation mix without (left) and with (right) the RLDC approach, keeping all other scenario characteristics unchanged.

Figure 10 illustrates how the model approximation of RLDCs acts in the GHG mitigation scenario. While potential VRE generation increases to about 75% (including curtailment) of electricity generation in 2050 the base load box reduces to a width of about 5000 full-load hours per year (left side, the minimum load box is not shown here). For 2030 Figure 10 (right) shows the endogenous annual dispatch of dispatchable generators, i.e., how the different parts of annual residual load are covered. The minimum load box is filled with must-run generation from natural gas CHP plants as well as partly dispatchable RES generation from geothermal and hydro plants. Intermediate load is covered with generation from biogas plants and combined-cycle natural gas plants. Peak load is covered by combined-cycle and open-cycle gas plants. In addition, 14 GW of capacity reserve are required (reserve margin of 20% of peak load), which is provided by capacity that has been decommissioned for daily operation such as mainly hard coal or lignite capacity (compare with Figure 11).

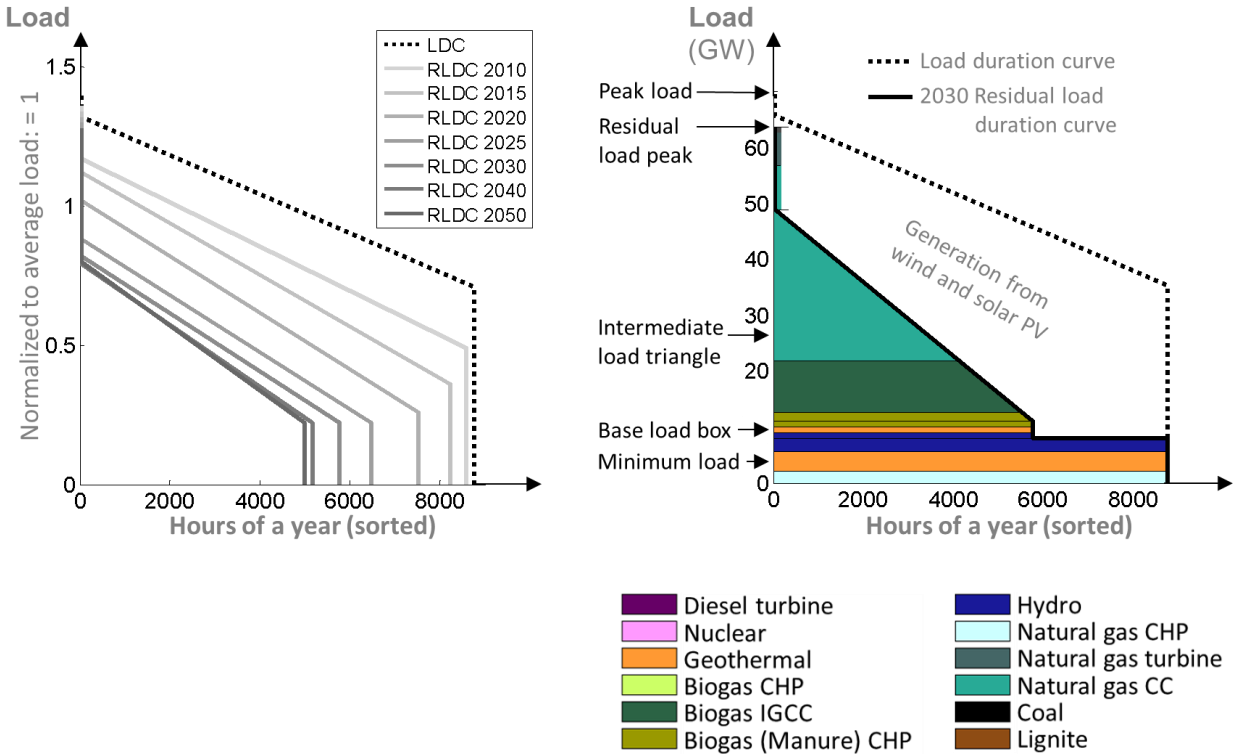


Figure 10: The endogenous development of the linear approximation of RLDCs shows how residual load transforms in the GHG mitigation scenario as VRE generation grows in time (left). For 2030 the annual dispatch of dispatchable generators illustrates how the different parts of annual residual load are covered (right).

