The economics of power system transitions

Modeling pathways and policies for storage, grids and renewables

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Summary

Opposing the approaching climate catastrophe necessitates a rapid transition of power systems: Fossil fuel-based electricity generation needs to be replaced by low- or no-carbon-emitting renewable energy (RE). This implies huge disruptions concerning the infrastructure of power systems and their institutional design. This thesis addresses several of the challenges associated with the transition to RE: It studies the provision of power system flexibility by conventional generators, storage and grid. Furthermore, it analyzes the implications of instrument choice and policy design for an efficient RE support and the system integration of RE. The thesis is partitioned in four self-contained articles (Chapters 2 – 5), which are framed by a general introduction and conclusions.

Methodologically, the thesis is based on theoretical and numerical partial equilibrium optimization models that minimize the cost for electricity provision or maximize net benefits of RE deployment. Inherent to all models is the use of a two-level hierarchy. It allows to depict different time-horizons for decisions (short vs. long-term) or to implement strategic interactions of different players. The arising constrained and nested problems are solved with the Karush-Kuhn-Tucker optimization technique by use of backward induction. Furthermore, second-best solutions are acknowledged, which are caused for instance by capacity rigidity or game-theoretic coordination problems. I test the derived hypotheses and ease intuition by calibrating the models with German or Italian power system data.

Despite these common characteristics, the models are uniquely tailored to address specific research questions. The first article analyzes optimal deployment paths to RE when conventional capacities are rigid and limited in their generation flexibility. In addition to a RE technology with variable generation, it incorporates different conventional technologies that may or may not react to changes in

the availability of RE. I obtain the optimal levels of RE deployment for exogenous RE capacity costs and conventional capacity levels. The second article evaluates the interdependence between storage and transmission. To this end, I develop a two-region model with transmission and the option to deploy storage. By employing a comparative statics approach, I analyze how storage deployment may affect the optimal choice of transmission capacity. The model is applied to Italian data.

The third article studies public goods provision and policy instruments for RE support in two-level governance systems. The model is based on a Nash game between one federal and multiple state governments that decide simultaneously on RE support in their jurisdictions. Consequently, state-specific suppliers deploy RE capacities on the basis of the combined support they receive. I analyze how the incentives for state governments to support RE align with the federal instrument choices. Fundamental insights are applied to a recent RE policy shift in Germany. The fourth article is based on a multi-objective load-flow model that incorporates two grid levels: transmission and distribution. It focuses on *prosumage* households who produce, consume and store electricity and who are connected to the power system via a distinct distribution link. Various policy scenarios are evaluated for their potential to reduce the necessary link capacity by incentivizing a system-beneficial prosumage operation and compared to the first-best. To this end, a two-level Stackelberg game is implemented in which the policy and capacity decisions precede the dispatch decisions. The model is calibrated and solved numerically using German data.

The results obtained in this thesis can contribute to the efficient transition of power systems. In the first article, I find that early deployment of RE is hampered by the existence of inflexible conventional generation capacity. However, as soon as RE begins to substitute inflexible capacities, RE deployment accelerates, and the utilization of flexible generators likely increases. Only after inflexible generators cease to be used, deployment slows down again. In article two, I show that the two flexibility options storage and transmission can either be substitutes or complements. The effective relation depends on the location-choice for storage, the characteristics of transmission congestion and the alignment of marginal generation costs between the connected regions. Derived theoretical conditions for both relations are proven to exists in different Italian regions.

Article three shifts the focus to policies for RE support and integration. Here, I find that the incentives for state governments to support RE depend directly on the federal instrument choice. If the federal government supports RE via a price instrument, states that bear a greater burden in financing the federal policy under-subsidize RE to reduce nationwide deployment and thus their costs. Under a quantity instrument, states with a high burden increase their RE subsidies to drive down the nationwide quota price. For Germany, this indicates that the states' incentives to support RE have reversed after a recent federal policy shift from price to quantity instruments.

Focusing on the impacts of prosumage in the fourth article, I show that regulatory interventions are necessary if household storage shall be used to mitigate distribution grid requirements; otherwise, system costs could rise despite increasing flexibility. Numerical model results, derived with a calibration to German power system data, indicate that even simple feed-in policies can be effective. A uniform limit on maximum grid feed-in can leave distribution system operators better off, even if they fully compensate prosumage households for lost revenue. Policies imposing more differentiated limits at the regional level only result in small efficiency improvements.

The necessary power system transitions bring about many challenges. The insights of this thesis may provide guidance for planners and operators of power system infrastructures as well as for policymakers. I hope that the thesis contributes to the urgent and inevitable process of decarbonizing electricity generation and thereby to preserve the chance of preventing a catastrophic climate change.

Zusammenfassung

Ein schneller und umfassender Wandel der Stromsysteme ist notwendig, um die drohende Klimakatastrophe noch abzuwenden. Fossile Brennstoffe müssen im großen Stil durch CO_2-arme oder CO_2-neutrale erneuerbare Energien (EE) ersetzt werden. Die damit einhergehende *Systemwende* erfordert tiefgreifende Änderungen in der technischen, ökonomischen und institutionellen Organisation von Stromsystemen. Diese Arbeit befasst sich mit verschiedenen Herausforderungen, die im Zusammenhang mit dieser Systemwende stehen. Ich untersuche darin die Bereitstellung von Flexibilität durch konventionelle Kraftwerke, Speicher und Netze, die eine wichtige Rolle bei der EE-Integration spielt. Außerdem analysiere ich das Zusammenwirken verschiedener Politikinstrumente zur EE-Förderung sowie die Koordination von EE, Speichern und Netzen durch regulatorische Anreize. Die Arbeit ist in vier eigenständige wissenschaftliche Artikel unterteilt (Kapitel 2 – 5), die von einer allgemeinen Einleitung und Schlussfolgerungen gerahmt werden.

Methodisch basiert die Arbeit auf partiellen Gleichgewichtsbetrachtungen des Stromsektors. Es werden theoretische und numerische Optimierungsmodelle genutzt, um die Kosten für die Stromversorgung zu minimieren oder den Netto-Nutzen des EE-Ausbaus zu maximieren. Alle entwickelten Modelle sind zweistufig aufgebaut. Dies ermöglicht die Berücksichtigung unterschiedlicher Entscheidungshorizonte (kurz- und langfristig) oder die Implementierung strategischer Interaktionen zwischen verschiedenen Akteuren. Die daraus resultierenden geschachtelten Optimierungsprobleme unter Nebenbedingungen werden mit der Karush-Kuhn-Tucker-Methode sowie unter Verwendung der Rückwärtsinduktion gelöst. Dabei werden Lösungen abseits der optimalen Gleichgewichte (second-best) berücksichtigt. Die Abweichungen vom Optimum werden beispielsweise durch rigide

Kapazitäten oder spieltheoretische Koordinationsprobleme verursacht. Ich veranschauliche und überprüfe die empirische Relevanz der theoretischen Ergebnisse durch Modellkalibrierungen mit deutschen oder italienischen Daten.

Trotz ihrer genannten Gemeinsamkeiten sind die Modelle individuell auf spezifische Forschungsfragen zugeschnitten. Der erste Artikel analysiert, wie die optimalen Ausbaupfade für EE von der Flexibilität der bestehenden Kraftwerke abhängen. Dafür werden neben einer EE-Technologie mit stochastisch fluktuierender Erzeugung verschiedene konventionelle Erzeugungstechnologien berücksichtigt. Diese unterscheiden sich in ihrer Fähigkeit, auf die schwankende Verfügbarkeit der EE-Erzeugung zu reagieren. Für einen gegebenen konventionellen Kraftwerkspark sowie exogene Kapazitätskosten werden die kostenminimierenden EE-Kapazitäten ermittelt. Der zweite Artikel untersucht die Interdependenz zwischen den Flexibilitätsoptionen Stromspeicherung und -übertragung. Hierfür wird ein Modell mit zwei miteinander vernetzten Regionen implementiert. Mittels komparativer Statik wird analysiert, wie sich der Ausbau von Speicherkapazitäten auf die optimale Größe der Übertragungskapazität auswirkt.

Der dritte Artikel beschäftigt sich mit der Förderung öffentlicher Güter in zweistufigen Governance-Systemen am Beispiel des Ausbaus von EE. Er liefert Erkenntnisse darüber, wie die Anreize von Landesregierungen EE zu fördern, mit der Instrumentenwahl auf Bundesebene zusammenhängen. Das dafür entwickelte Modell basiert auf einem Nash-Spiel zwischen einer Bundes- und mehreren Landesregierungen, die gleichzeitig über die Förderung von EE in ihren Zuständigkeitsbereichen entscheiden. In Abhängigkeit von der kombinierten Förderung werden dann landesweise EE-Kapazitäten errichtet. Im vierten Artikel wird ein mehrkriterielles, numerisches Lastflussmodell entwickelt, das zwei Netzebenen beinhaltet: Übertragung und Verteilung. Im Mittelpunkt stehen *Prosumage*-Haushalte, die Strom produzieren, verbrauchen und speichern und über eine Verteilnetzverbindung mit dem Stromversorgungssystem verbunden sind. Ich vergleiche verschiedene Politiken hinsichtlich ihres Potenzials, die notwendige Verbindungskapazität durch ein systemdienliches Prosumageverhalten zu reduzieren. Dafür wird ein zweistufiges Stackelberg-Spiel implementiert, bei dem die Politik- und Kapazitätsentscheidungen den Dispatch-Entscheidungen vorausgehen.

Die Ergebnisse dieser Arbeit können zu einer effektiveren Systemwende beitragen. Der erste Artikel zeigt, dass der frühe Ausbau von EE durch die Existenz unflexibler konventioneller Erzeugungskapazitäten gehemmt wird. Sobald EE jedoch unflexible Erzeugung verdrängen, beschleunigt sich ihr Ausbau. Gleichzeitig ist wahrscheinlich eine erhöhte Auslastung flexibler Kraftwerke zu beobachten. Erst wenn sämtliche unflexible Erzeugung zum Erliegen kommt, verlangsamt sich der EE-Ausbau wieder. Im zweiten Artikel zeige ich, dass die beiden Flexibilitätsoptionen Speicher und Netz sowohl ein substitutives als auch ein komplementäres Verhältnis haben können. Ihre tatsächliche Interdependenz hängt von der Standortwahl des Speichers, der Netzbelastung sowie der Korrelation der Grenzerzeugungskosten zwischen den verbundenen Regionen ab. Die Relevanz der theoretischen Ergebnisse, weise ich anhand verschiedener italienischer Regionen nach.

Das Kernergebnis des dritten Artikels ist, dass die Anreize für Landesregierungen EE zu unterstützen, direkt von der Instrumentenwahl zur EE-Förderung auf Bundesebene abhängen. Unterstützt der Bund EE mit einem Preisinstrument, so entscheiden sich Länder, die bei der Finanzierung der föderalen Politik eine größere Last tragen, für eine zu geringe Förderung. Damit verringern sie den gesamtnationalen EE-Ausbau und damit ihre eigenen Kosten. Im Rahmen eines Mengeninstruments erhöhen Länder mit hoher Finanzierungslast ihre EE-Förderung, um den bundesweiten Quotenpreis zu senken. Für Deutschland bedeutet dies, dass sich die Anreize der Länder EE zu fördern, nach der Reform des Erneuerbare-Energien-Gesetz von 2017 umgekehrt haben.

Mit Blick auf Prosumage-Haushalte in Artikel vier zeige ich anhand einer Kalibrierung für Deutschland, dass der Verteilnetzbedarf durch regulatorische Anreize verringert werden kann. Dabei können schon einfache Regulierungen wie eine einheitliche Begrenzung der maximalen Netzeinspeisung wirksam sein. Von dieser profitieren Verteilnetzbetreiber selbst dann, wenn sie Prosumage-Haushalte für entgangene Einnahmen vollständig entschädigen. Politiken, die regional-differenziertere Einspeise-Grenzwerte vorschreiben, führen hingegen nur zu geringen Effizienzsteigerungen. Wird keine Regulierung implementiert, können die Systemkosten bei zunehmenden Speicherkapazitäten durch den erhöhten Netzbedarf steigen.

Die notwendige Energiesystemwende bringt viele Herausforderungen mit sich. Die Erkenntnisse aus dieser Arbeit können für Planerinnen und Betreiberinnen von Stromversorgungsinfrastrukturen sowie für politische Entscheidungsträgerinnen als Orientierungshilfe dienen. Ich hoffe, mit den gewonnenen Einsichten die drängende Systemwende unterstützen zu können und somit dazu beizutragen, einen katastrophalen Klimawandel zu verhindern.

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List of Acronyms and Abbreviations

DC	Direct current
DSO	Distribution system operator
EE	Erneuerbare Energien
FIT	Feed-in tariff
GAMS	General Algebraic Modeling System
GHG	Greenhouse gases
KKT	Karush-Kuhn-Tucker
EPEC	Equilibrium program under equilibrium constraints
MGC	Marginal generation costs
MILP	Mixed-integer linear problem
MPEC	Mathematical program under equilibrium constraints
NLP	Nonlinear problem
PV	Photovoltaic
TSO	Transmission system operator
RE	Renewable energy
RES	Renewable energy sources
VRE	Variable renewable energies

To Fridays for Future.

I hope this work will serve your case.

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If we knew what it was we were doing, it would not be called research, would it?

