7-2011

Variable Renewable Energy in Modeling Climate Change Mitigation Scenarios

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Abstract

This paper addresses the issue of how to account for short-term temporal variability of renewable energy sources and power demand in long-term climate change mitigation scenarios in energy-economic models. An approach that captures in a stylized way the major challenges to the integration of variable renewable energy sources into power systems has been developed. As a first application this approach has been introduced to REMIND-D, a hybrid energy-economy model of Germany. An approximation of the residual load duration curve is implemented. The approximating function endogenously changes depending on the penetration and mix of variable renewable power. The approach can thus be used to account for variability and correlations between different sources of renewable supply and power demand within the intertemporal optimization of long-term (energy system) investment decisions in climate change mitigation scenarios. Moreover, additional constraints are introduced to account for flexibility requirements concerning load-following and ancillary services. The parameterization is validated with MICOES a highly resolved dispatch model. Model results show that significant changes are induced when the new residual load duration curve methodology is implemented. With variability, scenarios show that the German power sector is no longer fully decarbonized because natural gas combined-cycle plants are built to complement renewable energy generation. The mitigation costs increase by about 20% compared to a model version in which variability is not taken into account.

JEL classification code: Q42, Q54

1. Introduction

Integrated Assessment Models (IAMs) show that renewable energy sources play an important role in future energy system development in general and for climate change mitigation in particular (e.g. [1], [2]). Especially for the decarbonization of the power sector many mitigation scenarios project substantial shares of renewables. However variable renewable energy technologies (VRE) (e.g. wind turbines, solar PV) lack the flexibility needed to deal with certain aspects of power system operation, in particular balancing supply and demand, since they are difficult to dispatch[1] and subject to significant variability across a wide range of time scales. As the relative amounts (penetration) of time-variable renewables increase, it can be expected that integration will become more challenging and costly, and load-following more difficult to achieve. When optimizing mitigation scenarios variability issues affect investment decisions and mitigation costs. Hence accounting for variability in an Integrated Assessment model (IAM) like REMIND ([3], [4], [5], [6]), GCAM [7], IMAGE ([8], [9]), MESSAGE ([10], [11]) TIAM-WORLD [12], MERGE [13] or DEMETER [14] is crucial for deriving robust mitigation scenarios. However, these kinds of models use long time-steps of years that do not allow for direct representation of short-term variability.

A sound representation of short term variability is important in long-term energy-economy scenarios for two reasons. First, the electricity sector is identified as a key-sector for decarbonization over the course of the next decades, but short-term variability might render necessary significant residual CO_2 emissions that limit the minimum achievable carbon intensity of the power sector. The second reason is that mitigation costs could crucially depend on the additional costs of deploying technical mitigation options at large scale. Hence the integration of variable renewables into the power sector could significantly increase the total mitigation costs.

[1] The output of variable renewable power plants such as wind and solar can hardly be controlled. Moreover in Germany like in many other countries a feed-in priority for electricity from renewable energies has been introduced.

We present an approach that has been implemented into the REMIND-D ([6]) model to combine the long-term energy system investment decisions and the short-term power system variability in a single optimization framework. The representation of short-term variability is stylized to avoid increasing the numerical complexity of the models. However, the new implementation captures the major challenges of integrating variable renewables without explicitly increasing the temporal resolution of the model. Moreover, the dependence of these challenges on the penetration level and the mix of variable renewable resources is accounted for.

2. The Approach – modeling the residual load duration curve

As a first application the presented approach has been implemented in REMIND-D, a hybrid energy-economy model that derives mitigation scenarios for Germany. The same approach is currently being implemented into the regionalized global model version REMIND-R. After introducing the REMIND modeling framework the following subsections describe the elements of the approach. These are 1) the load duration curve (LDC) to include load variations, 2) the residual load duration curve (RLDC) to account for variables renewables and 3) the validation and parameterization with the dispatch model MICOES and the introduction of a flexibility constraint to capture flexibility requirements.

2.1. The REMIND modeling framework

The REMIND model family ([3], [4], [5], [6]) consists of dynamic general equilibrium models of the integrated energy-economy-environment system that maximize welfare based on nested constant elasticity of substitution (CES) macro-economic production functions. The models comprise a detailed description of energy carriers and conversion technologies. By embedding technological change in the energy sector into a representation of the macroeconomic environment, the REMIND models combine the major strengths of bottom-up and top-down models. The equilibrium solution is calculated by inter-temporal non-linear optimization methods, assuming perfect foresight by economic actors. This implies that technological options requiring large up-front investments and having long pay-back times (e.g. via technological learning) are taken into account in determining the optimal solution.

The REMIND models are hybrid models in which the power sector is only one of several interacting components. As a result, adding enough temporal resolution to treat variability explicitly would significantly increase the complexity of the models and overstrain their numerical ability. The temporal resolution for investment decisions is five years. The equations that account for balancing of power demand and supply are thus characterized only by average annual values. Hence temporal variability across a wide range of time scales must be treated in a stylized way in the model.

2.2. The load duration curve

In the first step of the approach the variability of power demand is accounted for by implementing the LDC in the model. The LDC is derived by sorting the load curve i.e. the time series of power demand (Figure 1) in descending order, thereby losing chronological information. A linear approximation (Figure 2) of the LDC is parameterized to allow implementation in the model. Hence in the REMIND-D model the overall load is made up of three different parts: A base load box, an intermediate load triangle, and an additional peak load part. Note that the base load box is not identical with so-called base load. Within the model every generation technology can in theory contribute to covering each part of load. Within the approximation the peak load part does not actually contain load. However it assures that additional generation capacity is built to cover power demand peaks that only occur for a few times during a year. The peak part is parameterized by approximating the upper-left part of the LDC with a vertical line (Figure 2). The approximation of the LDC is derived such that the deviation between the three linear pieces and the actual LDC data is minimized and the integral of the original LDC is conserved. The LDC is a specific representation of the distribution of variable load containing the requirements for generation capacities needed to cover load: How much capacity is needed for residual load and what are the corresponding maximal capacity factors[2]? The capacity factor determines the economics of a power plant and is therefore crucial to the investment decision for a dispatchable power plant. With the integration of variable renewable energy into power systems the load that needs to be covered by dispatchable power plants changes. This effect is captured within the concept of the RLDC that is introduced next.