Figure 11 shows the development of the capacity mix for non-VRE capacities. With the RLDC approach, required generation capacity in 2050 is three times higher than in the case without RLDCs even though the total electricity generation is slightly reduced. Combined-cycle gas plants and gas turbines (open cycle gas plants) are cost-efficient options to provide firm capacity due to their low specific-investment costs.

This significant increase of total installed generation capacity is caused by a more accurate reflection of demand variability in particular peak demand situations and the low capacity credit of VRE with the RLDC approach. Without the new approach, REMIND-D does not account for power sector variability, which is tantamount to assuming that power demand and supply are homogenous in time¹⁵ [28]. This corresponds to a situation in which power demand is constant and VRE provides base-load electricity and reduces capacity requirements as if they could supply constant power output. This bias strongly underestimates capacity requirements in real power systems with high VRE shares. In the scenario without the RLDC approach, installed firm

¹⁵ This is different in the global model REMIND-R, which applies share-dependent cost markups to wind and solar power to represent storage, transmission and curtailment needs since version 1.3 [32].

capacity could only serve about 35% of peak capacity. Moreover, gas power plants are discriminated against because their specific value for covering peak load is not reflected when neglecting variability.

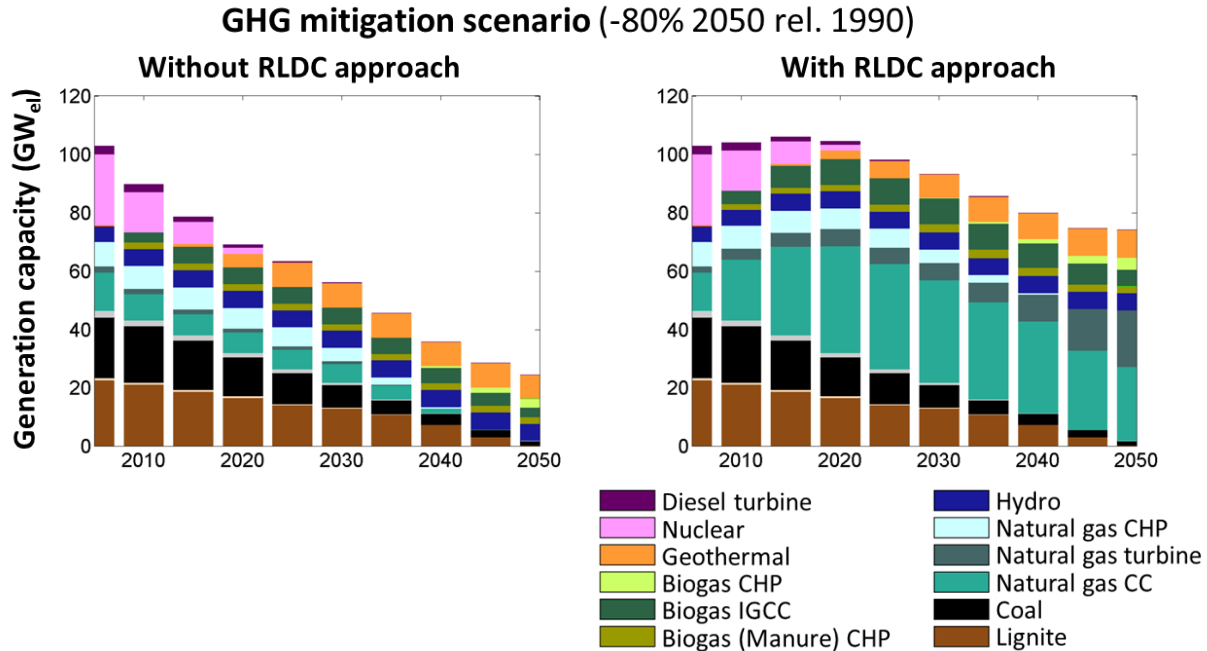


Figure 11: The development of the non-VRE capacity mix without (left) and with (right) the RLDC approach.

With the RLDC approach, mitigation becomes more expensive because the important mitigation option VRE incurs additional integration costs on a power system level. Also, the mitigation effect of a unit VRE capacity is reduced. The power generation from VRE needs to be partly curtailed or transformed by costly power-to-gas storage with limited efficiency, while more dispatchable plants and generation are required to provide capacity and operating reserves.