Albert Einstein

1
Introduction

THE ADVANCING CLIMATE CRISIS is the greatest societal challenge of the 21^{st} century. To oppose it, immediate action and tremendous efforts to sharply decrease greenhouse gas (GHG) emissions are necessary. Yet, the current country pledges for climate action are largely insufficient and predicted to induce warming between 2 °C and more than 4 °C compared to preindustrial levels (probability greater than 90 %; Fawcett et al., 2015). Such warming levels would have substantial consequences such as exacerbated droughts, floods, storms, temperature extremes and ecosystem losses with adverse implications for societies water security, food production systems and human health (Rogelj et al., 2019).

In order to keep global mean temperature increase at a maximum of 1.5 °C, GHG emissions must be halved relative to current levels by 2030. Also, net-zero carbon dioxide (CO_2) emissions together with additional deep reductions in other GHG are necessary by 2050 (Rogelj et al., 2019). Yet, global emissions show no sign of peaking. In 2018, CO_2 emissions from fossil fuel use increased by about 2.7 % compared to 2017 (Le Quéré et al., 2018) and almost half of the total amount was associated with electricity generation (Tong et al., 2019). Adding up committed CO_2 emissions from existing and planned electricity infrastructure alone accounts for 546 Gt if operated as historically (Tong et al., 2019). Just from those emissions, there would be a likelihood of up to 50 % that the 1.5 °C warming target will not be met (Rogelj et al., 2019).

On the positive side, during the last two decades, there were steep cost decreases and massive worldwide capacity extension of renewable energy (RE) (Ritchie & Roser, 2019). While RE extension was until now not sufficient to compensate for the global increase in energy demand (Jackson et al., 2018), this might change soon. Already today, RE is increasingly competitive for power generation in highly integrated power systems (IRENA, 2019) as well as in remote areas (Robert & Gopalan, 2018). This can reduce the free-rider problem associated with the public goods character of climate change mitigation efforts: If electricity from RE is cheaper than fossil-based power generation, countries that maximize their own welfare would switch to RE generation. Furthermore, RE does have local co-benefits that increase their value (Buonocore et al., 2016). Lastly, RE in power generation may contribute to the decarbonization of other sectors by electrification (Robinius et al., 2017).

Nevertheless, there is still a long way to go for the transition to fully renewable power systems. In 2018, the worldwide share of RE in power generation was 26.2 % with hydropower accounting for about 16 % and wind and solar for about 8 % (REN21, 2019). Moving towards the necessary 100 % of RE poses a number of challenges. First of all, the market value of RE decreases with higher penetrations due to the merit-order effect (e.g. Hirth, 2013), which may compromise the efficient transition paths (Helm & Mier, 2019). Public opposition may arise against RE (e.g. Bidwell, 2016) and transmission network extension (Cohen et al., 2016). Furthermore, the longevity of power plants and increasing electricity demand may induce path dependencies and thus exacerbate the phasing out of fossil generators (Fouquet, 2016, Tong et al., 2019). Besides, their owners may try to resist the transition due to their vested interest (Kim et al., 2016). Also, power systems themselves can be adversely affected by climate change (Pechan & Eisenack, 2014, van Vliet et al., 2016). The variability of RE generation leads to increasing flexibility needs (Hirth & Ziegenhagen, 2015) that might, for instance, be provided by suitable power plants (Eisenack & Mier, 2018), storage (Zerrahn et al., 2018) or transmission (Rodríguez et al., 2014). The need for these and other infrastructures may lead to complex interdependencies and uncertainty about the future state of power systems (Schmid et al., 2017). In addition to the techno-economic challenges (cf. Davis et al., 2018), the design of policies and regulations must also be adapted in order to transition from power systems with centralized fossil generation to more decentralized and renewable generation (Abrell et al., 2019, Ambec & Crampes, 2019, Verzijlbergh et al., 2017).

This thesis advances knowledge on THE ECONOMICS OF POWER SYSTEM TRANSITIONS. It addresses some of the most pressing challenges concerning the shift to RE, which I discuss in more detail in the following. Power system flexibility is crucial as electricity supply and demand have to be balanced instantaneously. Since generation from RE is often variable and not completely predictable, increasing RE shares lead to a greater need for flexibility for balancing purposes (Hirth & Ziegenhagen, 2015). Vice versa, higher availability of flexibility may facilitate the deployment of RE. During the transition, this flexibility can be provided by suitable conventional plants (Kubik et al., 2015). In Chapter 2, I investigate interdependencies between RE and conventional generators. In particular, I study how the endowment with (in)flexible conventional power plants affects the optimal deployment paths of RE capacities.

Other infrastructures that are integral for the integration of RE are storage and transmission. Storage may shift electric loads in time and thus allows to balance temporal fluctuations of RE generation. Transmission may also level out temporal fluctuations through spatial aggregation (Drake & Hubacek, 2007, Rodríguez et al., 2014) and additionally allows to seize the RE potential of remote areas. In Chapter 3, I analyze the interdependencies of those two pivotal flexibility options.

Next, I turn my attention to policies and regulatory design for power systems. While theoretically possible, economic first-best outcomes are empirically not observable, for instance, due to the political barriers to implement efficient carbon pricing (Aldy & Stavins, 2012), the required high degree of temporal and regional differentiation of electricity prices (Green, 2007), or due to strategic interactions of different players (e.g. Schill & Kemfert, 2011). For this reason, support programs for RE play a crucial role in decarbonization efforts (Meckling et al., 2017), as subsidies for R&D (Acemoglu et al., 2012) or for RE generation (Abrell et al., 2019) can efficiently induce a switch to clean technologies. A central challenge for efficient policy design is that RE support is often simultaneously provided by different government levels with different interests (Fischer & Preonas, 2010, Goulder & Stavins, 2011). In Chapter 4, I study the efficiency of multi-level RE support policies with an emphasis on the instrument choice of the upper level.

Furthermore, the emerging RE and flexibility technologies need to be appropriately regulated to organize their interplay in the system efficiently (Pérez-Arriaga et al., 2017). In particular at smaller scales like households, economic or behavioral reasons may otherwise cancel out their benefits (Green & Staffell, 2017). In Chapter 5, I evaluate regulations that address a coordination problem between grid owners and power generating households with storage capacities, which arises from imperfect electricity pricing.

I employ partial equilibrium models of the power sector that use theoretical (cf. e.g. Helm & Mier, 2019, Eisenack & Mier, 2018, Ambec & Crampes, 2012, Gravelle, 1976, Bohn et al., 1984) and numerical (cf. e.g. Huppmann & Egerer, 2015, Zerrahn & Huppmann, 2017) optimization approaches. Multi-level decision hierarchies are used to depict the dichotomy between short and long-term decisions or strategic interactions between different decision-makers (Williams III, 2012, Ambec & Coria, 2018). Additionally, I put emphasis on second-best approaches in which not all optimality conditions can be satisfied (Abrell et al., 2019, Helm & Mier, 2018). I calibrate developed models using real-world data to address the relevance of theoretical results, to ease intuition and to derive policy recommendations.

The main work is presented in the Chapters 2 – 5. It represents four distinct research articles. Every chapter is independently self-consistent but also contributes to the overarching research topic as set out above. Chapter 2 is single-authored while Chapters 3 – 5 were collaboratively written. Information on co-authors and publication statuses (as upon thesis submission) are provided at the beginning of each chapter. Chapter 6 draws general conclusions and discusses some limitations of the thesis. In the following, each of the main chapters is shortly summarized. Table 1.1 provides an overview of the challenges addressed and methods used in the main chapters of the thesis.

Table 1.1: Overview on addressed challenges and methodological features for main chapters of the thesis.

	Chapter 2	**Chapter 3**	**Chapter 4**	**Chapter 5**
Challenges addressed				
Flexibility provision	✓	✓		✓
Storage and transmission		✓		✓
Infrastructure interdependence	✓	✓		✓
Policy and regulation			✓	✓
Methodology				
Theoretical	✓	✓	✓	
Numerical				✓
Multi-level	✓	✓	✓	✓
Second-best	✓		✓	✓
Calibrated application		✓	✓	✓

Chapter 2 – **How to go green? The effects of power system flexibility on the efficient transition to renewable generation** – is based on the observation that variable renewable energies (VRE) are widely and quickly deployed in historically fossil-dominated power systems. Yet, some fossil technologies are more suitable than others for integration with VRE due to their higher flexibility. In this chapter, I develop an analytically tractable model to study the optimal transition to a VRE-dominated system when the endowment of flexible and inflexible conventional generators is rigid. I find that the existence of inflexible fossil generators hampers early deployment of VRE. However, deployment speed increases after VRE begin to substitute generation from inflexible generators, which happens after VRE and inflexible capacities strictly exceed demand together. At this time, the decreasing use of inflexible fossil generation is usually accompanied by an increasing utilization of flexible generators. Nevertheless, constructing additional flexible capacities is only profitable under restrictive conditions. The chapter contributes to a better understanding of the impact of flexibility on efficient VRE deployment and thus helps to achieve an efficient transition process.

Chapter 3 – **Electricity storage and transmission: Complements or substitutes?** – also focuses on flexibility provision. It analyzes the interplay of two infrastructure options for flexibility: storage and transmission. It is motivated by the fact that electricity from renewable sources often cannot be generated when and where it is needed. Expanding storage capacities and transmission grids may deal with these temporal and spatial discrepancies. Often, it is assumed that the two technologies substitute each other, such that deploying one reduces the need for the other. Using a theoretical model, we show that storage capacities and transmission grids can also be complements if electricity system costs are minimized. We present the conditions that determine the kind of interdependence at specific storage locations: the characteristics of transmission congestion, i.e., during peak or off-peak and uni- or bidirectional as well as the alignment of marginal generation costs between adjacent regions. By applying our theoretical insights to Italian power system data, we obtain empirical evidence that storage and transmission can act as either substitutes or complements. Planners of long-lasting and costly infrastructure can use the results to avoid design errors such as a misplacement of storage within the system.

Chapter 4 – **Renewable energy policies in federal government systems** – analyzes governmental support policies for RE, which are widely used to decarbonize power generation and implemented at various governance levels. We use an analytically tractable two-level model to study the effects of overlapping RE policies from the federal and state governments. We find that there are contrasting incentives for states to support RE deployment, depending on whether the federal government implements a feed-in tariff (FIT) or an auction system. Under federal FIT, states that bear a greater burden in financing the federal policy under-subsidize RE in order to reduce nationwide RE deployment and thereby lower their costs. Under federal auction, states that bear a greater burden to finance federal policy over-subsidize RE to drive down the quota price, and thereby also their costs. In an application to Germany, we illustrate that the recent shift from FIT to auctions increases incentives for state governments to support RE in the demand-intensive south while decreasing them in the wind-abundant north.

Chapter 5 – **Modeling coordination between renewables and grid: Policies to mitigate distribution grid constraints using residential PV-battery systems** – analyzes system effects from the interplay of prosumage households and grids. The deployment of distributed photovoltaic (PV) generation in the distribution grid requires costly grid reinforcements and expansions. Prosumage – consisting of a household-level PV unit coupled with a battery storage system – has been proposed as an effective means to facilitate the integration of renewable energy sources and reduce distribution grid stress. However, tapping its full potential requires regulatory interventions; otherwise, system costs could rise despite increasing flexibility. We analyze the effectiveness of different policy schemes to mitigate the need for distribution capacity expansion by incentivizing beneficial storage operation. Our novel top-down modeling approach allows analyzing effects on market prices, storage dispatch, induced distribution grid requirements, system costs, and distributional implications. Based on German power system data, numerical results indicate that distribution grid requirements can be reduced through simple feed-in policies. A uniform limit on maximum grid feed-in can leave distribution system operators better off, even if they fully compensate prosumage households for foregone revenue. Policies imposing more differentiated limits at the regional level result in only marginal efficiency improvements. Complete self-sufficiency (autarky) is socially undesirable, as it confines important balancing potential and can increase system costs despite adding storage.

2

How to go green? The effects of power system flexibility on the efficient transition to renewable generation

Abstract
For decarbonization purposes, variable renewable energies (VRE) are widely and quickly deployed in historically fossil-dominated power systems. Yet, some fossil technologies are more suitable than others for integration with VRE due to their higher flexibility. I utilize an analytically tractable model to study the optimal transition to a VRE-dominated system when the endowment of flexible and inflexible conventional generators is rigid. I find that the existence of inflexible fossil generators hampers early deployment of VRE. However, deployment speed increases after VRE begin to substitute generation from inflexible generators, which happens after VRE and inflexible capacities strictly exceed demand together. At this time, the decreasing use of inflexible fossil generation is usually accompanied by an increasing utilization of flexible generators. Nevertheless, constructing additional flexible capacities is only profitable under restrictive conditions. By contributing to a better understanding of the impact of flexibility on efficient VRE deployment, this work may facilitate an efficient transition process.
Keywords: Energy transition, renewable energy, flexibility, rigid capacity endowment
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2.1 Introduction

Decarbonizing society requires a broad transition to renewable energy sources in power generation (Williams et al., 2012). A major challenge is that many renewable energy sources like wind and solar power are characterized by variable availability. Nevertheless, electricity demand and supply need to be balanced at all times. As a consequence, an increasing need for system flexibility exists, for balancing purposes, in order to increase the capacities of variable renewable energies VRE (Hirth & Ziegenhagen, 2015). During the transition phase, the existing endowment with fossil fuel-powered plants may provide this flexibility (Kubik et al., 2015). However, different conventional technologies are suited more than others to do this, e.g. due to differences in ramping times and minimum loads (Gonzalez-Salazar et al., 2017, Hentschel et al., 2016). For example, gas-fired plants can be dispatched rather flexibly, while coal and nuclear plants are less able to provide flexibility (Brouwer et al., 2015).