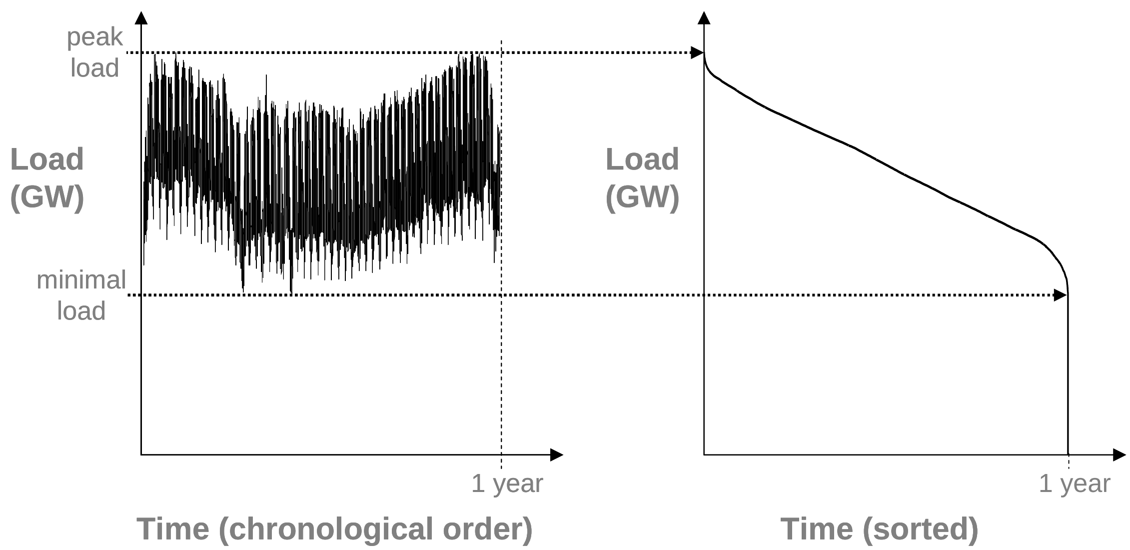

Figure 1 (schematic): ***The LDC (right) is derived by sorting the load curve (left) in descending order.***

[2] The capacity factor of a generating technology is the relation of its full-load hours compared to the total hours of one year. Hence it is a number between 0 and 1.

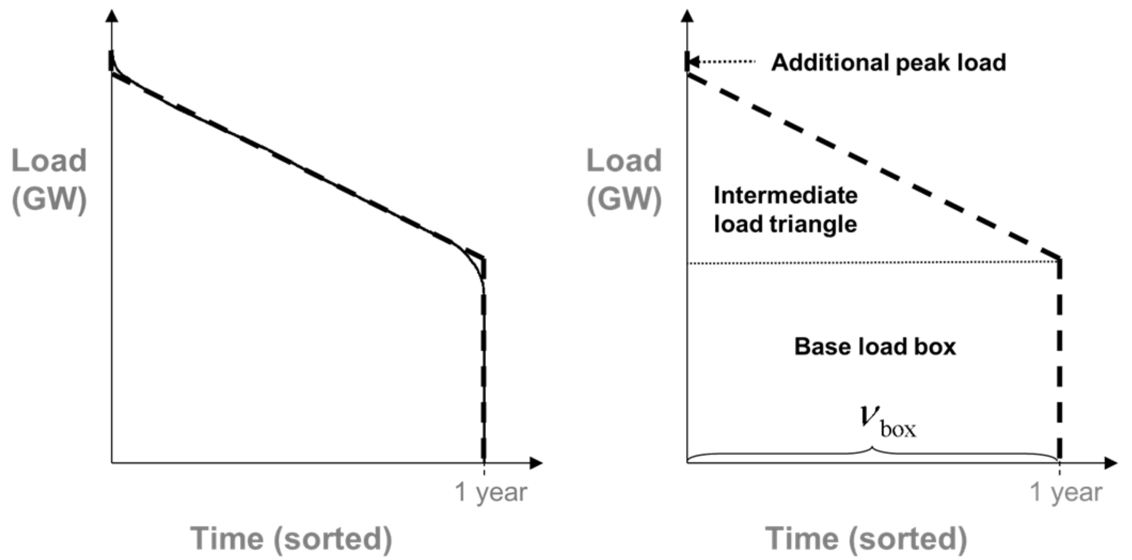

Figure 2 (schematic): ***The LDC is approximated by a linear function (left). Three different parts build up the load: A base load box, an intermediate load triangle, and an additional peak load part. The additional peak load part is approximated with a vertical line in the upper-left part of the LDC.***

2.3. The residual load duration curve

Residual load is the part of the load that cannot directly be covered by variable renewable energy sources. The residual load curve is a time series that is derived by subtracting the time series of variable renewable supply from the time series of power demand (Figure 3).

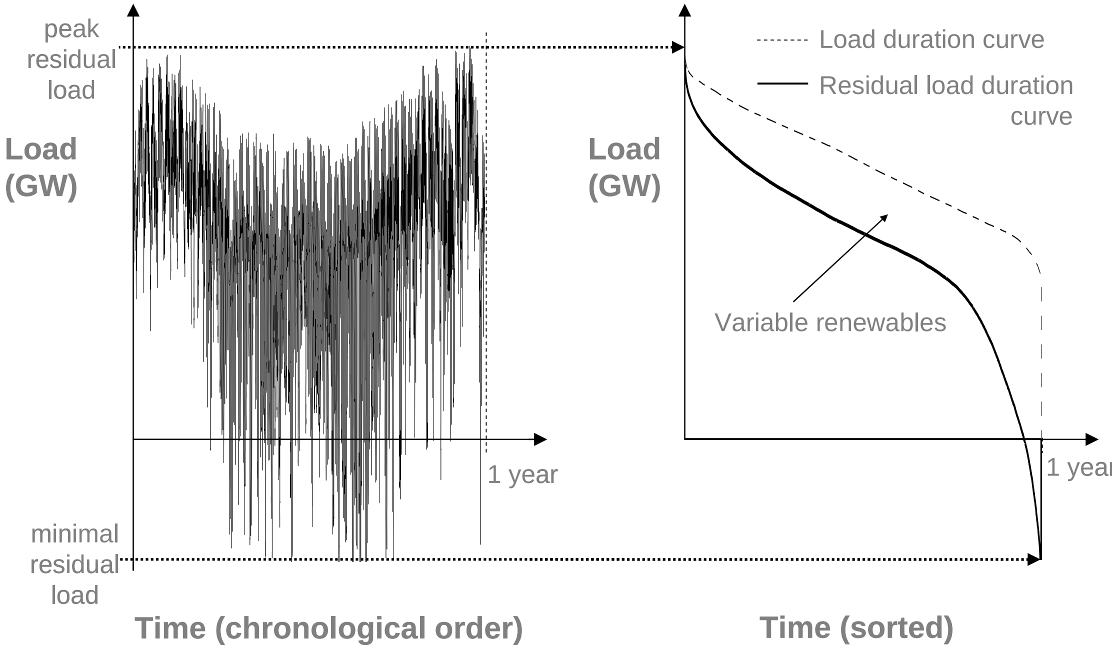

Figure 3 (schematic): ***The residual load curve (a time series) is derived by subtracting the time series of variable renewable supply from the time series of power demand (left). The RLDC (right) is derived by sorting the residual load curve in descending order. The area in between the RLDC and the LDC equals the potential contribution of variable renewables.***

The RLDC is derived by sorting the residual load curve in descending order (Figure 3). The area between the LDC and the RLDC is the potential electricity production of variable renewable energy sources. The negative part at the bottom right side corresponds to situations in which variable renewable supply exceeds demand. This overproduction cannot directly be used to cover load: without export or storage facilities it would need to be curtailed. The positive part of the RLDC must be balanced by dispatchable generation capacities.

Note that the RLDC requires a reordering of the time steps compared to the LDC. The area between the LDC and the RLDC therefore only describes the potential aggregated contribution of VRE to demand, while (chronological) information about the contribution of VRE at individual time steps is lost.