Figure 12 shows the mitigation costs of the ambitious mitigation scenario, in terms of cumulative discounted consumption losses over the period 2010-2050, compared to the baseline scenario. Here we also analyze a model version with an intermediate implementation step: a representation of RLDCs but without power-to-gas storage. From left to right we add elements of the novel method resulting in three different mitigation cost figures. With the RLDC but without power-to-gas storage, mitigation costs increase from 1.20% to 1.41%. Thus, introducing variability enlarges mitigation costs by 18%. This is a considerable increase given that the technology portfolio remains unchanged and the new equations only affect the power sector. On the other hand the consideration of variability fundamentally reshapes the operation and planning of the

power system and limits renewable energy, which is the only low-carbon energy supply option in these scenarios. Power-to-gas storage can reduce this increase by about one third, with mitigation costs amounting to 1.34% consumption losses under implementation of the full RLDC approach. The impact of variability on mitigation costs might further decrease with the availability of more alternative mitigation options in the power sector such as nuclear power or CCS, as well as with increased flexibility options such as demand-side management and large-area pooling, which would change the RLDC due to a spatial aggregation of VRE supply and demand over a large area like Europe. As the analyzed scenarios assume full autarchy of the German power sector, there is no cross-border electricity trade that might improve the match between VRE supply and demand and thereby reduce integration challenges through European cooperation.

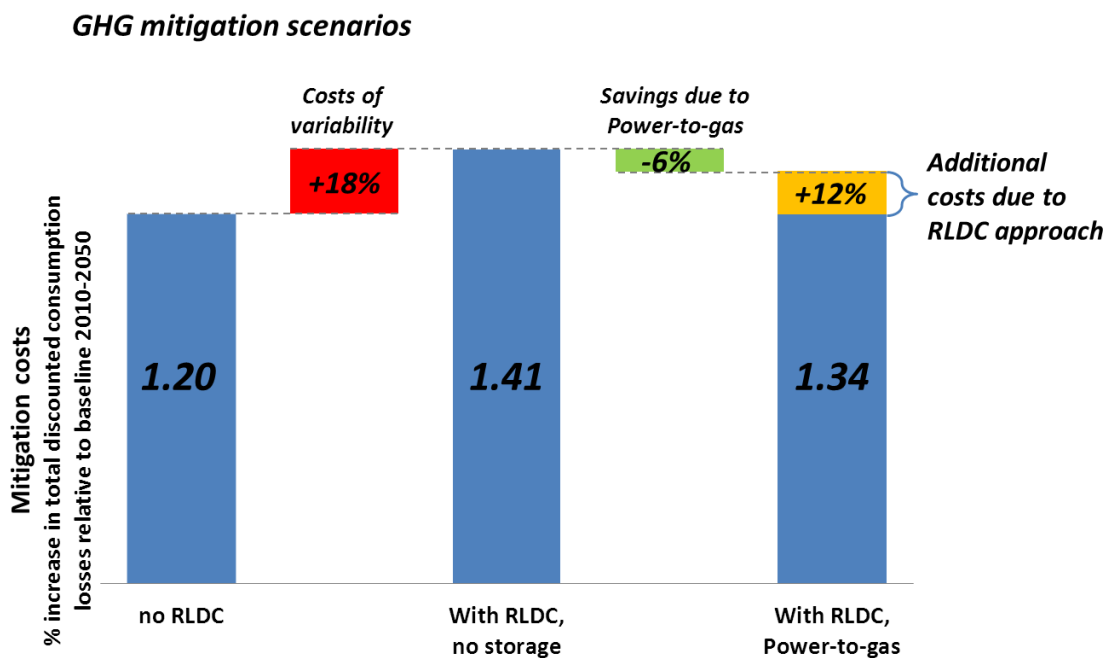


Figure 12: Mitigation costs in terms of cumulative discounted consumption losses compared to the respective baseline scenarios. Considering variability enlarges mitigation costs by 18%. Power-to-gas storage can reduce this increase by one third.

4. Summary and conclusion

Improving the representation of power sector variability is among the highest priorities for the further refinement of integrated energy-economy climate models used for analyzing long-term climate change mitigation scenarios. Our novel approach can serve as an appropriate model representation of power sector variability because of three main merits. It firstly covers the most

important variability impacts, secondly is valid for a broad scenario space with different energy system configurations and thirdly provides flexibility of choosing among multiple pathways of integrating VRE. In an application for the model REMIND-D, the substantial impact of the approach on model results confirms that power sector variability matters. Thus, implementing the RLDC approach in a long-term energy-economy model would improve the robustness and credibility of mitigation scenarios. In particular, it would foster a more accurate estimation of mitigation costs and the role of VRE in low-carbon transformation scenarios.