As an additional challenge, already existing and planned fossil power generation infrastructure is projected to push emissions beyond the carbon budget to achieve the 1.5 °C target if operated as historically (Tong et al., 2019). It follows that many power plants will have to be retired prematurely. Because of the high specificity of plants, it is thus very unlikely that the capacity mix of conventional and VRE plants will be at an optimal state or even follow an optimal path during the transition process. So far, this fact is often neglected and compromises the results of many recent studies on the efficient energy transition (e.g. Eisenack & Mier, 2018, Ambec & Crampes, 2019, Helm & Mier, 2019).

Addressing these challenges, I distinguish between flexible and inflexible conventional generation technologies. I assume that their capacity endowment is rigid, i.e. it cannot be adapted to changing levels of VRE capacity. I address the following research questions: (i) What are the efficient power generation levels of all technologies? (ii) How does the efficient deployment path of VRE depend on the rigid endowment with flexible and inflexible conventional generation capacities? (iii) Under which conditions can it be beneficial to invest in additional flexible generation capacities?

To this end, I develop a theoretical model that incorporates four generation technologies: *VRE* with stochastic availability, cheap and inflexible *coal*, and medium expensive and flexible *gas* – all with respective capacity limits. Lastly, there is an expensive and flexible *backup* technology without a capacity limit. I assume that the flexible generators may react to the stochastic availability of VRE: they can make their decision after the availability is known, while the inflexible generation cannot react (cf. Eisenack & Mier, 2018). I evaluate how a given inelastic electricity demand can be satisfied at least cost. I first derive the optimal generation levels for given capacities. Consequently, I obtain the efficient capacities of VRE for all possible endowments of (in)flexible conventional generators and for given VRE unit capacity costs (cf. Helm & Mier, 2019). Furthermore, I evaluate the marginal benefits of adding further flexible generation capacities.

I find that the transition to a renewable power system crucially depends on the initial endowment with flexible and inflexible conventional generators. In general, coal capacities will suppress initial VRE deployment and gas capacities accelerate midterm VRE deployment. In the early phases of VRE deployment, coal generation is used at full capacity. During that time, VRE deployment substitutes gas generation. After coal generation and VRE generation at high availability strictly exceed the demand, some VRE generation is curtailed. At first, it is still cost-efficient to operate with coal at full capacity. Yet, for successively increasing VRE capacity, generation from coal decreases. Here, the efficient VRE deployment speeds up and is likely complemented by rising use of gas generation. At this stage, it might be worthwhile to add further flexible gas capacities. Finally, coal generation ceases, which in turn reduces the speed of efficient VRE deployment again. These findings may contribute to a more efficient planning of future power systems and the design of appropriate policies.

The remainder of the paper is structured as follows: First, I position the paper in the relevant literature. Next, in Section 2.3, I provide an overview of the theoretical model. In Section 2.4, I obtain the efficient dispatch for all technologies, while in Section 2.5, I analyze the optimal deployment of VRE and evaluate if it is viable to also increase flexible generation capacities during the transition. I discuss my results, conclude and provide an outlook in Section 2.6. The Appendices contain the nomenclature and formal proofs.

2.2 Related literature

The question of how to efficiently transition power systems to be more sustainable is subject to great research efforts. A common approach is the development of detailed numerical models. Those provide predictions or possible paths of power system development for specific regions and various (policy) scenarios.[1] Such models are well suited for specific analyses but less well suited for general insights on the fundamental principles of power systems. Cochran et al. (2014) provide a meta-analysis of twelve model studies evaluating the feasibility and implications of power systems with high shares of renewables for different countries and regions. They find that the technology mix varies significantly not only due to regional contexts but also because of different assumptions and model constraints.

Theoretical models are a useful supplement to simulations and provide a more general analysis of the relations of different infrastructure options. Results from the peak-load pricing literature provide insights about optimal dispatch and capacity decisions of generators (Steiner, 1957), storage (Gravelle, 1976) and transmission (Bohn et al., 1984, Lecinq & Ilic, 1997, Neetzow et al., 2018b). Furthermore, uncertainty (Chao, 1983, Kleindorfer & Fernando, 1993) or limits in generation flexibility (Eisenack & Mier, 2018) can be included. In recent research, renewable energies were added to the picture. Chao (2011), Ambec & Crampes (2012) study optimal pricing and investment in power systems with VRE. Chao (2011) finds that VRE substitute conventional technologies with higher marginal generation costs and complement the ones with lower marginal generation costs. A related stream extends the considerations to include the design and efficiency of policies for VRE. Fischer & Newell (2008) analyze the nexus of policies and learning. More recently, Ambec & Crampes (2019) compare the efficiency between a carbon tax and VRE policy. Abrell et al. (2019) consider technology differentiated subsidies and Meya & Neetzow (2019) study simultaneous VRE support of multiple governance levels.

To analyze a system transition, a focus on the temporal progression of VRE deployment is needed. A number of studies have employed dynamic modeling approaches to study transition paths for replacing emission-intensive energy production with renewables. Amigues et al. (2015) study a situation where scarce conventional resources force a switch to renewable generation. In Coram & Katzner (2018) the transition is induced by an allowable emission stock. Although renewable deployment strictly decreases over time in the latter study, it initially increases in the prior study. The contrasting results are likely caused by differ-

[1] Detailed numerical power system models are plentiful. Regional focuses include Europe (Haller et al., 2012b, Schaber et al., 2012, Jägemann et al., 2013, Heide et al., 2010), the US (Fthenakis et al., 2009, Mai et al., 2014, Jacobson et al., 2015) or other regions (Lawrenz et al., 2018, Elliston et al., 2012, Mason et al., 2010).

ences in their cost assumptions. In a more elaborate model, Pommeret & Schubert (2019) also study a dynamic path to a renewable energy system. They take storage and different characteristics of renewables into account – including variability. Notably, they assume that there are abundant capacities of conventional generators. However, all these studies consider only one perfectly flexible conventional technology and that deployment costs stay constant over time.

Coulomb et al. (2018) also employ a dynamic approach, but they additionally distinguish conventional generation in abundant high-emission coal and scarce low-emission gas. They find that coal use strictly decreases for increasing renewable capacities, while gas use and gas capacities are initially increased and only reduced after coal generation fully ceases. In their analysis, renewable generation is deterministic and both conventional technologies are perfectly flexible, such that there are fixed rates of substitution between all generators. Further evaluations on gas use during power system transition include Baranes et al. (2017), who couple a theoretical analysis with empirical observations. They find that at high natural gas prices a further price increase substitutes VRE deployment, while for low prices there exists a complementary relation. They refer to the flexibility of gas to be used with VRE as a possible explanation.

In general, some studies conclude that gas can be a climate-beneficial complement to VRE because of its lower emission intensity compared to coal during power generation (Pless et al., 2015, Coulomb et al., 2018). In particular, this is the case if natural gas use can be substituted by renewable gas from biomass or electrolysis with excess renewable electricity (Mac Kinnon et al., 2018). On the other hand, increasing gas use may delay the switch to renewable generation (Zhang et al., 2016, Shearer et al., 2014, Stephenson et al., 2012). The net climate effect of gas does furthermore depend on the policies in place (Brown et al., 2018) and the speed of the transition (Hausfather, 2015). While the generation flexibility is often acknowledged as one of the benefits of gas in tandem with VRE, none of the aforementioned studies models the flexibility explicitly.

The general role of flexibility for VRE integration is in the focus of a rich body of literature as laid out by the review papers of Lund et al. (2015) and Kondziella & Bruckner (2016). Lund et al. (2015) provide a helpful conceptualization of flexibility measures, where they distinguish demand and supply-side approaches, for example, as well as storage and other technology options. In addition to the flexibility of generators, they acknowledge the option of VRE curtailment.

Kondziella & Bruckner (2016) conduct a meta-study on physical quantities of flexibility needed to integrate increasing shares of VRE. They find that flexibility requirements increase in relation to rising shares of VRE. Despite many studies on the need of flexibility, to the best of my knowledge, there are no theoretical approaches that take into account the impacts of limited generator flexibility on VRE deployment. In this sense, it is significant that Lund et al.'s (2015) section on supply side flexibility offers only one reference.

This paper closes the research gap on the effects of limited conventional flexibility on the efficient transition to VRE. To this end, I build on the work of Helm & Mier (2019), who analyze the efficient capacity mix of VRE and conventional generation for (exogenously) decreasing deployment costs of VRE. They find that once the maximum renewable generation is able to serve the full demand, efficient deployment and the replacement of fossil generators slows down and thus impedes the transition to a purely renewable power system. I enhance their approach by distinguishing between a flexible and an inflexible conventional generation technology. To do this, I follow Eisenack & Mier (2018), who expand the peak-load pricing literature by including limits on generation flexibility. As opposed to both of these studies, I do not assume that conventional capacities can be perfectly adapted to changes in VRE capacities. Instead, I consider an exogenous and rigid endowment which cannot be changed during the transition.

2.3 Model overview

I consider a power system that is initially endowed with coal (C) and gas (G) generation capacities only. Furthermore, variable renewable capacities (R) can be deployed. A backup technology (B) provides the power that is not generated (domestically) by the previous technologies. For instance, backup might represent the possibility to import power, some additional peak technology or even lost load. I consider an inelastic demand D, which must be satisfied by generation from the given capacities $D = \sum_j g^j, \ j = R, C, G, B$. The endowment with conventional capacities is assumed to have emerged historically to some non-necessarily optimal mix of coal and gas capacities. As their lifespans are long – compared to the time available to transition power systems (Tong et al., 2019) – capacities are fixed at some exogenous level.[2] The capacities K of the two conventional technologies

[2] In the initial system without VRE, there would be no reason to install flexible capacity for the given model setup (cf. Eisenack & Mier, 2018). However, in reality, there are further

are large enough to satisfy demand together but not alone, i.e., $K^C + K^G \geq D; K^C, K^G < D$. I assume that backup generation is not bound to a capacity limit. For VRE, I consider that unit capacity costs c^{KR} successively decrease, thus inducing an increase in efficient VRE capacity K^R.[3] I neglect depreciation of capital.

The realizable generation from the given VRE capacity is uncertain (cf. Ambec & Crampes, 2012, Helm & Mier, 2019). Its availability is given by the continuous random variable $\tau \in (0, 1)$. The effective VRE generation is bounded by the available generation capacity but can also be lower because of costless curtailment: $g^R \leq \tau K^R$. I assume that τ is uniformly distributed. The probability density function is then given as $f(\tau) = 1$ with cumulative function $F(\tau) = \tau$.

While gas and backup generation are assumed to be *flexible*, generation from coal is *inflexible*. Inflexible generation is not able to react to the variability of the renewable energy source. Thus, the coal generation dispatch has to be committed *before* the random variable τ realizes. As opposed to that, gas and backup generation can be dispatched *after* the realization of τ (cf. Eisenack & Mier, 2018). The capacity unit generation costs c^j are considered to be constant and relate as follows: $c^B > c^G > c^C > c^R = 0$.

The model setup naturally implies multiple sequential levels of decision making. I assume that decisions are made by a benevolent planner that minimizes total system costs TC consisting of capacity costs for VRE $c^{KR}K^R$, with $c^{KR} > 0$ and dispatch costs DC for the electricity provision.[4] In the long run, the planner decides on the efficient VRE capacity for a given unit cost. In the short run, taking the capacities as fixed, she decides on the generation of coal *before* she knows about VRE availability, and on the generation of backup, gas and VRE *after* the availability has realized. Applying backward induction, in the following sections, I first address the short-run dispatch problem before turning towards the long-run efficient capacity decision.

uncertainties like fluctuating commodity prices and system flexibility is required not only because of VRE but also due to volatile demand. A first-best endowment is thus very unlikely.

[3]In the paper, I often explain how generation and capacities change “over time” when interpreting the results for falling VRE capacity costs. By doing so, I implicitly assume a linear cost decrease over time.

[4]Due to the integrated decision making without any strategic interactions, all decisions could also be made at once. However, a sequential structure facilitates the intuition and the clarity of the solution process.

2.4 Efficient generation with limited flexibility

2.4.1 Dispatch problem formulation

The problem of obtaining the efficient dispatch decisions for given capacities can be formulated as a two-level program which reflects the sequential decision-making process:

$$\text{level 1:} \quad E[DC]^* = \min_{g^C} \left[c^C g^C + c^G E[g^G(\tau)] + c^B E[g^B(\tau)]\right] \tag{2.1}$$

s.t.

$$g^C - K^C \leq 0 \qquad (\lambda^C), \tag{2.2}$$

$$\text{level 2:} \quad DC^*(\tau) = c^C g^C + \min_{g^B, g^G, g^R} \left[c^G g^G(\tau) + c^B g^B(\tau)\right] \tag{2.3}$$

s.t.

$$D - g^C - g^G(\tau) - g^B(\tau) - g^R(\tau) = 0 \qquad (\alpha(\tau)), \tag{2.4}$$

$$g^G(\tau) - K^G \leq 0 \qquad (\lambda^G(\tau)), \tag{2.5}$$

$$g^R(\tau) - \tau K^R \leq 0 \qquad (\lambda^R(\tau)). \tag{2.6}$$

where positive shadow costs on the respective constraints are given in parenthesis. As τ is unknown when deciding on efficient coal generation, it intuitively follows that coal generation will not change for different realizations of τ.