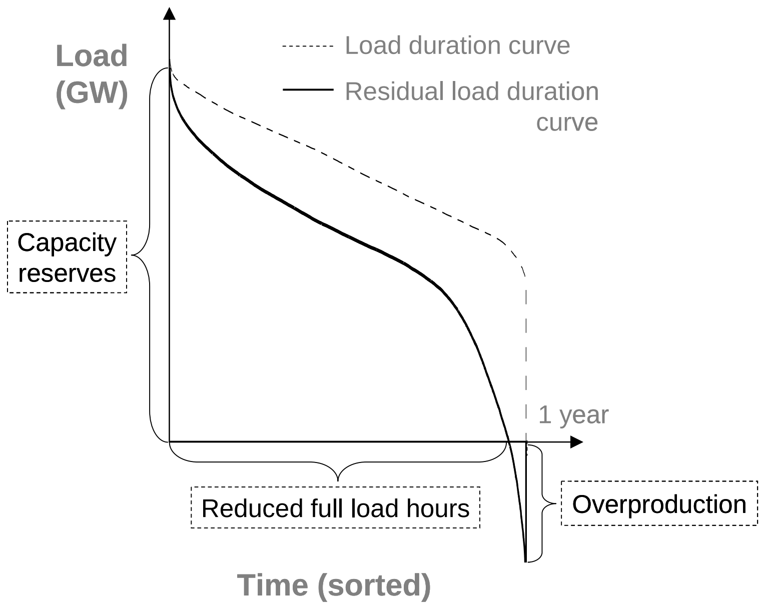

Figure 4 (schematic): ***The RLDC reveals major challenges of integrating variable renewables into power systems: The full-load hours for dispatchable generation capacities are reduced. A small capacity credit of variable renewables requires significant capacity reserves. Overproduction of variable renewable capacities cannot be used directly and might need to be curtailed. Load and feed-in data for Germany is used to derive the curves ([15], [16], [17], [18], [19]).***

The RLDC contains crucial information about variability and correlation of power demand and renewable supply. The concept reveals major challenges of integrating variable renewables into power systems (Figure 4). First, the full-load hours for dispatchable generation capacities are reduced. Without variable renewables there is a significant fraction of load, often referred to as base load, which is not varying and could therefore be balanced by power plants that provide constant output throughout the year. With variable renewables dispatchable power plants need to ramp up and down more often. A reduction of full-load hours tends to require more flexible generation capacity with lower specific investment costs and higher fuel prices, e.g. gas power plants rather than base load power plants.

The RLDC captures a second major challenge: variable renewable capacities provide a rather small capacity credit. The upper-left end of the RLDC converges to the LDC. Hence, there is only a small fraction of variable renewable output that can be relied upon in peak-demand situations. Therefore, the system requires significant dispatchable capacity reserves. Thirdly, overproduction of variable renewable capacities cannot be used directly and might need to be curtailed, if it cannot be stored or transmitted. The potential of transmission to reduce curtailment highly depends on the spatial correlations of distributed renewable supply. With larger distance of interconnected renewable sources the correlations tend to decrease and therefore the resultant output is smoothed and curtailment might be reduced. Storage is another option to make use renewable overproduction. However the potential reduction of curtailment might be limited and costly. This indicates that efficient deployment of variable renewables would rather tend to reduce the need for curtailment by utilizing suitable correlations of demand and renewable supply.

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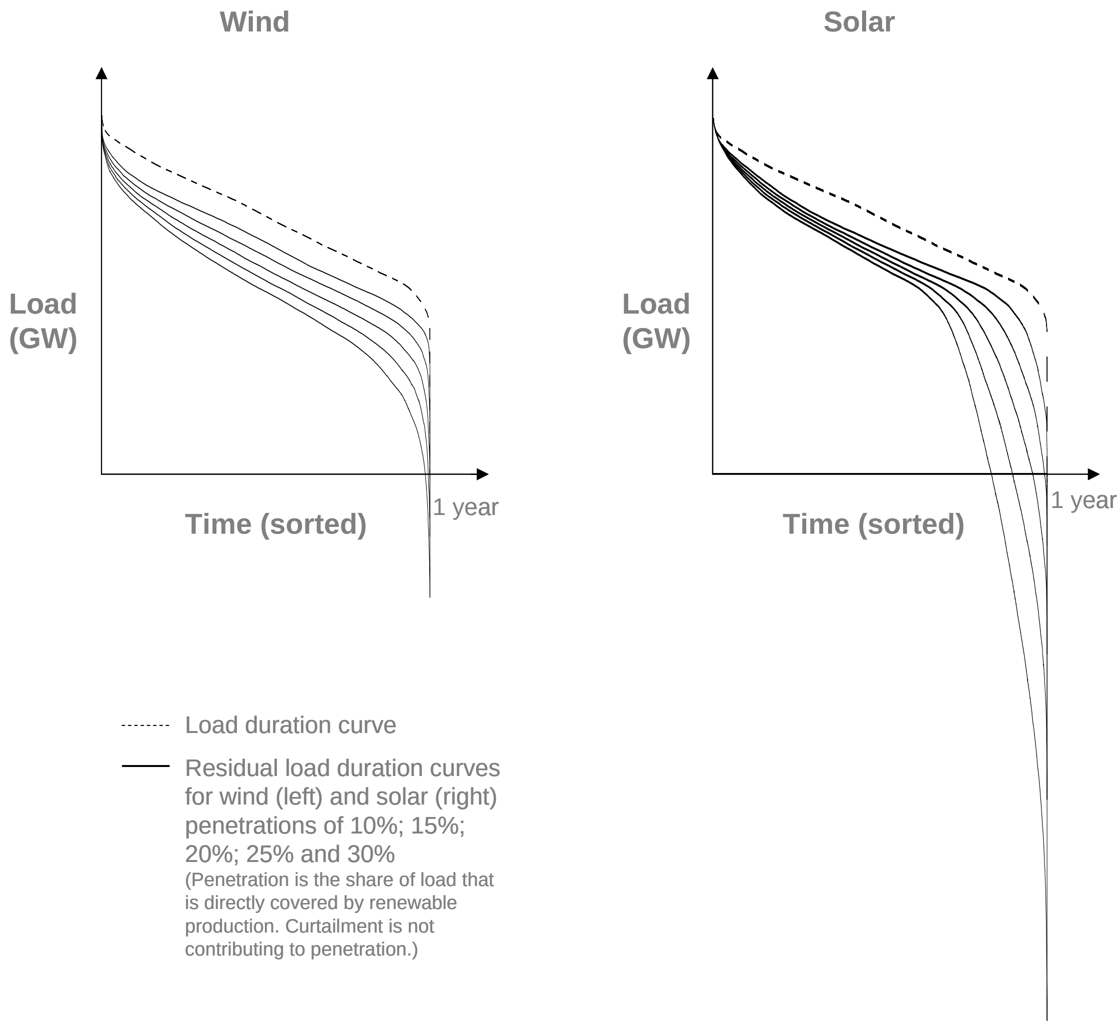

Figure 5: ***The challenges of integrating variable renewables increase with higher penetrations. Data analysis for Germany indicates that with high penetrations solar power (right) is less appropriate for covering load than wind power (left). Load and feed-in data for Germany (linearly scaled up) is used to derive the curves ([15], [16], [17], [18], [19]).***

The issues of integrating variable renewables get more challenging with higher penetrations (Figure 5), the reduction of full-load hours is accelerated, while the fraction of overproduction increases. Moreover the capacity credit of variable renewable capacities decreases, hence the contribution of variable renewables to peak capacity increases only slowly. The specific character of the challenges also depends on the mix of variable renewables. An analysis of German renewable supply and load data indicates that the statistical load matching properties of solar power seem to be less appropriate than those of wind power. Solar power in Germany contributes little to peak load because power demand is highest during winter evening. With higher penetrations of solar power the fraction of curtailment and the reduction of full-load hours become more severe than with comparable penetrations of wind power. Though wind is more fluctuating than solar, its general load matching properties are better than those of solar energy. This is because of better correlations of wind power supply and power demand on seasonal and diurnal time scales. A major problem when matching power demand and supply of variable renewables is that a certain share of the RLDC, the lower-left part, always requires alternative generation capacities, as long as over production cannot be stored and reallocated in time.