The novel approach incorporates power demand and supply variability through the use of RLDCs. RLDCs are a purely physical concept based only on demand and VRE supply data, yet deliver the economic impact of the most important aspect of variability of demand and supply. The unfavorable matching of the temporal profiles of VRE supply with demand results in so-called profile costs due to lower utilization of dispatchable power plants. These profile costs can be substantial at high VRE shares and tend to be higher than integration costs for additional grid and balancing requirements of VRE ([22], [41]). More specifically, for a broad range of shares of wind and solar PV the novel approach represents a number of cost-driving aspects of power sector variability such as firm capacity requirements, the reduction of FLH of non-VRE plants, over-production of VRE and minimum load and operating reserve constraints. Hereby, the modeled energy system can endogenously adjust in response to increasing VRE deployment, namely via a shift in the non-VRE capacity mix, deployment of power-to-gas storage or curtailment of over-produced VRE generation.

We demonstrate the RLDC approach with REMIND-D [42], [43], a long-term energy-economy model for Germany. The impacts on the results compared to a version without any representation of variability are substantial. With the RLDC approach implemented, power generation from VRE reduces by 35% in the baseline scenario and by 27% in an ambitious mitigation scenario in 2050. The model requires significantly more non-VRE capacity, in particular gas-fired plants. The consideration of variability changes key macro-economic figures: Mitigation costs increase by 18%. The availability of power-to-gas storage can reduce this increase by one third. Note that the scenarios neglect cross-border electricity trade that might improve the match between VRE supply and demand and reduce integration challenges.

Future research should address the remaining limitations of the RLDC approach. An important question is how to address short-term storage technologies and demand-side management in long-term energy-economy models. Finding a representative RLDC for a large region requires assumptions about how to aggregate regional-specific VRE supply and demand patterns. Assuming perfect grid interconnections (copper plate assumption) overestimates the smoothing effect on variability by pooling variable demand and VRE supply over large areas. In addition, the RLDC approach does not allow to explicitly modeling power exchange between sub-regions and corresponding grid infrastructure. Hence, the approach is most appropriate for models that resolve large regions, which do not trade electricity among each other. Complementing the approach with a carefully parameterized function for additional grid costs of VRE is a promising way forward. Also, better parameterization of those complementing parameters that cannot be rigorously derived from physical quantities and time series, e.g., minimum load band and reserve margin requirements, for a range of power sector set-ups would improve the validity of the approach. The basic direction of improving the RLDC approach is to complement the endogenous representation of RLDCs with other elements, such as cost parameters for detailed variability aspects and exogenous deployment of integration options like short-term storage, which can be derived from higher-resolved models.

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A. Appendix

A.1. Residual load duration curves

This section briefly introduces LDCs and RLDCs. Electricity demand is variable (see Figure 13, left) and price-inelastic (in the short-term) and consequently electricity providers need to adjust generation instantly. Variable demand also implies that power plants differ in their annual FLH. This can be illustrated with a LDC, which is derived by sorting the load curve, i.e., the time series of power demand for one year or longer (Figure 13) from highest to lowest values. The maximum of a LDC indicates the capacity required to cover total annual electricity demand, which equals the area below the curve. The curve is shaped by the temporal distribution of variable demand, which determines the potential FLH of power-generating plants.