First, before the realization of the VRE availability is known, coal generation is chosen to minimize expected ($E[\cdot]$) dispatch costs $E[DC]$ (Eq. 2.1). This decision is subject to the capacity constraint of coal generation (Eq. 2.2). Second, real dispatch costs are minimized by choosing generation from VRE, gas and backup technology for a given coal generation and the realized VRE availability (Eq. 2.3). This is done subject to the balancing constraint, which equalizes supply and demand (Eq. 2.4) and the capacity constraints for gas and VRE generation (Eq. 2.5, Eq. 2.6).[5]

Applying backward induction, I first solve the lower-level problem for any (exogenously) given coal generation and VRE availability. Consecutively, I solve for efficient coal generation under consideration of the optimality conditions of the lower-level problem and the expectations on the VRE availability.

[5]There are also non-negativity conditions for generation. I consider those implicitly by allowing the optimality conditions following the Lagrangian $\mathcal{L}$ to be $\forall j : \frac{\partial \mathcal{L}}{\partial g^j} \geq 0$ for $g^j = 0$.

2.4.2 Efficient generation of VRE, gas and backup plants

The efficient generation of VRE, gas and backup plants is given by the lower-level optimization problem Eqs. (2.3)-(2.6). The solution of this program yields three non-marginal dispatch states, which are formally specified in Lemma 2.1. They describe the optimal dispatch for a given generation g^C and a known realization of τ.

Lemma 2.1. *The optimal dispatch decision for given g^C and τ can be described by the three feasible states $\omega^B, \omega^G, \omega^R$.*

$$\begin{aligned}
\omega^B &: g^B(\tau) > 0 \implies \alpha(\tau) = c^B, \\
&\quad g^G(\tau) = K^G, g^R = \tau K^R, g^B(\tau) = D - K^G - g^C - \tau K^R \qquad (2.7) \\
\omega^G &: g^B(\tau) = 0, g^G(\tau) = D - g^C - \tau K^R > 0 \implies \alpha(\tau) = c^G, \\
&\quad g^R(\tau) = \tau K^R \qquad (2.8) \\
\omega^R &: g^B(\tau) = 0, g^G(\tau) = 0 \implies \alpha(\tau) = 0, \\
&\quad g^R(\tau) = D - g^C \leq \tau K^R. \qquad (2.9)
\end{aligned}$$

Proof. See Appendix 2.B. *Q.E.D.*

Lemma 2.1 specifies a merit order curve (Figure 2.1). Backup generation g^B is only used if gas generation g^G is at its capacity limit (state ω^B) and gas generation g^G is only used if coal and renewable generation together do not suffice to satisfy demand (ω^G). Finally, renewable generation together with g^C may satisfy demand (ω^R) with excess VRE potential curtailed. The obtained merit order is different from the standard merit order with VRE and fully flexible generation. Due to its early commitment and inability to react to the realization of VRE generation, the generation of coal rather than its capacity is pivotal. Furthermore, coal cannot be the marginal, i.e., price setting generator. As a consequence, even though it is efficient to use coal, the obtained merit order does not reflect its marginal generation costs. Instead, coal generation corresponds to the marginal costs of VRE generation, which I assumed to be zero. VRE and coal generation together represent a variable component that shifts the merit order right for high VRE availability and large coal use.

2.4.3 Efficient generation of coal plants

Next, I turn to the upper-level dispatch problem, i.e., the choice of an efficient coal generation. As the full range of possible VRE availabilities needs to be considered when dispatching coal, several of the three states $\omega^B, \omega^G, \omega^R$ might have to be taken into account with different probabilities. For high availability, there could be excess generation, while for low availability expensive gas and backup generation is needed. I call the union of states that might occur after the VRE availability realizes a *configuration of states*. The efficient coal generation can be obtained for any given configuration. To obtain the configurations, I first determine the switch between states. To this end, I define levels for the realization of VRE generation $\underline{\tau}, \overline{\tau} \in (0, 1)$ such that $\underline{\tau}$ indicates the lowest level of realized VRE generation for which $g^B = 0$, i.e., no backup generation is needed; $\overline{\tau}$ indicates the lowest level of realized VRE generation for which $g^G = 0$, i.e., there is no gas generation needed after the realization of VRE availability. These levels $\underline{\tau}, \overline{\tau}$ determine the state configuration. If, for instance, under the given capacities a high VRE availability leads to state ω^R a medium availability to ω^G and a low availability to ω^B, I write the respective configuration as Ω^{RGB}. If, however, there is no use of the backup technology even for low VRE availability, this can be expressed by $\underline{\tau} = 0$ resulting in the configuration Ω^{RG}. All theoretically possible relations between $\underline{\tau}, \overline{\tau}$ and the states' configurations are given in Table 2.1.

Table 2.1: Mapping of $\underline{\tau}, \overline{\tau}$ for different configurations of states. States excluded by assumptions in parenthesis.

	$\overline{\tau} = 0$	$0 < \overline{\tau} < 1$	$\overline{\tau} = 1$
$\underline{\tau} = 0$	(Ω^R)	Ω^{RG}	Ω^G
$0 < \underline{\tau} < \overline{\tau}$	n.a.	Ω^{RGB}	(Ω^{GB})
$\underline{\tau} = \overline{\tau}$	n.a.	(Ω^{RB})	(Ω^B)

Given for $\underline{\tau}$ that states ω^G and ω^B exist and for $\overline{\tau}$ that states ω^R and ω^G exist, I set the backup and gas generation from Eqs. (2.7) and (2.8) to zero, respectively yielding the levels of $\underline{\tau}, \overline{\tau}$:[6]

[6]Another way to obtain these levels is to endogenize them in the upper-level decision, i.e., to write Eq. (2.1) as $E[DC]^* = \min_{g^C, \underline{\tau}, \overline{\tau}} [...]$.

$$D - K^G - g^C - \underline{\tau} K^R = g^B = 0 \implies \underline{\tau} = \frac{D - K^G - g^C}{K^R},$$
$$D - g^C - \overline{\tau} K^R = g^G = 0 \implies \overline{\tau} = \frac{D - g^C}{K^R}. \tag{2.10}$$

Given the previous assumptions on coal and gas capacities, i.e., $K^C + K^G \geq D$ and $K^C, K^G < D$, the number of configuration can be reduced. For Ω^R, Eq. (2.10) would imply $g^C = D$. The configuration can thus be excluded. For Ω^{GB}, Ω^B, costs could be reduced by increasing coal generation. Hence, these configurations are only feasible if $g^C = K^C$. However, gas generation is always sufficient to satisfy demand if coal operates at its capacity limit and no backup generation would be needed. It follows that the configurations can be excluded. Finally, for Ω^{RB}, Table 2.1 together with Eq. (2.10) would imply that $K^G = 0$. Thus, the feasible configurations are $\Omega^G, \Omega^{RG}, \Omega^{RGB}$ (Figure 2.1).

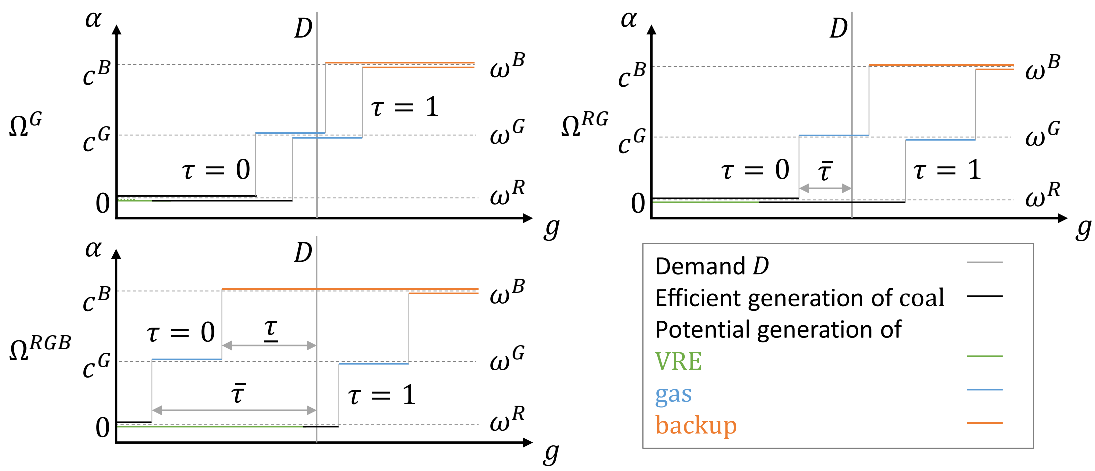

Figure 2.1: Feasible dispatch state configurations for different efficient choices for coal generation. The two curves for $\tau = 0$, $\tau = 1$ in each panel indicate the minimum and maximum VRE availability. All states – indicated by the possible intersections of supply and demand curves – covered for $\tau \in (0, 1)$ make up the configuration. Vertical shift of curves for illustrative purposes.

The upper level optimization problem Eqs. (2.1), (2.2) can then be rewritten as:[7]

[7]Note in Eq. (2.11) that $\int \dots \mathrm{d}F(\tau) = \int \dots \mathrm{d}\tau$ due to the assumed uniform distribution of τ.

$$
\begin{aligned}
E[DC]^* =& \min_{g^C} c^C[g^C|\omega^R \vee \omega^G \vee \omega^B] + c^G[g^G|\omega^G \vee \omega^B] + c^B[g^B|\omega^B] \\
=& \min_{g^C} \Bigg[c^C g^C + \int_{\underline{\tau}}^{\overline{\tau}} c^G(D - g^C - \tau K^R)\mathrm{d}\tau \\
& + \int_0^{\underline{\tau}} c^G K^G + c^B(D - K^G - g^C - \tau K^R)\mathrm{d}\tau \Bigg] \qquad (2.11) \\
& \text{s.t.} \quad \text{Eq. (2.2)}
\end{aligned}
$$

Cost for coal generation g^C occurs in all three states, costs for gas in states ω^G, ω^B and costs for backup generation only in state ω^B. The efficient levels of generation for g^B, g^G (Eqs. 2.7, 2.8) are directly inserted into the upper-level objective function and thereby satisfy the optimality of the lower-level problem (Eqs. 2.3-2.6).

The solution of this program provides the efficient choice of coal generation g^C for any given state configuration. However, within a configuration coal might hit its non-negativity or capacity generation constraint. As a consequence, I obtain five dispatch phases (I)-(V) that depend on the configurations of dispatch states as well as the efficient generation from coal. Each phase can be matched to a range of given VRE capacities. Lemma 2.2 provides the formal results.

Lemma 2.2. *Under the assumptions that coal and gas capacities are sufficient to satisfy demand together but not alone ($K^C + K^G \geq D$; $K^C, K^G < D$) there are five dispatch phases* (I)-(V) *which are associated with the following VRE capacity levels.*

$$
K^R \in \begin{cases}
\left(0, D - K^C\right) & \text{for (I)}, \\
\left(D - K^C, (D - K^C)\frac{c^G}{c^C}\right) & \text{for (II)}, \\
\left((D - K^C)\frac{c^G}{c^C}, K^G\frac{c^G}{c^C}\right) & \text{for (II)}, \\
\left(K^G\frac{c^G}{c^C}, (D - K^G)\frac{c^B}{c^C} + K^G\frac{c^G}{c^C}\right) & \text{for (IV)}, \\
\left((D - K^G)\frac{c^B}{c^C} + K^G\frac{c^G}{c^C}, \infty\right) & \text{for (V)}.
\end{cases} \qquad (2.12)
$$

For each phase the efficient coal dispatch differs because it is either linked to a distinct state configuration or hits a generation constraint as follows:

$$\Omega^{G}, g^{C} = K^{C} \qquad \text{for (I)}, \tag{2.13}$$
$$\Omega^{RG}, g^{C} = K^{C} \qquad \text{for (II)}, \tag{2.14}$$
$$\Omega^{RG}, g^{C} = D - K^{R}\frac{c^{C}}{c^{G}} \qquad \text{for (III)}, \tag{2.15}$$
$$\Omega^{RGB}, g^{C} = D - K^{R}\frac{c^{C}}{c^{B}} - K^{G}\left[1 - \frac{c^{G}}{c^{B}}\right] \qquad \text{for (IV)}, \tag{2.16}$$
$$\Omega^{RGB}, g^{C} = 0 \qquad \text{for (V)}. \tag{2.17}$$

Proof. See Appendix 2.C. *Q.E.D.*

The relations obtained in Lemma 2.2 are visualized in Figure 2.2. For increasing capacities of VRE, i.e. along the phases (I) to (V), coal generation weakly decreases. For small VRE capacities, coal is used at its capacity limit. Interestingly, coal is still fully used when coal and VRE capacities exceed the demand together (Ω^{RG}). Here, if the VRE availability turns out high, VRE generation needs to be curtailed. For further increasing VRE capacity, coal generation starts to decrease linearly. The decrease is slowed after the backup generation must be used for low VRE availability (Ω^{RGB}). Finally, coal generation ceases only after VRE capacity strictly exceeds the demand.[8]