The RLDC reveals requirements and constraints for generation capacities in a power system with variable renewable energy: How much dispatchable capacity is needed to cover residual load? What is the corresponding reduced value of maximal full-load hours when variable renewables are integrated? What is the fraction of renewable production that must be curtailed? Hereby the RLDC captures most of the challenges of integrating variable renewables into power systems, and implementing a representation of the RLDC and its dynamics in an IAM can sufficiently account for variability without explicitly increasing the temporal resolution of the model.

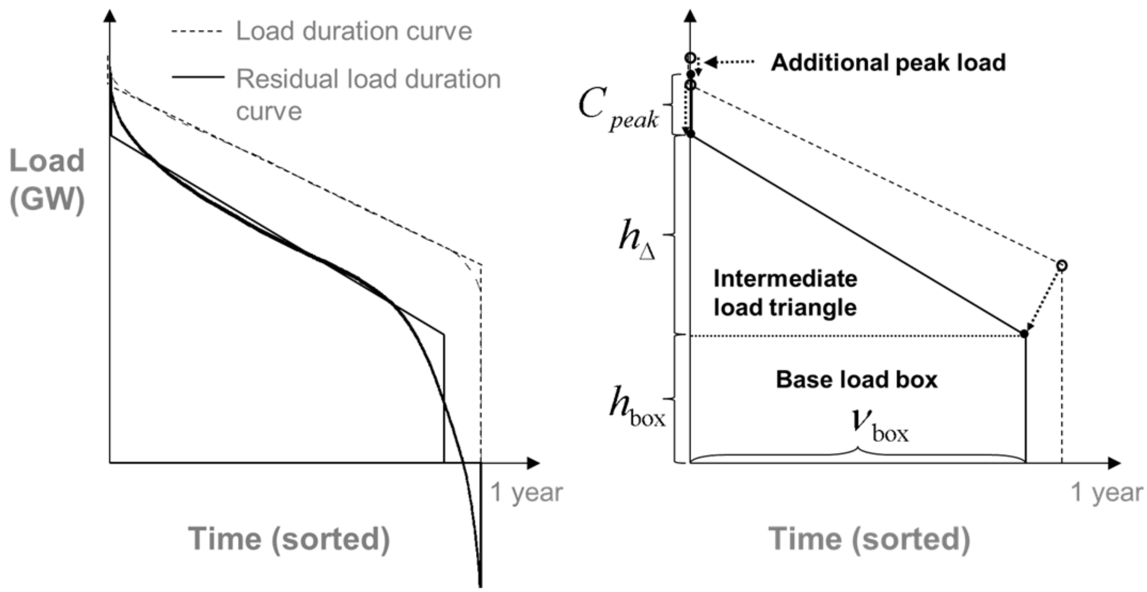

Figure 6 (schematic): ***The RLDC is approximated by a box and a triangle (left). This is implemented into the model as a transformation of the original LDC (right). The transformation is controlled by the change of four parameters (ν_{box}, h_{box}, h_Δ and C_{peak}) that are functions of the penetration level and mix of variable renewable power. As one result the average full-load hours v of the RLDC are reduced.***

For this purpose a linear approximation of the RLDC is implemented and parameterized into the model (Figure 6). The approximation (Figure 2) endogenously changes according to the penetration and mix of variable renewable power. This transformation is controlled by four parameters (ν_{box}, h_{box}, h_Δ and C_{peak}) that are functions of the penetration level and the mix of variable renewable penetration. Initial values prior to model optimization are derived from a comprehensive data analysis based on quarter-hourly data sets of wind energy feed-in and solar energy feed-in time series from the German transmission system operators and hourly data sets of load for Germany ([15], [16], [17], [18], [19]). *EnBW Transportnetze AG* recently started publishing solar feed-in data (for 2011 only), with earlier solar feed-in data available on request.

Since variable renewable energy with high penetrations contributes primarily to base load and only little to peak load the base box parameters (ν_{box}, h_{box}) decrease more rapidly compared to the other parameter values (Figure 1Figure 7). Thus the volume of the residual base load box reduces until the box is almost vanished

(Figure 8). The parameter C_{peak} corresponds to the capacity credit of the variable renewable energy plants. This parameter increases only slowly with penetration rates. Moreover, curtailment is a fifth parameter that is directly measured within the data analysis. For each value of penetration and mix of variable renewables the RLDC is derived in analogy to the approximation of the LDC: The deviation between the linear approximation and the RLDC is minimized and the integral of the two curves is identical.

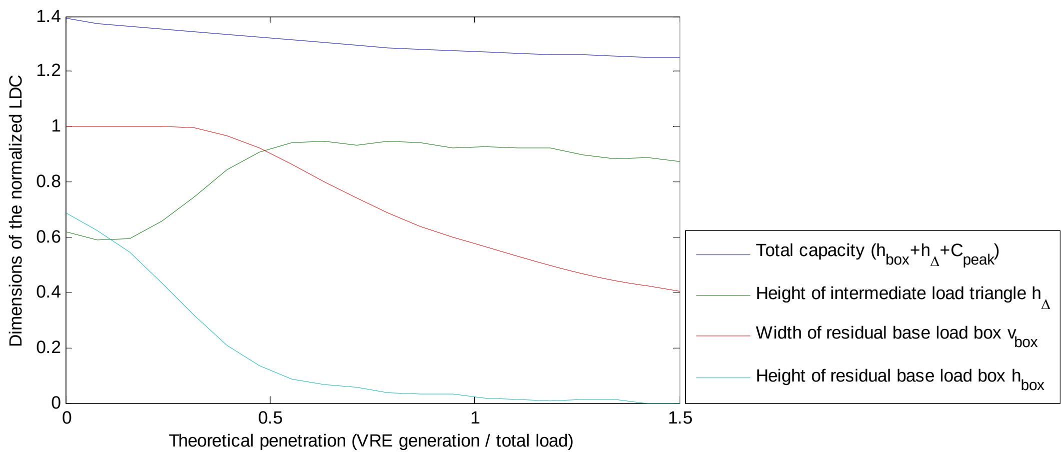

Figure 7: The measurements of the approximated RLDC (box and triangle) change with increasing penetration of variable renewable energy sources, e.g. the width of the box and the triangle v_{box} decreases. Hence the capacity factors decrease as well. Here the parameterization for a fixed mix of renewable energy sources is shown (wind generation : solar generation = 2:1). Theoretical penetration is the relation of potential generation of VRE (including curtailment) and total load.