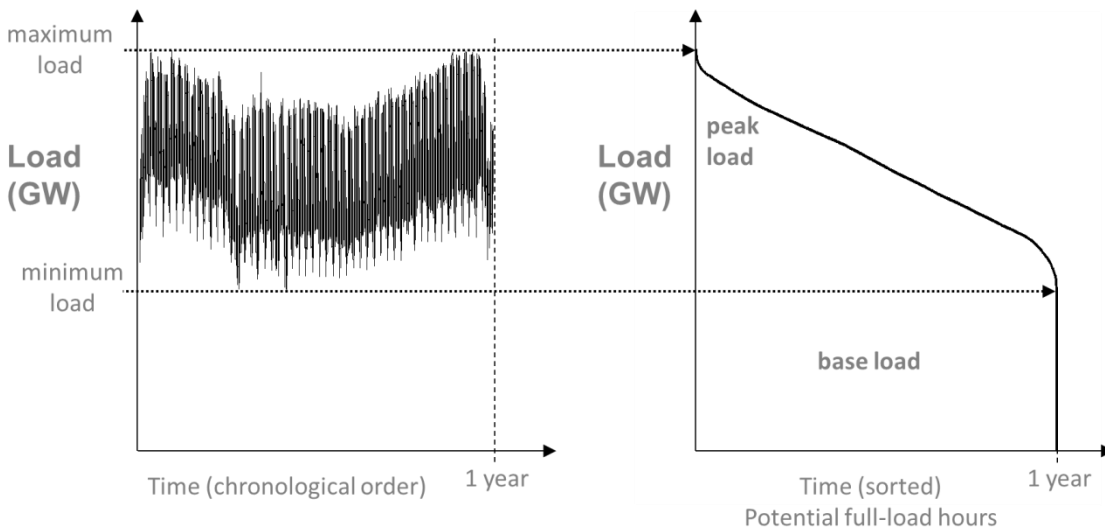


Figure 13 (schematic): The LDC (right) is derived by sorting the load curve (left) in descending order.

The residual load curve is a time series that is derived by subtracting the time series of VRE from the time series of power demand (Figure 14, left side). The RLDC is then derived by sorting the residual load curve in descending order (Figure 14, right side). The area between the LDC and the RLDC is the potential electricity generation from VRE. Note that the shape of the area does not indicate the temporal distribution of VRE supply, due to different sorting of load and residual load, yet this information is not relevant for the RLDC approach. RLDCs are shaped by the temporal distribution of residual demand and hereby determine the potential FLH of dispatchable plants, which are crucial to the optimal technology mix in a power system. In that sense the RLDC replaces the LDC in a situation with VRE.

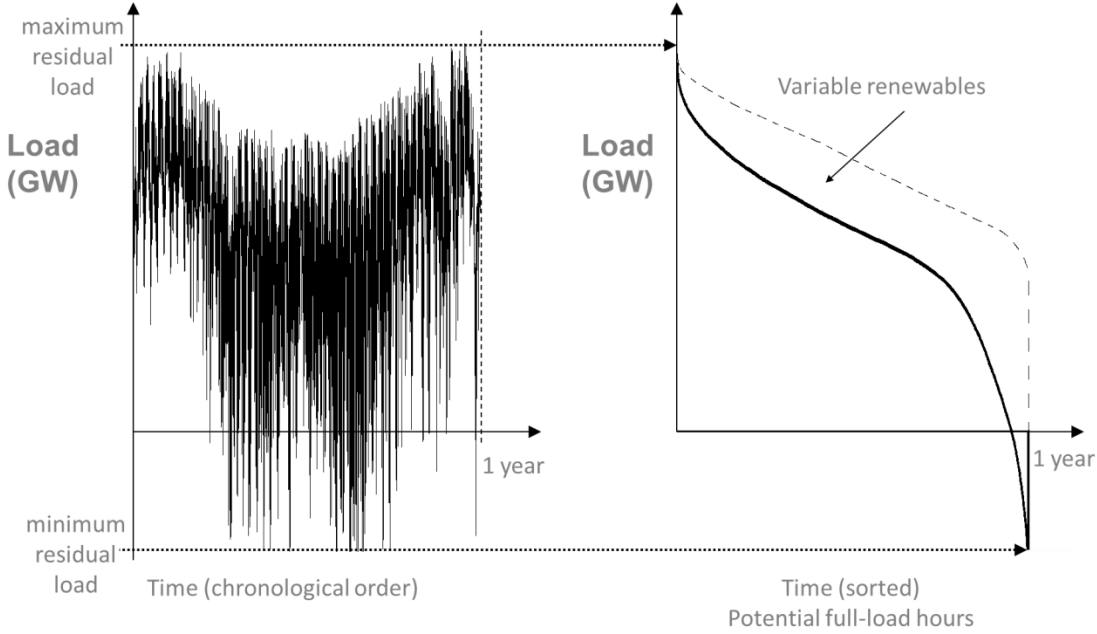


Figure 14 (schematic): The residual load curve (a time series) is derived by subtracting the time series of VRE from the time series of power demand (left). The RLDC (right) is derived by sorting the residual load curve in descending order. The area in between the RLDC and the LDC equals the potential contribution of VRE.