2.4.4 Expected generation of VRE, gas and backup

So far, I have obtained the efficient dispatch choices for any feasible configuration of dispatch states and related them to the level of VRE capacity. Yet, for VRE, gas and backup generation, the efficient choice depends on the realization of VRE availability. Still, for an unknown availability, I can obtain the expected generation of VRE, gas, and backup. The expected values indicate how generation changes in the long term for changing VRE capacities. Most interestingly, this yields information about the capacity factor of VRE as well as the use of the flexible gas generation. The expected generation of VRE, gas and backup can be obtained from:

[8] To see this, set $K^{R} \geq (D - K^{G})\frac{c^{B}}{c^{C}} + K^{G}\frac{c^{G}}{c^{C}} > D$, rearrange to obtain $D(\frac{c^{B}}{c^{C}} - 1) > K^{G}(\frac{c^{B}}{c^{C}} - \frac{c^{G}}{c^{C}})$. Now notice that increasing the right-hand side of this inequality by substituting c^{C} for c^{G} tightens the inequality. Yet, simplifying to $D > K^{G}$ shows that it still strictly holds.

$$E[g^R] = \int_{\overline{\tau}}^{1} D - g^C \mathrm{d}\tau + \int_{0}^{\overline{\tau}} \tau K^R \mathrm{d}\tau \tag{2.18}$$

$$E[g^G] = \int_{\underline{\tau}}^{\overline{\tau}} D - g^C - \tau K^R \mathrm{d}\tau + \int_{0}^{\underline{\tau}} K^G \mathrm{d}\tau \tag{2.19}$$

$$E[g^B] = \int_{0}^{\underline{\tau}} D - K^G - g^C - \tau K^R \mathrm{d}\tau. \tag{2.20}$$

Inserting for the three feasible configurations the values for $\underline{\tau}, \overline{\tau}$ from Table 2.1 and Eq. (2.10) as well as the efficient coal generation (Lemma 2.2; summarized in Figure 2.2) directly yields the effective expected generation.[9]

In the following paragraphs, I further characterize the generation for all dispatch phases. For phase (I), the intuition goes that VRE and coal capacities are fully used but still too low to satisfy demand even for the highest availability of RE. This is because this phase only occurs for low VRE capacities. Thus, gas generation must be used no matter the VRE availability. Backup generation is not needed, because gas is always able to cover the remaining demand for fully used coal capacity. Here, any additional VRE generation is fully used and perfectly substitutes generation from gas. The switch to phase (II) marks the point where VRE generation at high availability and coal exceed the demand together. As a consequence, VRE generation is increasingly curtailed. Under (II), the full coal capacity will still be used. Here, due to curtailment, VRE generation can only imperfectly substitute the generation from gas. For further increasing VRE capacity, phase (III) will be reached, under which coal generation starts to be reduced and additional generation from gas guarantees the sufficient supply if VRE availability turns out low. From this point, we see an imperfect substitution of coal use for increasing VRE capacity (one additional unit of VRE decreases coal use by $\frac{c^C}{c^G} < 1$ units; see Eq. 2.15). Expected gas generation and substitution under (III) can be obtained from Eq. (2.19) as

$$\text{for (III):} \quad E[g^G] = \frac{K^R}{2}\left[\frac{c^C}{c^G}\right]^2 \iff \frac{\mathrm{d}E[g^G]}{\mathrm{d}K^R} = \frac{1}{2}\left[\frac{c^C}{c^G}\right]^2 > 0. \tag{2.21}$$

[9] I abstain from showing all explicit results, which are mostly inconveniently complex and of no great importance for the implications of the paper. Still, I make further use of some of them in the following and provide a better intuition on their outcomes.

Notably, the expected generation from gas is imperfectly complemented by VRE capacity (one additional unit of VRE increases expected gas use by $0 < \frac{1}{2}\left[\frac{c^C}{c^G}\right]^2 < \frac{1}{2}$ units).

Gas use under low VRE availability is now successively increased up to the point where gas generation reaches its capacity limit in the case that no VRE generation is available ($g^G(\tau \to 0) \to K^G$). This implies the switch to phase (IV), where demand must additionally be covered from the backup generation. The expected gas and VRE generation follow from Eqs. (2.18), (2.19) and imply

for (IV):

$$\frac{\mathrm{d}E[g^R]}{\mathrm{d}K^R} = \left[\frac{K^G}{K^R}\right]^2 \frac{(c^B - c^G)^2}{2(c^B)^2} + \frac{c^C}{c^B}\left[1 - \frac{c^C}{c^B}\right] > 0, \tag{2.22}$$

$$\frac{\mathrm{d}E[g^G]}{\mathrm{d}K^R} = \left[\frac{K^G}{K^R}\right]^2 \left[\frac{c^G}{c^B} - \frac{1}{2}\right] \gtreqless 0 \iff 2c^G \gtreqless c^B. \tag{2.23}$$

While expected VRE generation is strictly concavely increasing for additional VRE capacities, expected gas generation may increase if its marginal generation costs are rather large or decrease if they are small compared to the costs of backup.[10] Hence, the relation of expected gas generation and VRE capacity is ambiguous, but low gas and high backup cost generally increase their substitutability. For coal generation, there is always a substitution with additional VRE capacity. Contrary to the effect on gas, the substitution effect grows stronger as the the marginal costs of the backup technology shrink (per additional unit of VRE capacity, $\frac{c^C}{c^B}$ units of coal generation are substituted; see Eq. 2.16).

Finally, for high VRE capacity, coal generation ceases, which marks the switch to phase (V). This leads to a lower utilization rate, i.e., higher curtailment rates, of additional VRE capacity as it may no longer substitute the decreasing generation from coal. While expected VRE generation asymptotically approaches the demand, expected generation from gas and backup asymptotically approach zero. An overview of the relation of configurations, VRE capacity and (expected) generation is given in Figure 2.2. Proposition 2.1 summarizes the results.

[10] If this result appears counter intuitive, note that efficient expected gas generation is indeed decreasing in its marginal costs. Only the change upon changing VRE capacity is positively related to its costs.

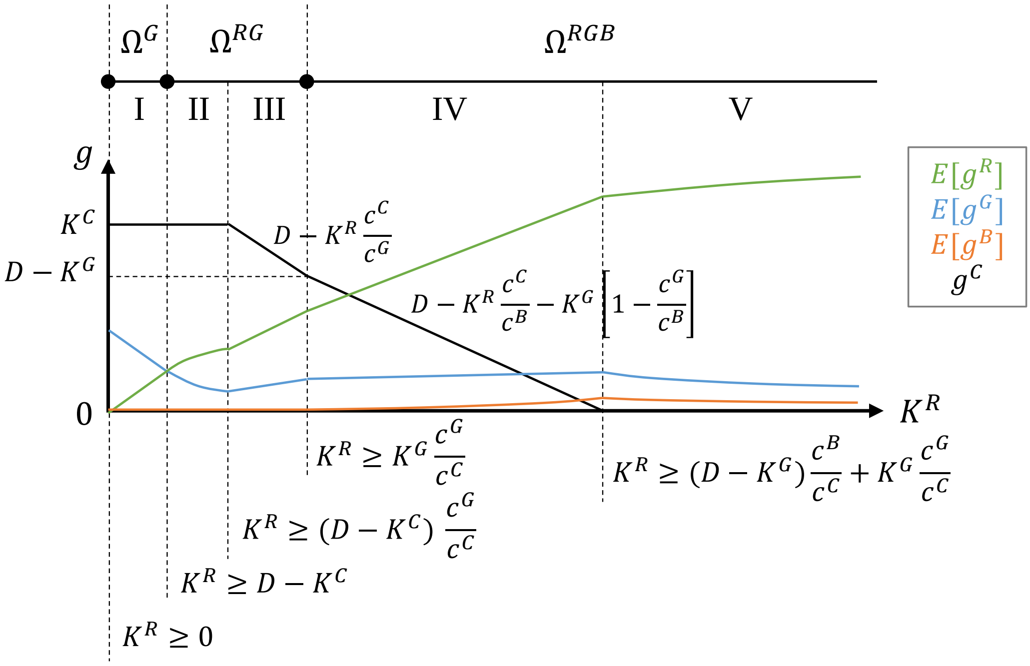

Figure 2.2: Relation of phases, VRE capacity and efficient (expected) generation.

Proposition 2.1. *For $K^R \leq (D - K^C)\frac{c^G}{c^C}$, coal is used at full capacity and increasing VRE capacity reduces the efficient gas generation. For $K^R > (D - K^C)\frac{c^G}{c^C}$, efficient coal use starts to decrease and use of gas generation rises if either $K^C + K^G > D$ or $c^G > c^B/2$. Eventually for $K^R \geq (D - K^G)\frac{c^B}{c^C} + K^G\frac{c^G}{c^C}$, coal generation ceases while expected VRE generation approaches total demand and expected gas and backup generation approach zero.*

2.5 Efficient transition to renewable generation

We have seen that the expected changes in utilization for different power generation capacities is far from a linear process when VRE capacities are increased. While expected VRE generation is sometimes linear and sometimes concave in its capacity, the expected generation from gas and backup is in parts decreasing or increasing. These characteristics of efficient power generation affect the efficient deployment dynamics of VRE capacities. Furthermore, under some circumstances, it might pay off to increase flexible gas capacities to facilitate the VRE integration, i.e., by reducing the need for coal or backup generation as well as VRE curtailment. In the following, I first analyze the efficient deployment of VRE capacities for falling unit capacity costs. Consecutively, I evaluate under what circumstances it can be efficient to increase gas capacities to be used as a transition technology while moving towards a fully renewable power generation.

2.5.1 Deployment of VRE capacities

To obtain the optimal choice of VRE capacities, I minimize expected total costs $E[TC]$ from dispatching generation and deploying VRE at a constant unit cost c^{KR} (cf. Helm & Mier, 2019):

$$E[TC]^* = \min_{K^R} E[DC]^* + c^{KR}K^R. \tag{2.24}$$

As laid out before, I assume that coal and gas capacities are exogenous and thus not subject to the decision. Inserting the efficiency conditions for generation from Lemmas 2.1, 2.2 into the configuration specific solutions for $\underline{\tau}, \overline{\tau}$ together with Table 2.1 yields the following FOCs:

$$\text{(I)}: \frac{\partial E[TC]^*}{\partial K^R} = -\frac{c^G}{2} + c^{KR} \geq 0, \tag{2.25}$$

$$\text{(II)}: \frac{\partial E[TC]^*}{\partial K^R} = -\left(\frac{D - K^C}{K^R}\right)^2 \frac{c^G}{2} + c^{KR} \geq 0, \tag{2.26}$$

$$\text{(III)}: \frac{\partial E[TC]^*}{\partial K^R} = -\frac{(c^C)^2}{2c^G} + c^{KR} \geq 0, \tag{2.27}$$

$$\text{(IV)}: \frac{\partial E[TC]^*}{\partial K^R} = -\left(\frac{K^G}{K^R}\right)^2 \frac{c^B c^G - (c^G)^2}{2c^B} - \frac{(c^C)^2}{2c^B} + c^{KR} \geq 0, \tag{2.28}$$

$$\text{(V)}: \frac{\partial E[TC]^*}{\partial K^R} = -\frac{c^B(D - K^G)^2 + c^G K^G (K^G - 2D)}{2(K^R)^2} + c^{KR} \geq 0. \tag{2.29}$$

The derivatives might be larger than zero only if $K^R = 0$, i.e., if VRE capacities are constrained by their non-negativity condition.

I have already proven that efficient VRE capacities increase throughout the phases from (I) to (V). Thus, following Eq. (2.25), there exists a maximum level of unit capacity cost for VRE: $c^{KR} = c^G/2$. If unit capacity costs are higher than this, no VRE capacity will be deployed. The level is a direct consequence of the substitution of gas generation in the case of low VRE capacity. Due to the expected generation of half its capacity, unit costs of VRE capacities must fall below half the generation costs of gas to be competitive. In other words, the levelized costs of VRE generation, which amount for $2c^{KR}$, must fall below the ones of gas, c^G.[11] Furthermore, the conditions do not depend on the VRE capacity for phases (I) and (III). Here, the marginal benefits of VRE deployment due to reduced dispatch costs are constant. As a consequence, there is only one particular equilibrium for a distinct level of marginal costs. For (I) that implies that for $c^{KR} = c^G/2$ VRE capacities are immediately deployed up to the switch into phase (II). Similarly, at $c^{KR} = (c^C)^2/2c^G$ there is an immediate switch from (II) to (IV) with a possibly instantaneous increase in VRE capacity. Solving the FOCs of phases (II),(IV),(V) for positive K^R yields the efficient choice of VRE capacity:

$$\text{(II)} : K^R = (D - K^C)\sqrt{\frac{c^G}{2c^{KR}}}, \tag{2.30}$$

$$\text{(IV)} : K^R = K^G\sqrt{\frac{(c^B - c^G)c^G}{2c^B c^{KR} - (c^C)^2}}, \tag{2.31}$$

$$\text{(V)} : K^R = \sqrt{\frac{D^2 c^G + [D - K^G]^2(c^B - c^G)}{2c^{KR}}}. \tag{2.32}$$

In all three phases VRE capacity is convex in its unit capacity costs. To see this, generalize to $K^R = \frac{s}{\sqrt{tc^{KR} - u}}$, where s is some strictly positive constants and t, u are strictly positive constants in (IV) and $t = 2, u = 0$ in (II), (V). K^R is convex in c^{KR} if the second derivative is positive, i.e., $\frac{\mathrm{d}^2 K^R}{(\mathrm{d}\ c^{KR})^2} = \frac{3st^2}{4(tc^{KR} - u)^{5/2}} > 0$. That clearly holds for $u = 0$ and hence (II) and (V). It also holds for $tc^{KR} - u > 0$. In Eq. (2.31), the denominator generalized as $tc^{KR} - u$ must be strictly positive to obtain a real solution for K^R. Thus, the second derivative will also be positive for (IV).