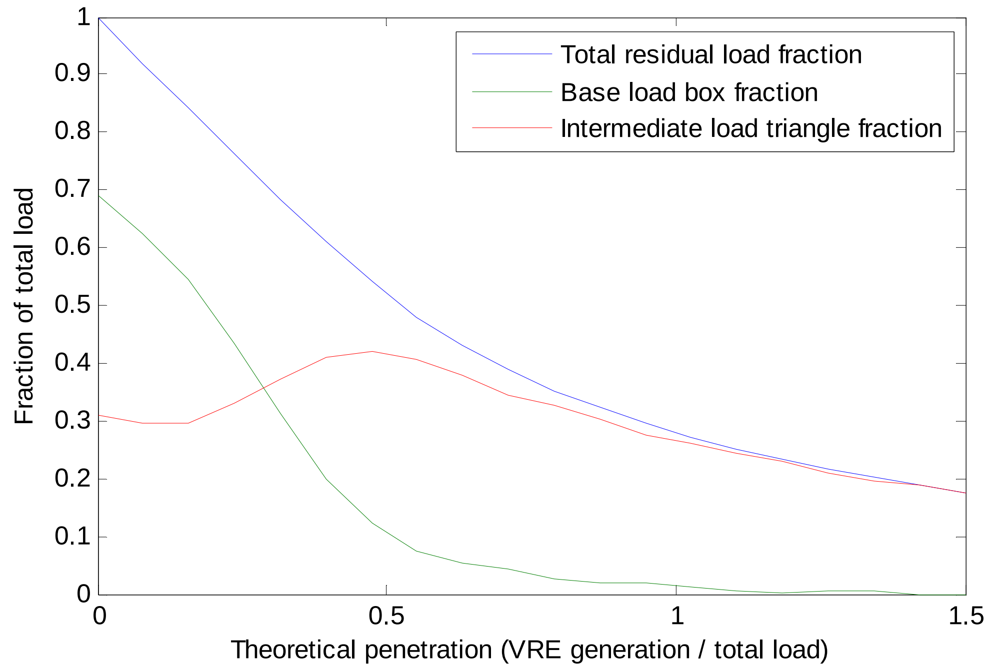

Figure 8: ***The residual fraction of total load decreases with increasing penetration of variable renewable energy sources. The volume of the base box decreases compared to the volume of the intermediate load triangle. Here the parameterization for a fixed mix of renewable energy sources is shown (wind generation : solar generation = 2:1).Theoretical penetration is the relation of potential generation of VRE (including curtailment) and total load.***

The RLDC consists of three different parts: A residual base load box, a residual intermediate load triangle, and an additional peak load part. The contribution of variable renewable power to the LDC is already accounted for with the transformation the shape of the RLDC. Within the optimization framework three equations that balance electricity and capacity demand and supply for each of the three parts of residual load must be fulfilled. For this purpose in each time step (of 5 years) the overall installed capacity of every dispatchable technology is split among the three load types. For example, a technological capacity that in one time step operates in residual peak load cannot contribute to the residual intermediate load triangle or the residual base load box in the same time step. Hereby the capacity factor of a specific technology is endogenously determined and depends on the full-load hours of the part of the RLDC where a power plant is operating.

2.4. Validation and parameterization with the dispatch model MICOES

The introduced RLDC approach contains a few approximations. Firstly the RLDC itself is approximated by a linear function. Secondly the chronological order of the time series of residual load is neglected by using RLDC. Hence there is one challenge of integrating VRE that within the RLDC approach has not been directly considered. With higher penetration of renewables the requirements for operating reserves increase due to higher variability and uncertainty of residual load. To balance residual load, dispatchable power plants need to operate more flexible than they would have to only due to variable load, and it will be necessary to check if important aspects of the variability of renewables or the operation of the power system, especially on short time scales of hours, are missed. The RLDC approach is validated with MICOES, a highly resolved dispatch model. In case the validation shows gaps within the RLDC approach then additional constraints like a suggested flexibility constraint need to be introduced.

MICOES is a model for optimization of power plant dispatch. It is especially designed to reflect short-term electricity supply decisions, with a temporal resolution of one hour. Operating reserves on time scales smaller than one hour are incorporated in the model by parameterized restrictions. The objective of the model is the cost-optimal coverage of a given time series of power demand. For this purpose, the residual load in Germany is used which is estimated by subtracting the feed-in of renewable energy sources (preferential feed-in) and (industrial) must-run generation from the load demand.

For meeting demand, power plants are dispatched according to their position in the so-called merit order, which is determined by the variable costs of the generating technologies. Furthermore, technical restrictions and corresponding additional costs of thermal power plants such as minimum load, load change ratios, minimum downtime, and minimum uptime are derived from literature and incorporated in the model. Hence MICOES goes beyond the approach of a mere merit order model.

MICOES is a mixed-integer model solved using GAMS programming language. It does not incorporate a representation of electricity grids.

The validation of the REMIND-D parameterization using RLDC is done by transferring REMIND model output of a representative single year to MICOES and comparing their model results. In particular the endogenously optimized generation capacities of REMIND-D are implemented in MICOES. Then MICOES optimizes the operation of the power plants while covering a highly resolved time series of residual load. Firstly MICOES evaluates if there are any moments in which power demand cannot be covered. Secondly the power plants operation can be compared. A decisive measure is the capacity factor of generating technologies that is endogenously determined in both models. If the capacity factors of MICOES are similar to those optimized in REMIND-D then the RLDC approach allows the optimization of investment decisions in the power sector with the consideration of optimized short-term operation decisions.

In case MICOES shows that the RLDC approach does calculate a REMIND-D power system with insufficient flexibility or suboptimal power plant operation (e.g. different capacity factors) it needs additional constraints to account for short-term effects.

To account for flexibility requirements concerning load-following and ancillary services a flexibility constraint was introduced into the model as an optional equation. This is based on an idea that has been implemented in the MESSAGE model [20]. A balance equation levels flexibility requirements with flexible generation supply. For this purpose each generating technology is characterized by a coefficient between -1 and 1 (Figure 9). For dispatchable generation technologies the coefficient is positive representing the flexibility of generation from that technology. For variable renewable technologies the coefficient is negative representing the additional flexibility required for each unit of generation from that technology. Power demand also has a negative coefficient in order to account for the flexibility of generation required to meet changes and uncertainty when covering load.