A.2. Equations of the RLDC approach

In the following we show the core equations of the RLDC approach. All equations are valid for each time step, i.e., every variable depends on the time, which is not shown here. For every non-VRE power generating technology te the respective total endogenously installed capacity $C_{tot,te}$ is endogenously decomposed into three parts ($C_{box,te}$, $C_{\Delta,te}$, $C_{peak,te}$) that operate in the three different parts of the RLDC: the base load box, the intermediate load triangle, and the peak-capacity part (Figure 15, left).

$$C_{tot,te} = C_{box,te} + C_{\Delta,te} + C_{peak,te} \quad (1)$$

When adding all the capacity units that operate in one part of the RLDC, e.g., for base load $C_{box,te}$, this should equal the total capacity demand for this RLDC part, e.g., C_{box} .

$$C_{box} = \sum_{te} C_{box,te} \quad (2)$$

There are two more analogous equations for C_{Δ} and $C_{reserve}$. C_{box} , C_{Δ} and $C_{reserve}$ also are endogenous variables determining the shape of the RLDC, which depends on the endogenous share and mix of VRE. The relation between share and mix of VRE and the shape of the RLDC is exogenously parameterized as described in Section 2.1.

There are two balancing equations for the generation in the base load G_{box} and intermediate load part G_{Δ} .

$$G_{box} = C_{box}v_{box} = \sum_{te} C_{box,te}v_{box} \quad (3)$$

$$G_{\Delta} = \frac{1}{2}C_{\Delta}v_{box} = \sum_{te} C_{\Delta,te}v_{\Delta,te} \quad (4)$$

The capacity factors v for the different parts of the RLDC endogenously depend on the generation share and mix of VRE. As a consequence the RLDC approach is non-linear and cannot be applied in purely linear models. Planned outages of power plants are assumed to be conducted in the "1 - v " part of the year, i.e., while the plants are not needed. Unplanned outages are compensated by the additional reserve capacity margin. The capacity factor of units that operate in the base load part v_{box} , is independent of the specific technology te . By contrast the capacity factors in the intermediate load part $v_{\Delta,te}$ is different for different technologies te . This is because the capacities need to cover the triangle shape as illustrated in Figure 15 (right). Each capacity $C_{\Delta,te}$ has an average capacity factor $v_{\Delta,te}$ and covers a range of capacity factors from $v_{\Delta,te}^{min}$ to $v_{\Delta,te}^{max}$ as defined in the model equations 5 and 6.