As a consequence, if unit capacity costs decrease linearly over time, there will be an accelerated deployment of VRE capacity within each phase. However, deployment may be slowed again after switching phases. Furthermore, and as hypothesized, the endowment with gas and coal capacities affects the efficient deployment of VRE. In phase (II), coal capacity has a suppressing effect on VRE deployment, while gas capacity has no effect. In phases (IV), (V) where coal capacity is never fully used, efficient VRE deployment only depends on the gas endowment. In

[11] Usually levelized costs contain capacity and dispatch costs. Here, they are simplified as I neglect capacity cost of gas and assume that VRE dispatch costs are zero.

phase (IV), VRE deployment is positively proportional to gas endowment, while gas capacity reduces VRE deployment during phase (V). Furthermore, the endowment may affect the switch between phases. This is not the case between the phases (I)-(IV) because of the constant efficient values for c^{KR} in (I) and (III). The switching cost between (IV), (V) can be obtained from equalizing Eqs. (2.31), (2.32) to obtain

$$\widetilde{c^{KR}} = \frac{(c^C)^2(c^B(D-K^G)^2 + c^G(2D-K^G)K^G)}{2(c^B(D-K^G)+c^GK^G)^2}. \tag{2.33}$$

The derivative with respect to gas capacity

$$\frac{\mathrm{d}\widetilde{c^{KR}}}{\mathrm{d}K^G} = \frac{(c^C)^2(c^B-c^G)c^GDK^G}{(c^B(D-K^G)+c^GK^G)^3} \geq 0, \tag{2.34}$$

which is strictly larger than zero for strictly positive gas capacity shows that increasing gas capacities imply a switch from (IV) to (V) at higher costs. Figure 2.3 sketches these findings, Proposition 2.2 summarizes them.

Proposition 2.2. *Deployment of VRE capacity becomes efficient as soon as its levelized costs are lower than the ones of gas $2c^{KR} \leq c^G$. Under the assumption of constant unit VRE capacity costs, VRE deployment is instantaneously undertaken until $K^R = D - K^C$. If VRE capacity costs fall further, efficient VRE capacity increases convexly until $c^{KR} = \frac{(c^C)^2}{2c^G}$. Here, VRE deployment is instantaneously increased up to $K^R = K^G\frac{c^G}{c^C}$. For consecutively falling costs, efficient VRE capacity increases again convexly with a kink when coal generation ceases.*

It is informative to also analyze the two extremes of possible endowment in which either coal or gas capacities approach the total demand while the other tends to zero.[12] If gas capacity approaches the total demand and coal capacity approaches zero, the initial deployment of VRE capacity given from the maximum level of unit capacity cost and Eq. (2.30) reaches $K^R = D$. Notably, this amount is the maximum of Eq. (2.30) and any additional coal capacity reduces the initial

[12] Remember that by assumption $K^G, K^C < D; K^G, K^C > 0$. Relaxing this might lead to other feasible configurations and thus other outcomes for efficient VRE deployment. We may, however, analyze scenarios that are arbitrarily close to the extremes, i.e., $K^G \to D, K^C \to 0; K^G \to 0, K^C \to D$.

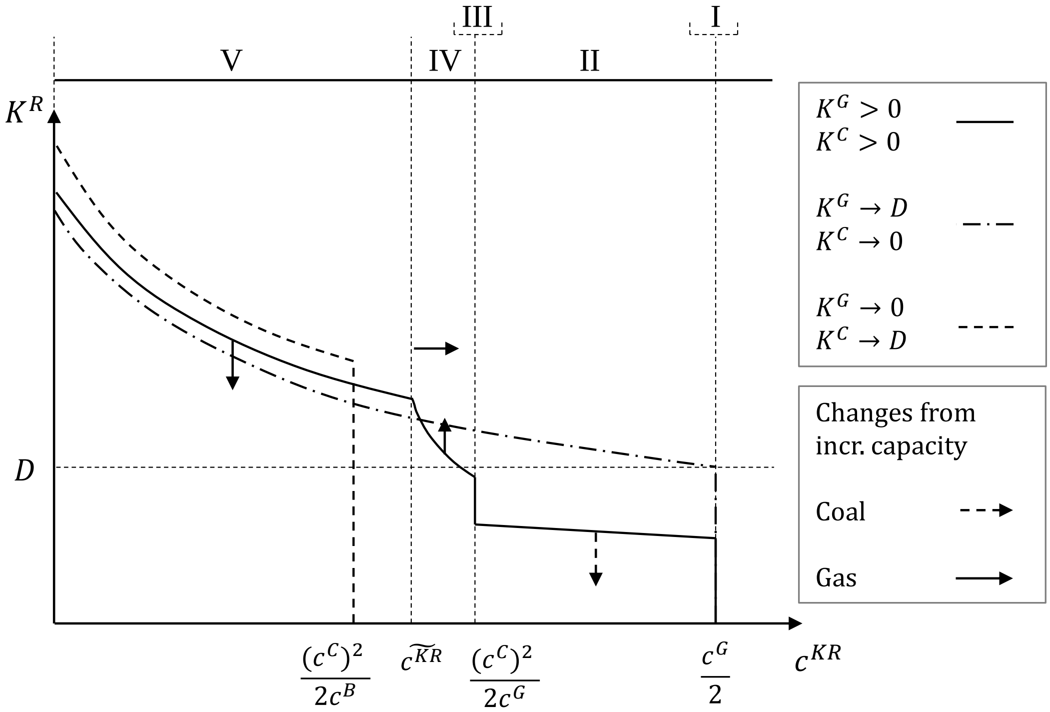

Figure 2.3: Optimally deployed VRE capacity for given unit capacity costs and different endowment with coal and gas capacities. The displayed phases (I) to (V) correspond to the scenario with mixed capacities ($K^G > 0, K^C > 0$). Arrows indicate changes due to increasing coal or gas capacities. Read from right to left, i.e., phase (I) to (V) such that VRE unit capacity costs are decreasing and VRE deployment is increasing.

deployment. Due to the high level of flexibility in the gas dominated system, only after $K^R > D$ VRE curtailment becomes necessary for high VRE availability. Now, if capacity costs decrease further, VRE capacity will follow from Eq. (2.30). Due to $K^G \to D, K^C \to 0$, phase (V) follows directly on (II) at $K^R \geq K^G \frac{c^G}{c^C}$. This can be seen directly from the VRE capacities that induce switching (Eq. 2.12), but it is also intuitive as phases (III), (IV) are characterized by $g^C > 0$. Now looking at phase (V), i.e., Eq. (2.32) with $K^G \to D$, one sees that the efficient solution for VRE deployment is simplified to the solution in phase (II), Eq. (2.30). Thus, for this system after the instantaneous deployment of VRE capacity in phase (I), there is a smooth and continuous increase in VRE capacity for falling unit capacity costs.

Next, I analyze a mostly inflexible system with coal endowment approaching the full demand and gas approaching zero. Following directly from Eq. (2.31), there will be no VRE deployment during phase (IV) and thus neither for (I)-(III) because VRE capacities must always increase for consecutive phases. In phase (V) with $K^G \to 0$ it is required that $K^R \geq D\frac{c^B}{c^C}$ (Eq. 2.12). Inserting this in Eq. (2.32), I obtain the maximum VRE unit capacity cost for which it is efficient to deploy VRE to be $c^{KR} = \frac{(c^C)^2}{2c^B}$. This cost level is strictly lower than the one in a system with gas capacity ($\frac{c^G}{2}$). Thus, VRE capacity deployment in a coal only system starts later than in a more flexible system with gas generators. As soon as the maximum cost level is reached, VRE capacities are instantaneously deployed up to a level of $K^R = D\frac{c^B}{c^C}$, while coal generation stops. As I have shown that gas capacities in phase (V) suppress VRE deployment from that point on and for further falling capacity costs, the efficient VRE capacity exceeds the one in the systems with gas capacity reaching $K^R = D\sqrt{\frac{c^B}{2c^{KR}}}$ (following Eq. 2.32).

The results on the extremes of possible conventional endowment are also visualized in Figure 2.3. Comparing the mixed endowment with the two extremes, we see that VRE deployment with mixed capacities starts at the same costs as in a fully flexible system. Yet, the efficient VRE deployment turns out to be lower the larger the coal capacities are. When VRE capacity costs are low enough, coal starts to be phased out. At this point there is a boost in VRE deployment, which quickly approaches and finally exceeds the efficient path in the fully flexible endowment scenario.[13] Interestingly, this acceleration in VRE deployment occurs only after VRE curtailment is already necessary due to large capacities. If there is only inflexible endowment, the beginning of VRE deployment will be delayed. However, as soon as deployment starts, VRE capacities will even exceed the ones in the flexible or mixed systems.

2.5.2 The use of gas as a transition technology

It is often debated whether flexible conventional generators, in particular gas-fired plants, are necessary for the transition to a renewable power system (e.g. Shearer et al., 2014, Hausfather, 2015). On the one hand, gas generation has a rather low CO_2-intensity. From a climate perspective, it is thus preferable to coal. Furthermore, due to greater flexibility gas can cope better with variable generation from renewable capacities (Mac Kinnon et al., 2018). On the other hand, increased use of gas might delay the transition to VRE and thus confer

[13]Even though it is not directly obvious from the formal results on VRE capacity, VRE deployment must be higher in the mixed scenario because it starts lower in phase (II) and ends up higher in (V).

climate benefits (Zhang et al., 2016). In Section 2.4, I analyzed when and how persisting gas plants should be operated during the transition to high shares of VRE. Here, I examine whether and when it might be efficient to invest in new flexible (gas) generators. As before, I focus on the cost and flexibility aspects of the different technologies. Hence, my analysis complements the work of Coulomb et al. (2018), who assume a perfectly flexible generation of coal and gas and an allowable budget of CO_2 emissions.

It is efficient to invest in additional gas capacities if the expected dispatch cost reduction from new capacities exceed their marginal costs. Here, I depict the dispatch cost reduction as the marginal benefits of capacity (MB). As opposed to the levelized costs approach, the costs from additional gas generation are thus reflected in the marginal benefits and are weighed against savings in coal and backup generation. I assume that marginal capacity costs are constant and given as c^{KG}.[14] The expected marginal benefits, i.e., dispatch cost reduction, of investing in gas for given VRE and coal capacities are given as

$$E[MB^G] = -\frac{\mathrm{d}E[DC]^*}{\mathrm{d}K^G}. \tag{2.35}$$

Lemma 2.1 shows that gas capacities are only utilized at their full capacity when also backup generation is used. This is only the case for phases (IV), (V). Thus, for (I)-(III) it is obvious that additional gas capacities have no benefit because they would not be used. Inserting the efficiency conditions for generation from Lemmas 2.1, 2.2 and the configuration specific solutions for $\underline{\tau}, \overline{\tau}$ together with Table 2.1 into Eq. (2.35) yields the following expected marginal benefits for gas capacity:

$$\text{(IV)}: E[MB^G] = \left(1 - \frac{c^G}{c^B}\right)\left(c^C - c^G \frac{K^G}{K^R}\right), \tag{2.36}$$

$$\text{(V)}: E[MB^G] = (c^B - c^G)\frac{D - K^G}{K^R}. \tag{2.37}$$

The switching condition for phase (IV) $K^R \geq K^G \frac{c^G}{c^C} \implies c^C - c^G \frac{K^G}{K^R} \geq 0$ implies that $E[MB^G] \geq 0$ in phase (IV). Furthermore, the expected marginal

[14]As my approach is static, c^{KG} could be interpreted as marginal cost per time unit of operation.

benefits strictly increase for rising VRE capacity in phase (IV) and strictly decrease in phase (V). As a consequence, $E[MB^G]$ are maximized at the switch from (IV) to (V). Their maximum, $E[\overline{MB}^G]$, can be derived by inserting the respective switching VRE capacity (Eq. 2.12) into either Eq. (2.36) or (2.37). It is

$$E[\overline{MB}^G] = c^C \frac{(c^B - c^G)(D - K^G)}{c^B(D - K^G) + c^G K^G}. \tag{2.38}$$

Setting $E[\overline{MB}^G] = c^{KG}$ and solving for K^G yields the maximum efficient gas generation capacity:

$$\overline{K}^G = \frac{D}{c^B - c^G}\left[c^B - \frac{c^C c^G}{c^C - c^{KG}}\right]. \tag{2.39}$$

It can only be efficient to deploy additional gas capacities if the initial endowment is strictly lower than $\overline{K}^G$, which increases in the marginal generation cost of backup and coal.[15] Interestingly, this capacity does not depend on the initial endowment with coal capacity. As a consequence, even if gas capacities are chosen to be optimal, there can be overcapacity, i.e. coal and gas capacities combined exceed demand. Remember, however, that the assumption of $K^C + K^G \geq D$ underlies the analysis. Thus, coal and gas capacity will in general not operate at their capacity limits at the same time and their efficient capacities are independent.