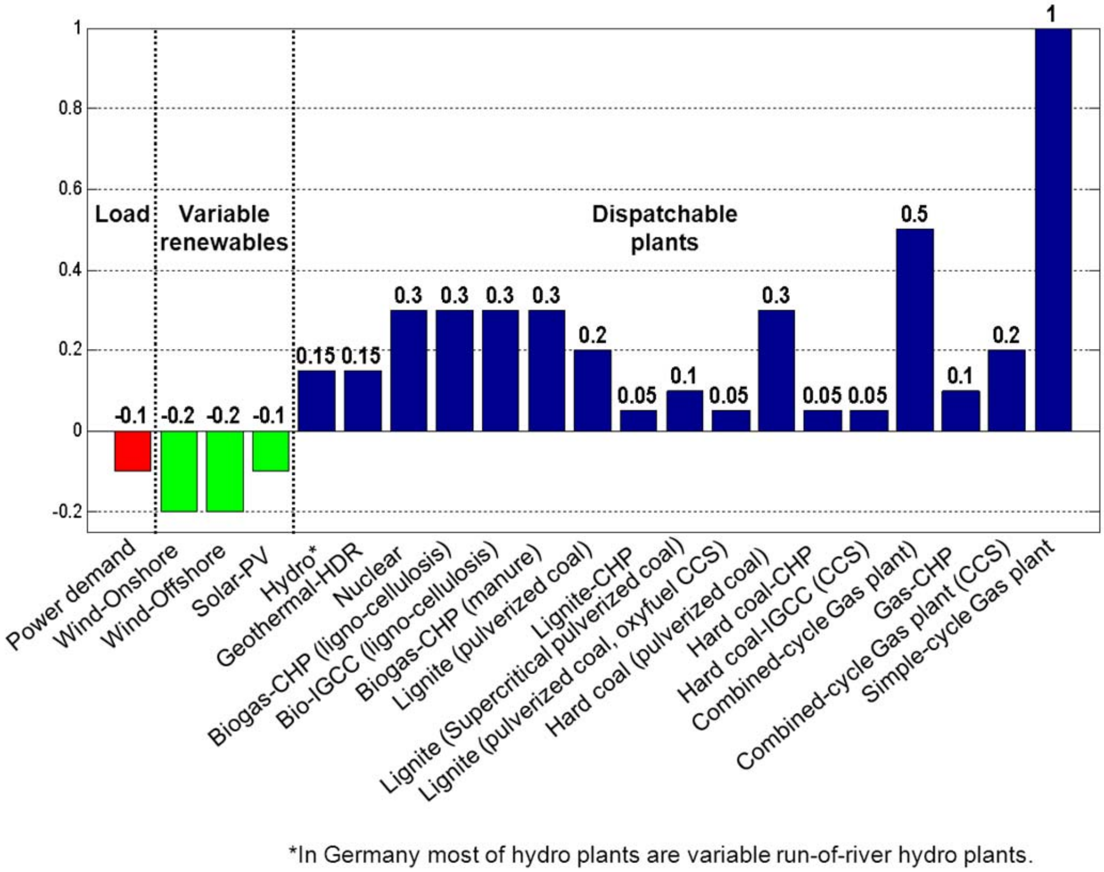

Figure 9: ***Flexibility coefficients by technology are introduced to account for the flexibility requirements of following (residual) load and providing ancillary services.***

The coefficient of a technology on the one hand is determined by technical parameters like ramp rates or control ranges[3]. On the other hand the coefficients can represent aspects of common practice. In Germany combined heat and power plants (CHP) based on natural gas and coal are ramped up and down less than they technically could. This is reflected in low corresponding flexibility coefficients. In contrast biogas plants also with CHP are assumed to be operated in a comparable flexible manner. The coefficient of the simple-cycle gas turbine is assumed to have the highest possible flexibility coefficient due to a wide control range and high ramp rate. Nuclear power plants are parameterized according to their technical parameter even though nuclear power plants in Germany are ramped up and down less than they technically could.

[3] Control range: Power range of a power plant in which the output can be flexibly controlled.

3. Results

3.1. Scenario description

With REMIND-D we have run a number of scenarios for Germany to analyze the effect of the new variability implementations. The comparison of model runs with and without the presented approach reveals implications of variability for the future development of power systems. Three different scenarios are defined. These scenarios are a business-as-usual scenario (BAU), a climate policy scenario without technologies of carbon capture and storage available (POL - no CCS) and a second mitigation scenario, where all technologies are available (POL - CCS). Both mitigation scenarios (POL) are constrained with a carbon budget of 20 $GtCO_2$ (2010-2050) that is endogenously distributed, implying a ~80% emissions reduction in 2050 compared to 1990. Within the BAU scenario some climate policy is already assumed that leads to a carbon budget of 30GtCO2 (2010-2050) and roughly a ~35% emissions reduction in 2050 (1990).

Each of the three scenarios is calculated with three different model versions with increasing level of consideration of variability. The first model version does not consider variability. The equations that account for balancing of power demand and supply are characterized only by average annual values. The capacity factors of power plants are exogenously determined and fixed over time. Within the second model version, the core of the approach, the linear RLDC, is implemented. The third model version contains the full implementation including the RLDC and the flexibility constraint that accounts for flexible generation and operating reserves.

3.2. Scenario results

We show electricity production in three different scenarios (Figure 10). Each scenario is calculated with three different implementation steps with increasing level of consideration of variability.

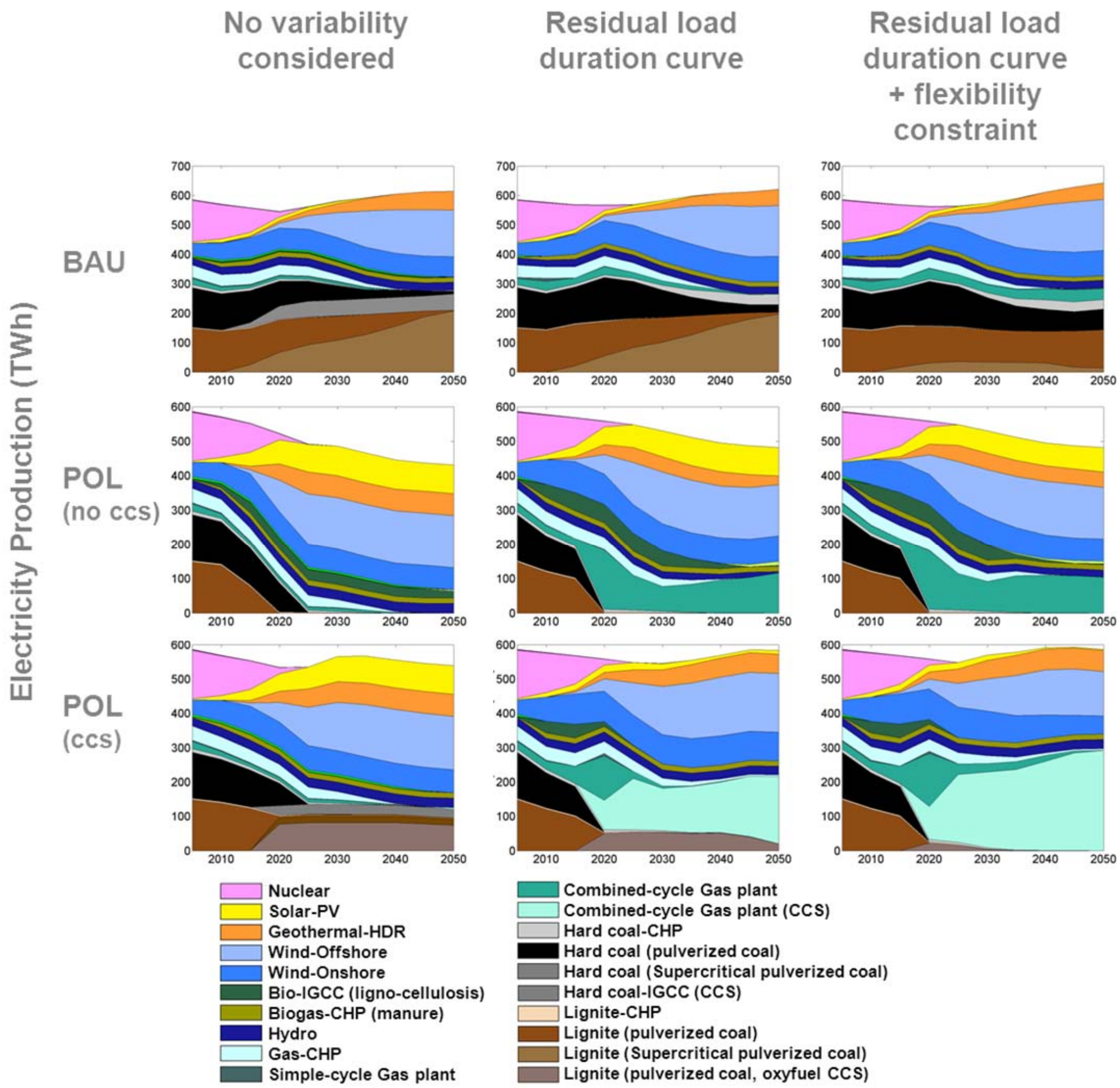

Figure 10*: Results of the electricity production of three different scenarios: a business-as-usual scenario (BAU), a climate policy scenario without technologies of carbon capture and storage available (POL - no CCS) and a second mitigation scenario where all technologies are available (POL - CCS). Each scenario is calculated with three different implementation steps with increasing level of consideration of variability.*

Model results show that significant changes are induced within even the first methodological step of implementing the RLDC, especially in the POL - scenarios. The addition of the flexibility constraint only causes some further small changes.