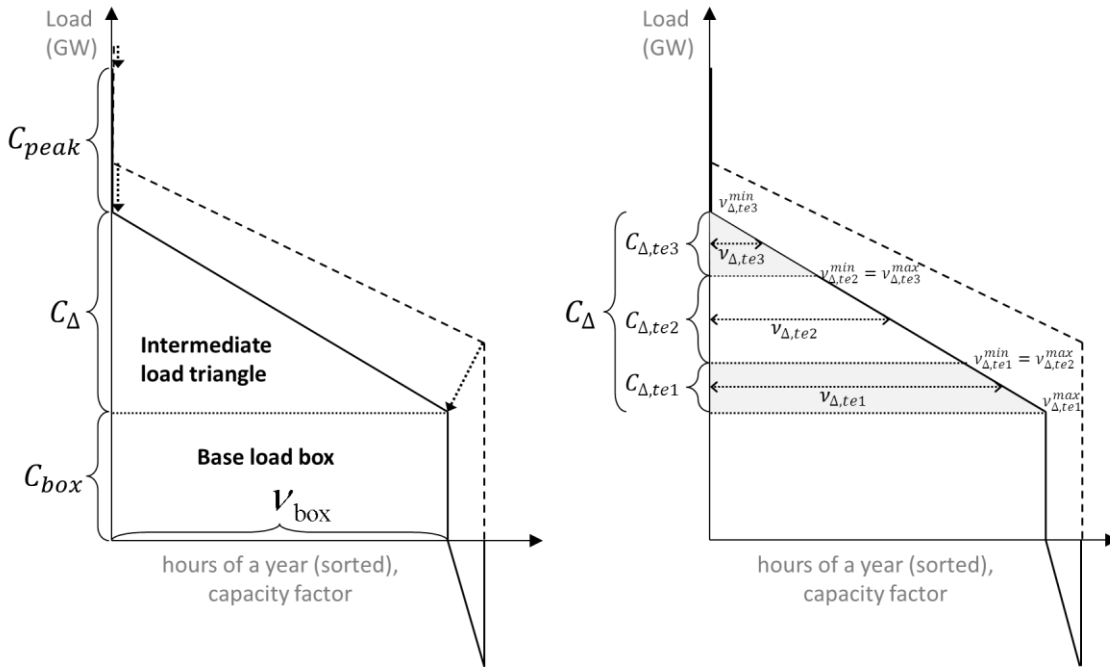


Figure 15: Four parameters describe the RLDC shape (left). The capacity units $C_{\Delta,te}$ that operate in the intermediate load triangle have different capacity factors $v_{\Delta,te}$ in order to cover the triangle shape (right).

$$v_{\Delta,te}^{min} := v_{\Delta,te} - \frac{1}{2} C_{\Delta,te} \frac{v_{box}}{C_{\Delta}} \quad (5)$$

$$v_{\Delta,te}^{max} := v_{\Delta,te} + \frac{1}{2} C_{\Delta,te} \frac{v_{box}}{C_{\Delta}} \quad (6)$$

Note that all these variables are endogenous. As a consequence, the order of the capacities in the intermediate load triangle is endogenously chosen in the optimization. It can change between different time steps of the scenario driven, e.g., by changing fuel costs and carbon prices. It needs a few more equations to ensure that the intermediate load capacities stack and their endogenous capacity factors behave such that their generation covers the triangular shape. If a modeler wants to avoid these additional equations there are two alternatives. One could exogenously determine the order of stacking within the intermediate load triangle, or use boxes instead of the triangular approximation (Figure 3).

The additional equations for matching the triangle build on probability theory. An RLDC can be interpreted as a cumulative distribution function $F(v)$ of load¹⁶. $F(v)$ also represents the cumulative distribution of capacity over the range of capacity factors. The triangle part of the RLDC corresponds to the distribution of capacities $C_{\Delta,te}$ and can be described with a constant density function $f(v) = \frac{d}{dv} F(v) = C_{\Delta}/v_{box}$, i.e., capacity is distributed uniformly over the capacity factor range 0 to v_{box} . To realize this for the capacities $C_{\Delta,te}$ in the model, we make use of a law from probability theory: every density function is uniquely determined by all its moments, i.e., there is no other probability distribution with the same sequence of moments. In fact, already the first four low-order moments determine some fundamental properties of a distribution such as mean value, variance, skewness and kurtosis. Hence, we add model equations that make sure that a number of low-order moments of the distribution of $C_{\Delta,te}$ match those of a uniform density function. The resulting cumulative distribution of $C_{\Delta,te}$ would consequently converge to the triangular shape of the RLDC.

The moments ($k \in N$) of any density function $f(v)$ can be defined with the expectation operator E :

¹⁶ Note that it would need to be flipped horizontally and indexed to peak load to be identical to the typical format of a cumulative distribution function.

$$E(v^k) := \frac{\int_{-\infty}^{\infty} v^k f(v) dv}{\int_{-\infty}^{\infty} f(v) dv} \quad (7)$$

As discussed above, the objective is to derive equations that equal the moments of the ideal triangular distribution $E_{\Delta}(v^k)$ with the moments $E_{te}(v^k)$ of the endogenous capacities $C_{\Delta,te}$ and capacity factor ranges $v_{\Delta,te}^{min}$ and $v_{\Delta,te}^{max}$:

$$E_{\Delta}(v^k) = E_{te}(v^k) \quad (8)$$

We start with calculating the left side. For the intermediate load triangle, $f(v)$ is a uniform function $f(v) = C_{\Delta}/v_{box}$ in the limits of $v = 0$ and $v = v_{box}$ and the corresponding moments can be calculated directly:

$$E_{\Delta}(v^k) = \frac{\int_0^{v_{box}} v^k \frac{C_{\Delta}}{v_{box}} dv}{\int_0^{v_{box}} \frac{C_{\Delta}}{v_{box}} dv} \quad (9)$$

$$= \frac{1}{k+1} v_{box}^k \quad (10)$$

For evaluating the right side of equation (8), the model-endogenous moments can be derived by decomposing the integrals in equation (7) into additive parts that correspond to technologies te and their capacity factors range, $v_{\Delta,te}^{min}$ to $v_{\Delta,te}^{max}$:

$$E_{te}(v^k) = \frac{\sum_{te} \int_{v_{\Delta,te}^{min}}^{v_{\Delta,te}^{max}} v^k f_{te}(v) dv}{\sum_{te} \int_{v_{\Delta,te}^{min}}^{v_{\Delta,te}^{max}} f_{te}(v) dv} \quad (11)$$