Setting $\overline{K}^G > 0$, I derive the highest unit capacity cost of gas which may still lead to an efficient positive gas capacity deployment:

$$\overline{K}^G > 0 \iff c^{KG} < c^C\left[1 - \frac{c^G}{c^B}\right]. \tag{2.40}$$

If this unit cost for gas capacity is exceeded, it can never be efficient to deploy additional gas capacities even if there were none in the original endowment. On the one hand, this cost threshold is directly proportional to the marginal generation cost of coal. In fact, the VRE capacity at the switch from (IV) to (V) where gas capacity is most valuable is inversely proportional to the marginal cost of coal

[15] The respective derivatives are $\frac{\mathrm{d}\overline{K}^G}{\mathrm{d}c^B} = \frac{c^G c^{KG} D}{(c^B - c^G)^2 (c^C - c^{KG})} > 0$; $\frac{\mathrm{d}\overline{K}^G}{\mathrm{d}c^C} = \frac{c^G c^{KG} D}{(c^B - c^G)(c^C - c^{KG})^2} > 0$. Note, that in this static consideration it must be $c^C > c^{KG}$ as otherwise generation from coal would always be preferred over gas capacity extension.

generation. Thus, if coal generation is more expensive, coal will be phased out at lower VRE capacities, inducing higher benefits for gas capacity. On the other hand, if the marginal generation cost of gas generation approaches the marginal cost of backup, then the marginal benefits of gas capacity tend to zero. This is intuitive as backup generation without any capacity constraints may then be used instead of gas.

The here derived threshold values (Eqs. 2.38-2.40) are obtained for the situation where gas capacity is most valuable. However, additional gas capacities would certainly be deployed for a range of VRE capacities as those will increase while the plant is in operation. As a consequence, taking into account some temporal deployment dynamics, the actual thresholds for the efficiency of gas capacity additions are even more restrictive.[16] Whether it is efficient to deploy additional gas capacities during the transition then also depends on other factors as the transition speed. For instance, if the transition is slow, additional gas capacity might operate close to its maximum value for a long time, thus increasing its cost-efficiency. Proposition 2.3 summarizes the findings.

Proposition 2.3. *Expected marginal benefits of gas capacity are positive while gas generation is used at its capacity limit. They reach their maximum when coal generation ceases. Yet, it is never efficient to deploy more than the maximum efficient gas capacity* $\overline{K}^G = \frac{D}{c^B - c^G}\left[c^B - \frac{c^C c^G}{c^C - c^{KG}}\right]$ *or to deploy any additional capacities if the unit capacity costs reach or exceed the upper bound* $c^{KG} = c^C\left[1 - \frac{c^G}{c^B}\right]$. *The efficiency conditions for gas deployment are even more restrictive if temporal deployment dynamics are considered.*

2.6 Conclusion

I have studied how different endowments of flexible conventional plants affect the efficient transition to a renewable power system. I show that limited flexibility does hamper early deployments of VRE. Later, during the phases when inflexible generation is reduced, the VRE capacity increases quickly, even exceeding the efficient levels of fully flexible systems. Thus, when VRE capacities are already very high, the limits in conventional generator's flexibility have no impairing effect on

[16] Of course the per time unit costs c^{KG} increase proportionally to a longer time period while the benefits of gas capacity decrease.

their deployment. However, the limits on flexibility lead to more discontinuations in the VRE deployment along the transition path (cf. Helm & Mier, 2019).

As opposed to the cost-efficient path with partly surging and partly stagnating VRE deployments, regulators may prefer a rather smooth transition to avoid sudden disruptions in the power system or the associated labor market and to synchronize other infrastructure development. As a consequence, regulators of rather inflexible power systems could decide to increase VRE subsidies or to promote research in VRE during the early deployment phases to facilitate the transition. Increasing flexibility, for instance by installing flexible generators or storage, does not facilitate early VRE deployment. The policy support can be reduced when VRE deployment speeds up, such that the transition path is smoothed over time.

Another core result is that it can be efficient to utilize flexible, inflexible and VRE capacities at the same time. This contradicts the assertion from Eisenack & Mier (2018) that inflexible generation can in general not be efficiently used together with VRE. The difference can be traced back to their assumption of optimal capacity choice while I consider non-optimal and rigid endowment of coal and gas. Even though their approach is reasonable for long-term planning, the need for a quick shift from mostly conventional to VRE-based power systems necessitates acknowledging off-equilibrium transition dynamics.

Concerning the role of gas as a transition technology, I show that the expected generation from flexible plants is likely to increase for rising capacity shares of VRE due to the increased need for flexible generation (cf. Kondziella & Bruckner, 2016). This finding persists under the consideration of a binding emission budget as shown by Coulomb et al. (2018). As opposed to my approach, they differentiate coal and gas by their respectively higher and lower emission intensities (and not by their flexibility potential). They obtain a qualitatively similar result: gas use increases in the interim, while coal generation falls and VRE capacities are increased. The alignment of the results from flexibility and emission perspectives facilitates the power system transition as low-emission plants have flexibility co-benefits and vice versa. Nonetheless, evaluating the ultimate efficiency of deploying new gas capacities will require the comprehensive analysis of cost, climate and flexibility issues of all technologies.

The generality of my results may be impacted by the employment of static optimization instead of the use of a dynamic approach. In particular, this simplification disregards the fact that the VRE endowment changes over a capacity's lifespan and thus affect benefits over time. For instance, additional VRE deployment will reduce the benefits of existing VRE capacities. Coram & Katzner (2018) undertake a dynamic analysis and find that efficient deployment decreases over time. However, they consider constant unit capacity costs at all times. Assuming decreasing costs may easily shift their results and induce deployment increases over time. Also empirically the worldwide VRE deployment has increased in the last two decades (Ritchie & Roser, 2019). While a dynamic analysis might depict a promising extension for future research, I expect my main results to carry over.

Evaluating my assumption of inelastic demand can be done by comparing the extreme endowment scenario where gas capacity approaches total demand with findings of Helm & Mier (2019), who consider reactive consumers but no inflexibility. Generally, inelastic demand is a reasonable and common assumption for electricity markets, for instance, because many consumers are not subject to wholesale market prices (Lijesen, 2007). Still, there are some modeling specifics to be addressed. An inelastic demand curve can only intersect the merit order supply curve at horizontal levels, implying constant marginal benefits of VRE as long as the marginal generation technology does not change. As opposed to that, an elastic demand leads to decreasing marginal benefits of VRE deployment when intersecting vertical parts of the merit order curve. Thereby, it also increases the number of dispatch phases that need to be considered. As a consequence, in Helm & Mier (2019) there are no instantaneous increases in efficient VRE deployment. By applying these insights to the scenario with mixed endowment of coal and gas, I expect that the VRE deployment path is smoothed, in particular at the switches between different phases. Nevertheless, I expect the general findings on the effects of limited flexibility to persist. Here, my results underline the importance of considering the interplay between generation variability and the flexibility of conventional generators for efficient VRE deployment.

Furthermore, I follow a cost-minimizing approach that neglects most institutional and market features of power systems. Such features might include market structures (e.g. zonal vs. nodal pricing), market concentration, subsidies for renewable generation or deployment, prices on carbon and payment for capacity reserves (Newbery et al., 2018). Hence, the findings do not predict real-world VRE deployment, but rather a desirable path. If policies shall be designed to achieve an efficient power system transition, it is necessary to determine the optimal transition path as well as possible challenges beforehand. My paper contributes to advancing knowledge in this direction by emphasizing the role of flexibility for efficient transitions.

The obtained results apply to power systems worldwide. In particular, the openness towards all feasible conventional endowment scenarios allows the nuanced interpretation of countries and regions with distinct characteristics. Furthermore, the inflexible and flexible capacities can be understood not only as coal and gas, but also as other generation technologies. For instance, they might depict generation from nuclear and oil or even from renewable generation with similar characteristics in terms of generation costs and flexibility. Furthermore, applications beyond power systems are conceivable. The limits on flexibility might also apply to other sectors like transport, telecommunications or food production (Eisenack & Mier, 2018). In the case that also the endowment with production assets is rigid, the insights from this paper might be transferable.

To conclude, regulators and operators of power systems should be cautious when extrapolating past data on efficient VRE deployment into the future because, during the transition, deployment can successively speed up and be suppressed. Furthermore, cross-regional spillovers of knowledge on power system transitions might be limited if the capacity endowments of the systems are different. Therefore, it is all the more important to gain differentiated insights on efficient deployment strategies that can facilitate the transition towards sustainable power systems.

Future research may address the influence of further flexibility options like demand-side management, storage or grids. Those options are integral towards the realization of a fully renewable power system. The time and extent to which they must be implemented will be highly relevant for power system transitions and probably depend greatly on the flexibility of endowed plants. Furthermore, the developed theoretical model can be quantified with empirical data. In turn, the results can be compared to the extensive body of numerical studies that analyze efficient system transitions for different regions. This might be informative, especially concerning the effects of limited flexibility, which is so far seldom considered. Finally, my approach, which considers rigid instead of optimized conventional capacities, can be extended to study asset stranding of fossil fuel-based power system infrastructures.

Appendices

2.A Nomenclature

$\tau \in (0,1)$	Random variable determining VRE availability
$j \in \{R, C, G, B\}$	Generation technology for VRE, coal, gas, backup
g^j	Generation of technology j [kW]
D	Demand [kW]
K^j	Capacity of technology j [kW]
c^j	Marginal generation cost of technology j [$/kW]
c^{Kj}	Unit capacity cost of technology j [$/kW]
DC	Dispatch costs [$]
TC	Total costs [$]
$E[\cdot]$	Expectation operator
$\omega^R, \omega^G, \omega^B$	Instantaneous dispatch states
$\Omega^G, \Omega^{RG}, \Omega^{RGB}$	Feasible dispatch state configurations
α	Shadow cost of balancing constraint [$/kW]
λ^j	Shadow cost on capacity constraints [$/kW]
MB^G	Marginal benefits of gas capacity [$/kW]

2.B Proof of Lemma 1

Proof. The Lagrangian of that problem reads (no longer explicitly indicating the dependence on τ):

$$\begin{aligned}\mathcal{L}(\tau) = {} & c^C g^C + c^G g^G + c^B g^B + \left[D - g^C - g^G - g^B - g^R\right]\alpha \\ & + \left[g^G - K^G\right]\lambda^G + \left[g^R - \tau K^R\right]\lambda^R \end{aligned} \tag{2.41}$$

The first order optimality conditions (FOCs) including their complementary slackness conditions are then:

$$\frac{\partial \mathcal{L}(\tau)}{\partial g^B} = c^B - \alpha \begin{cases} = 0 \\ \geq 0 \end{cases} \iff g^B \begin{cases} > 0 \\ = 0 \end{cases}, \tag{2.42}$$

$$\frac{\partial \mathcal{L}(\tau)}{\partial g^G} = c^G - \alpha + \lambda^G \begin{cases} = 0 \\ \geq 0 \end{cases} \iff g^G \begin{cases} > 0 \\ = 0 \end{cases}, (g^G - K^G)\lambda^G = 0, \tag{2.43}$$

$$\frac{\partial \mathcal{L}(\tau)}{\partial g^R} = -\alpha + \lambda^R \begin{cases} = 0 \\ \geq 0 \end{cases} \iff g^R \begin{cases} > 0 \\ = 0 \end{cases}, (g^R - \tau K^R)\lambda^R = 0. \tag{2.44}$$

From the FOCs it follows that the shadow price for power generation α may take three different values for non-marginal cases. If backup generation is used $g^B > 0$ we have $\alpha = c^B$. As a consequence, the shadow costs of generating with gas or VRE are strictly positive: $\lambda^G(\tau) > 0, \lambda^R(\tau) > 0$ and thus the available capacities are fully utilized $g^G(\tau) = K^G, g^R(\tau) = \tau K^R$. The solution for g^B then directly follows from the balance in Eq. (2.4). I denote this state by ω^B as backup generation is the marginal, i.e., price setting, technology.

Otherwise, there might be no backup generation needed $g^B = 0$, either because there is a higher renewable availability or ex-ante more coal generation. If additionally there is strictly positive and below capacity limit gas generation $0 < g^G < K^G$, this implies $\lambda^G = 0 \implies \alpha = c^G$. Hence, the marginal value of electricity is given by the marginal cost of using gas generation. As before, it follows that $\lambda^R(\tau) > 0 \implies g^R(\tau) = \tau K^R$. The solution for g^G directly follows from Eq. (2.4). The transition between the state ω^B and this state occurs at the point where there is no more backup generation but gas still operates at capacity limit $g^B = 0, g^G = K^G$. It marks a marginal boundary case as VRE generation is at its limit and coal generation exogenous (cf. Eq. 2.4). Hence, this state will only be reached for exactly one realization of (the continuous) τ and thus with probability zero. Due to the assumption of fixed demand, there is no unique equilibrium for the marginal value of electricity in this case. Instead, there is a continuum of equilibria such that $\alpha \in (c^G, c^B)$. For completeness, I assume that in this state $\lambda^G = 0 \implies \alpha = c^G$.[17] I denote this state by ω^G as gas generation is the marginal, i.e., price setting, technology.