Hence the introduction of the RLDC already induces more flexibility within the power system even though the concept only has energy-economic character and does not specifically account for technical requirements.

Within the BAU – scenario with the introduction of the RLDC the supercritical hard coal power plant is not cost efficient anymore. This technology has a higher conversion efficiency and higher investment costs than usual hard coal power plants. However with the reduction of capacity factors in the RLDC the amount of produced electricity decreases and the additional investment costs are no longer compensated by efficiency gains. When using the flexibility constraint even the supercritical lignite coal power plant is not built anymore, due to a low flexibility coefficient (0.1) compared to a usual lignite coal power plants (0.2). Hence the potential role of supercritical lignite coal power plants depends on its flexibility.

Without variability, the POL – no CCS scenario shows 100% renewable energy sources in the electricity mix. The emissions from electricity generation reach vanishingly low levels after 2040 (Figure 11). When introducing the RLDC the German power sector cannot be fully decarbonized because natural gas combined-cycle plants are built to complement renewable energy generation (Figure 11). The reason for this change in behavior is that there is no option to decarbonize a certain fraction of the residual load due to inappropriate load matching properties of variable wind and solar and limited potential of dispatchable renewables like hydro, biomass and geothermal energy. Allowing for CCS the emissions are further reduced in the optimized scenario.

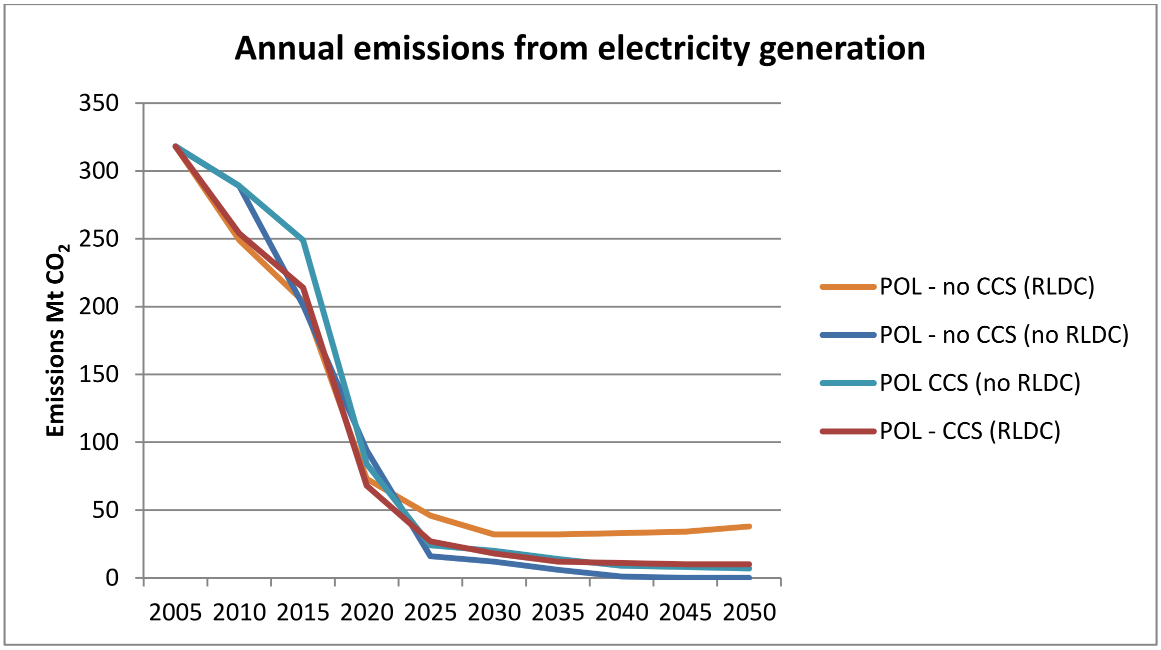

Figure 11: Annual CO_2 *emissions development for four POL scenarios (with/without CCS and with/without RLDC). With RLDC, the POL – no CCS scenario shows that the German power sector is not fully decarbonized any longer because natural gas combined-cycle plants are built to complement renewable energy generation.*

Within the POL – CCS scenario with the RLDC approach, coal with CCS technologies are partly substituted by natural gas combined-cycle plants with CCS when variability is considered. Firstly this is because the reduction of full-load hours within the RLDC fosters flexible generation capacity with lower specific investment costs and higher fuel prices e.g. gas power plants rather than base load power plants. Secondly the RLDC shows that a huge part of load, the lower-left part of the RLDC, can hardly be covered by variable renewables. This part needs to be met by dispatchable plants. However coal CCS technologies produce higher residual emissions than gas CCS technologies. That limits the amount of electricity from coal CCS technologies that can be used to cover lower-left part of the RLDC. Therefore gas CCS technologies are used in the optimal POL – CCS scenario. However the potential role of gas CCS power plants depends on their flexibility. Moreover the deployment of variable renewables, especially solar PV and partly wind onshore and wind offshore, is reduced compared to a model version where variability is not accounted for.

3.3. Mitigation costs

Mitigation costs are defined here as aggregated discounted consumption losses within a POL – scenario compared with the corresponding BAU – scenario as a reference. Within the BAU scenarios accounting for variability does not change the aggregated consumption (Figure 12). This can be explained by two effects that compensate each other. Firstly, additional costs due to the challenge of integrating VRE and secondly decreasing costs due to more efficient operation of plants since the capacity factor is optimized endogenously within the RLDC approach. For instance, in the model version without RLDC capacity factors are fixed.

Within the POL - no CCS scenarios the mitigation costs increase with variability. Most of these additional costs occur due to the RLDC. The mitigation costs increase significantly by about 20% compared to a model version in which variability is not taken into account. The basic reason for this increase is that VRE, especially wind and solar power, interact with the power system differently than conventional generating technologies. When integrated to the system VRE lead to increased system costs that need to be added to the pure production costs of renewable energy.

A further only minor increase of mitigation costs is induced with the additional use of the flexibility constraint. This indicates that the flexibility constraint might not be needed because the RLDC already accounts for the major part of challenges caused by short-term variability.