The density function $f_{te}(v)$ that describes the distribution of the capacity $C_{\Delta,te}$ of a technology is uniform (i.e. constant), because the capacity factors are equally spread around the average capacity factor $v_{\Delta,te}$ in a range from $v_{\Delta,te}^{min}$ to $v_{\Delta,te}^{max}$ (see equations 5 and 6 and Figure 15). $f_{te}(v)$ can therefore be eliminated from numerator and denominator, and the integrals can be solved:

$$E_{te}(v^k) = \frac{1}{k+1} \frac{\sum_{te} (v_{\Delta,te}^{max}{}^{k+1} - v_{\Delta,te}^{min}{}^{k+1})}{\sum_{te} (v_{\Delta,te}^{max} - v_{\Delta,te}^{min})} \quad (12)$$

The denominator can be calculated based on equations 5, 6 and (2):

$$\sum_{te} (v_{\Delta,te}^{max} - v_{\Delta,te}^{min}) \stackrel{(5),(6)}{\implies} \sum_{te} \left(C_{\Delta,te} \frac{v_{box}}{C_{\Delta}} \right) \stackrel{(2)}{\implies} v_{box} \quad (13)$$

Based on this, equation (8) can be evaluated such that the model variables $v_{\Delta,te}^{min}$ and $v_{\Delta,te}^{max}$ behave such that the corresponding capacities $C_{\Delta,te}$ converge to a triangular distribution.

$$v_{box}^{k+1} = \sum_{te} \left(v_{\Delta,te}^{max^{k+1}} - v_{\Delta,te}^{min^{k+1}} \right) \quad (14)$$

Low-order moments already determine some fundamental properties of a distribution such as mean value, variance, skewness and kurtosis. In fact, it can be shown that equation (14) for $k = 0$ is already implicitly accounted for by the equations 5, 6 and (2), and $k = 1$ is accounted for if equation (3) is given in addition. For the shown REMIND-D scenarios, it turned out to be sufficient to fix an additional 2 to 4 moments, i.e., implementing equation (14) for $k = 2 \dots 5$ into the model, to reach fairly well stacking of $C_{\Delta,te}$.

A.3. Equation and parameterization of the operating reserve constraint

In addition to the implementation of RLDCs, we implemented a balance equation for “flexibility” (equation (15)), which was developed and parameterized for the MESSAGE model [29]. Flexibility coefficients α are attributed to each source of generation and load to approximate a level of flexibility that is either provided (positive coefficients for dispatchable generation) or required (negative coefficients for load and VRE generation). The coefficients α_{te} are multiplied with the respective annual generation from each technology G_{te} . The negative coefficient for load α_{load} is multiplied with total annual load G_{total} . These terms are combined in a balance equation such that positive flexibility provisions cover negative flexibility requirements.

$$0 \leq \underbrace{\sum_{te(dispatchable)} \alpha_{te} G_{te}}_{flexibility\ contributions} + \underbrace{\sum_{te(VRE)} \alpha_{te} G_{te} + \alpha_{load} G_{total}}_{flexibility\ requirements} \quad (15)$$

Table 1 shows the flexibility coefficient parameterization used for the model runs in this paper. They are based on the estimates in Ref. [29], which have been derived with a generic unit-commitment model.

Table 1: Flexibility coefficient α per technology

Technology	Flexibility coefficient
Natural gas CC	0.5
Natural gas turbine	1
Diesel turbine	1
Lignite plant	0.15
Coal plant	0.15
Biogas CHP	0.3
Biogas (Manure) CHP	0.3
Biogas IGCC	0.3
Nuclear	0
Geothermal	0
Hydro	0.5
Solar PV	-0.05
Wind	-0.08
Wind offshore	-0.08
Load	-0.1