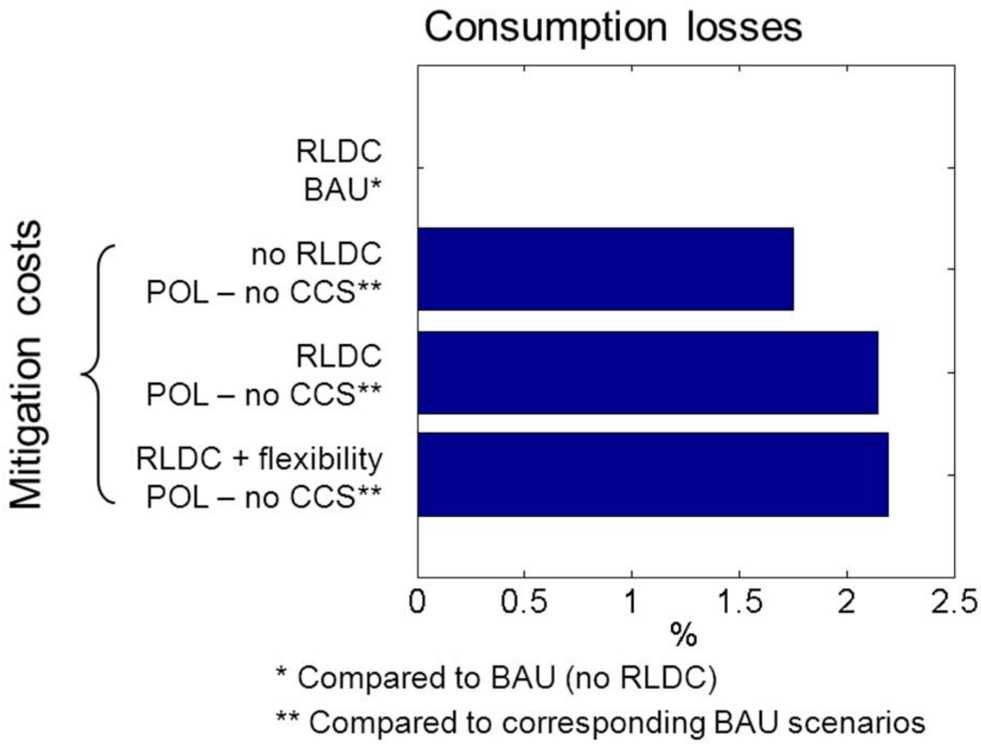

Figure 12: ***Within the BAU scenarios accounting for variability does not change the total consumption. Within the POL- no CCS scenarios the aggregated consumption losses (mitigation costs) increase with variability. Most of the costs occur due to the RLDC. Minor changes are induced with the additional use of the flexibility constraint.***

3.4. Validation

The RLDC approach is used to account for variability and correlations between different sources of renewable supply and power demand within the intertemporal optimization of long-term (energy system) investment decisions in climate change mitigation scenarios. Hereby the operation and planning of an energy system is endogenously optimized within a single optimization framework. The validation of the REMIND-D parameterization using RLDC is done by transferring REMIND model output of a representative single year to the dispatch model MICOES.

This is done for 2030 in the POL – no CCS scenario with the RLDC and no flexibility constraint. MICOES shows that the REMIND-D solution is technical feasible. The residual load (time series) could be covered at all times. Hence the introduction of the RLDC already induces more flexibility within the power system even though the concept only has energy-economic character and does not specifically account for technical requirements. Moreover the comparison of endogenously optimized capacity factors of generating technologies in both models for a representative year (2030) in the POL – no CCS scenario (RLDC, no flexibility constraint) shows good agreement (Table 1). Thus with the RLDC approach REMIND-D allows for simultaneous optimization of long-term investment and short-term operation decisions. This first validation indicates that the flexibility constraint might not be needed. However more scenarios and representative years need to be validated to reach a more comprehensive validation.

Comparison for 2030 (Scenario POL – no CCS)	Capacity factors (REMIND-D, investment model)	Capacity factors (MICOES, dispatch model)
Combined-cycle Gas plant)	0.21	0.19
Bio-IGCC (ligno-cellulosis)	0.51	0.54
Biogas-CHP (manure)	0.60	0.63
Simple-cycle Gas plant	0.00	0.01
Hard coal (pulverized coal)	0.00	0.01

Table 1: ***The comparison of endogenously optimized capacity factors of generating technologies in REMIND-D and MICOES in a representative year (2030) in the POL – no CCS scenario (RLDC, no flexibility constraint) shows good agreement.***

4. Conclusion and outlook

Time variable renewable energy technologies, especially wind and solar power, interact with the power system differently than conventional generating technologies. Their output is variable and can hardly be controlled, while fossil and dispatchable renewable plants, like biomass plants, can be adjusted up or down to match load. As the penetration of variable renewables increases integration becomes more challenging and costly. We present a stylized, dynamic, accounting of variability in energy-economy models that has been implemented in REMIND-D in order to better represent the issues that are important to variable renewable generation. Since these issues are well-captured within the RLDC, an approach based on an implementation of a linear approximation of this curve is used. The linear function endogenously changes depending on the penetration and mix of variable renewable power. Hence variability and correlations between different sources of renewable supply and power demand are accounted for within the intertemporal optimization of long-term (energy system) investment decisions in a mitigation scenario. Thus the RLDC approach allows for simultaneous optimization of long-term investment and short-term operation decisions. Moreover an additional flexibility constraint is introduced to account for flexibility requirements and operating reserves in order to provide load-following and ancillary services.

Model results show significant changes already induced within the first methodological step of implementing the RLDC. Mitigation costs increase by about 20% compared to a model version in which variability is not taken into account. However the large magnitude of these changes is reasonable because variability fundamentally affects the operation and planning of the power system. The addition of the flexibility constraint only causes some further minor changes. Hence the introduction of the RLDC already induces more flexibility within the power system even though the concept only has energy-economic character and does not specifically account for technical requirements. In some scenarios the deployment of variable renewables is reduced compared to a model version where variability is not accounted for.

In the mid-term future the approach presented here will be extended to consider flexibility measures like storage and demand side management (DSM). Storage technologies would be modeled by considering their effect on the RLDC. For example, overproduction and base load generation could be used to cover peak load. Similarly DSM could move peak demand into intermediate and base load. Moreover storage and DSM can provide flexibility and therefore would be implemented within the flexibility constraint with a positive coefficient.

As with any modeling approach, there are aspects that had to be neglected. So far spatial heterogeneity of variability of renewable supply and load, or the geographic issues of transmission are not accounted for. For the REMIND-D model version that represents Germany, which is comparatively well-interconnected, neglecting spatial issues is appropriate. Within the regionalized global model version REMIND-R spatial heterogeneity is planned to be considered by different regional parameterizations of the RLDCs and regionalized flexibility coefficients. Moreover the effect of spatially aggregating variable renewable supply has so far not been parameterized. RLDCs and flexibility coefficients might change due to reduced correlations of distributed renewable sources.

The presented approach is validated with MICOES a highly resolved dispatch model. However more scenarios and representative years need to be validated to reach a more comprehensive validation. So far comparing the model results of REMIND-D and MICOES indicate that the additional flexibility constraint might not be needed. Otherwise the flexibility coefficients need to be accurately parameterized because the aggregation of all different varieties of ancillary services and load-following time scales into one flexibility constraint is a simplification. If necessary the flexibility parameters could be derived from MICOES, which will allow the analysis of possible interdependencies of different flexibility coefficients.

Despite the reduced-form representation, incorporating variability, which is so fundamental to the operation and planning of the power system, is seen to improve the REMIND model's ability to derive robust mitigation scenarios.

5. Literature

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