Finally, there might be no backup and no gas generation needed $g^B = 0, g^G = 0$. If VRE generation is strictly positive and under the maximum available amount, i.e., $0 < g^R < \tau K^R$ it follows that $\alpha(\tau) = 0$. Note, that $g^R > 0$ must be satisfied following Eq. (2.4) as I assumed $K^C < D$. Similar to the line of argument above and with the same implications, the probability that coal generation must

[17] The marginal value of electricity is thus obtained from the marginal generation cost and not from the maximum willingness to pay. This issue of multiple equilibria could be fixed if one allows for some demand elasticity (cf. Helm & Mier, 2019). However, this comes at the cost of an increased number of states which greatly increases complexity. More caution is required if capacity levels are optimized because optimally chosen capacities are usually fully utilized hence greatly increasing the probability that boundary cases occur (cf. Eisenack & Mier, 2018).

exactly be complemented by the full available VRE generation to satisfy demand is only marginal (cf. Eq. 2.4). If the availability is lower, gas generation is needed (implying ω^G) and if it is higher there is excess VRE generation which is curtailed $g^R < \tau K^R$. For completeness, I assume that in the marginal state of $g^C + \tau K^R = D$ that $\lambda^R = 0 \implies \alpha = 0$. The solution for g^R directly follows from Eq. (2.4). I denote this state by ω^R as VRE generation is the marginal, i.e., price setting, technology.

Q.E.D.

2.C Proof of Lemma 2

Proof. The Lagrangian of Eq. (2.11) reads:

$$\begin{aligned}\mathcal{L} = &\int_{\overline{\tau}}^{1} c^C g^C \mathrm{d}\tau + \int_{\underline{\tau}}^{\overline{\tau}} c^C g^C + c^G(D - g^C - \tau K^R)\mathrm{d}\tau \\ &+ \int_{0}^{\underline{\tau}} c^C g^C + c^G K^G + c^B(D - K^G - g^C - \tau K^R)\mathrm{d}\tau \\ &+ (g^C - K^C)\lambda^C. \end{aligned} \tag{2.45}$$

Solving the integrals for the three feasible configurations by inserting the values for $\underline{\tau}, \overline{\tau}$ from Table 2.1 and Eq. (2.10) and taking the derivative with respect to g^C yields the following FOCs, where the conditions in Eq. (2.49) holds for all prior equations.

$$\Omega^G : \frac{\partial \mathcal{L}}{\partial g^C} = c^C - c^G + \lambda^C \begin{cases} \geq 0 \\ = 0 \end{cases}, \tag{2.46}$$

$$\Omega^{RG} : \frac{\partial \mathcal{L}}{\partial g^C} = c^C - c^G \frac{D - g^C}{K^R} + \lambda^C \begin{cases} \geq 0 \\ = 0 \end{cases}, \tag{2.47}$$

$$\Omega^{RGB} : \frac{\partial \mathcal{L}}{\partial g^C} = c^C - c^G \frac{K^G}{K^R} - c^B \frac{D - g^C - K^G}{K^R} + \lambda^C \begin{cases} \geq 0 \\ = 0 \end{cases}, \tag{2.48}$$

$$\iff g^C \begin{cases} = 0 \\ > 0 \end{cases}, (g^C - K^C)\lambda^C = 0. \tag{2.49}$$

For Ω^G it is clearly $\lambda^C > 0$ and thus

$$\text{for } \Omega^G : g^C = K^C. \tag{2.50}$$

For Ω^{RG}, if $g^C = 0$, gas generation would need to be able to cover the full demand if $\tau = 0$, i.e., $K^G \geq D$, which I have excluded by assumption. Thus, it must be $g^C > 0$ and solving Eqs. (2.47), (2.49) for g^C yields

$$\text{for } \Omega^{RG} : g^C = \begin{cases} K^C & \text{if } \lambda^C > 0, \\ D - K^R \frac{c^C}{c^G} & \text{if } \lambda^C = 0. \end{cases} \tag{2.51}$$

Finally, for Ω^{RGB}, it must be $g^C < K^C$ and hence $\lambda^C = 0$ because for $g^C = K^C$ coal and gas generation would always be able to cover demand even in times with no VRE availability. Thus, as backup generation is needed, coal generation must be below its full capacity. For $g^C > 0$, the efficient solution for coal generation is obtained by solving Eq. (2.48) for g^C. However, for large VRE capacities, this solution may turn negative. This can be avoided by considering the non-negativity constraint for coal generation:

$$\text{for } \Omega^{RGB} : g^C = \begin{cases} D - K^R \frac{c^C}{c^B} - K^G \left[1 - \frac{c^G}{c^B}\right] > 0, \\ 0. \end{cases} \tag{2.52}$$

The obtained five combinations of dispatch states and efficient coal generation, which I call phases in the following, correspond to the ones given in Lemma 2.2. Next, I provide the order of these phases and obtain the conditions on K^R that distinguish them.

Imagine starting from nearly zero capacities of VRE, i.e., $K^R \to 0$, and then successively increasing this capacity. For very low VRE capacity, $g^C + g^R < D$ and thus ω^R cannot occur. As two of the three feasible configurations include the state ω^R only Ω^G obtains for low VRE capacities. Efficient coal generation is given in Eq. (2.50). I define this as the phase (I). Once combined VRE and coal generation are sufficient to satisfy demand at least for the highest VRE availability ($\tau = 1$), we have the switch from Ω^R to Ω^{RG}. Following Lemma 2.1 and Eq. (2.51) this is the case once $K^R \geq D - K^C$, which can also be seen from setting $\overline{\tau} \leq 1$ in Eq. (2.10). To determine when it is efficient to use less than the full capacity, I set $g^C < K^C$ in Eq. (2.51) with $\lambda^C = 0$. Solving for VRE capacity yields $K^R \geq (D - K^C)\frac{c^G}{c^C}$, which is clearly larger than $D - K^C$, i.e., the VRE capacity where the switch to Ω^{RG} occurs. Hence, only after this threshold is reached and within Ω^{RG} coal generation falls under its capacity limit. I define phase (II) as Ω^{RG} with $g^C = K^C$ and phase (III) as Ω^{RG} with $g^C < K^C$.

For even higher VRE capacities, coal generation might get so low that gas is insufficient to cover demand at low VRE availability. This indicates the switch from Ω^{RG} to Ω^{RGB}. To obtain the respective level of VRE capacity, set $\underline{\tau} \geq 0$ in Eq. (2.10), insert g^C from Eq. (2.52) and solve for VRE capacity to obtain $K^R \geq K^G\frac{c^G}{c^C}$. Note further that $K^G\frac{c^G}{c^C} \geq (D - K^C)\frac{c^G}{c^C}$ directly follows from the assumption that $K^C + K^G \geq D$. If exactly $K^C + K^G = D$ their will be a direct switch from full capacity coal use in Ω^{RG} to Ω^{RGB}. I define phase (IV) as Ω^{RGB} with $g^C > 0$. For an even further increase of VRE capacity, efficient coal generation ceases. To obtain the associated level of VRE capacity set $g^C \leq 0$ in Eq. (2.52) and solve to obtain $K^R \geq (D - K^G)\frac{c^B}{c^C} + K^G\frac{c^G}{c^C}$. I define phase (V) as Ω^{RGB} with $g^C = 0$. *Q.E.D.*

3

Electricity storage and transmission: Complements or substitutes?

Abstract
Electricity from renewable sources often cannot be generated when and where it is needed. To deal with these temporal and spatial discrepancies, one frequently proposed approach is to expand storage capacities and transmission grids. It is often argued that the two technologies substitute each other, such that deploying one reduces the need for the other. Using a theoretical model, we show that storage capacities and transmission grids can also be complements if electricity system costs are minimized. We present the conditions that determine the kind of interdependence at specific storage locations: the characteristics of transmission congestion, i.e., during peak or off-peak and uni- or bidirectional as well as the alignment of marginal generation costs between adjacent regions. By applying our theoretical insights to Italian power system data, we obtain empirical evidence that storage and transmission can act as either substitutes or complements. Planners of long-lasting and costly infrastructure can use the results to avoid design errors such as a misplacement of storage within the system.
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3.1 Introduction

Efforts to decarbonize the energy system lead to a significant increase in the renewable energy supply (RES), for instance, in the supply of wind and solar power (Mitchell, 2016). Due to the geographical concentration in remote areas and fluctuating nature of many RES technologies, the real-time balancing of electricity demand and supply–both temporally and spatially–is a central challenge in the transformation of the energy system. This challenge can be addressed through a variety of system flexibility options. A prominent and widely discussed means of increasing flexibility is to increase the capacity of either electricity storage or transmission grids (e.g., The Economist, 2017, Baidawi, 31 November 2017, in The New York Times).

However, the extension of the grid has been delayed in many countries, partially due to its low social acceptability, for instance, across the EU (Cohen et al., 2016) and in the USA (Cain & Nelson, 2013). In addition, grid expansion requires large investments with long lead times. At the same time, the cost of storage is rapidly decreasing (Schmidt et al., 2017), and second-life batteries, e.g., from electric vehicles (cf. Neubauer & Pesaran, 2011), could lead to an unexpected increase in available storage capacities. If the two options are substitutes, storage may be a (temporary) alternative to a constrained grid extension. Yet, there is no consensus among experts about the interdependence between the two options, with some arguing that increased electricity storage capacity would make most grid expansion obsolete, and others claiming the opposite (Schmid et al., 2017, Purvins et al., 2011). Hence, deeper insights into the interdependence of the technologies are needed to enable the design of policies that will facilitate an efficient transition of the power system.

Storage generally allows electrical energy to be shifted over time, whereas transmission systems allow energy to be shifted over distance. Although they both operate in different dimensions, the two technologies are not necessarily independent of one another but may exhibit different kinds of interdependencies. These are the focus of the present study. In the literature to date, some authors have claimed that the two substitute each other, while others have suggested that they act as complements. The former argue, for instance, that increasing storage capacity reduces network congestion (Denholm & Sioshansi, 2009, MacDonald et al., 2016, Ghofrani et al., 2013, Abdurrahman et al., 2012, Xi & Sioshansi, 2016). A real-world example supports this argument: American Electric Power (AEP) has deployed a 5 MW battery to mitigate congestion (Electricity Advisory Committee, 2008). Others argue that optimal investment in storage is higher when additional transmission capacities are available (Haller et al., 2012a). Furthermore, there are also ambiguous results on the kind of interdependencies that exist (Steinke et al., 2013, Brancucci Martinez-Anido & de Vries, 2013, Zhou et al., 2014, Jamasb, 2017, Schill et al., 2017b, Neetzow et al., 2018b).

Factors cited in the literature as decisive for whether storage and transmission are complements are the share of RES in the system (Haller et al., 2012a); the spatial distribution of supply, demand, and storage (Haller et al., 2012a, Denholm & Sioshansi, 2009, Ghofrani et al., 2013, Schill et al., 2017b); the objective of the storage operation (Abdurrahman et al., 2012, Jamasb, 2017, Schill et al., 2017b); as well as the correlation between renewable feed-in and peak demand (Schill et al., 2017b). Furthermore, since spatial aggregation through additional transmission can level out fluctuating RES, storage might become less attractive (MacDonald et al., 2016).

Our study contributes to resolving these mixed findings. The theoretical model developed here provides a general mathematical condition that determines whether storage and transmission are complements or substitutes.[1] Interpreting that condition yields the following determinants: (i) the storage location, (ii) the timing and direction of transmission congestion, and (iii) the alignment of marginal generation cost (MGC) between adjacent regions. In particular if MGC are positively aligned, we find that storage at one end of the transmission line substitutes transmission capacity while it complements it at the other end. We show that our findings are empirically relevant by applying our model to regional Italian data. The derived insights can be used to inform decision-making in the power sector, e.g., on network planning and storage policies.

The remainder of this work is structured as follows. In Section 3.2, we present our two-region model, and in Section 3.3, we evaluate the optimal decisions for dispatch and capacity. We then derive a general condition for storage-transmission

[1] The literature defines (strategic) complements and substitutes in different ways (see, e.g., Hicks, 1970, Bulow et al., 1985) Here, we employ the following: Assuming a cost-minimizing decision, we investigate whether a marginal increase in capacity of one of the technologies results in less (substitutes) or more (complements) optimal (i.e., cost-minimizing) capacity of the other. As an example, in the former case, an increased storage capacity decreases the need for network expansion and increases it in the latter.

interdependence in Section 3.4 and specify the obtained insights for linear MGC in Section 3.5.1 and two periods in Section 3.5.2. For the latter, we then derive discrete interdependencies for all feasible dispatch combinations. In Section 3.6, we discuss the model applicability and provide empirical evidence. Section 3.7 concludes.

3.2 Modelling approach

The ambiguous results in the literature to date indicate the limitations of empirical methods and large-scale numerical energy system models to comprehensively answer the research question at hand. In fact, most studies (e.g. Denholm & Sioshansi, 2009, Haller et al., 2012a, Steinke et al., 2013, Zhou et al., 2014) are confined to a specific parameter constellation represented by complex simulation models, such that the underlying drivers of the results are difficult to isolate. Other studies derive their findings from qualitative reasoning (e.g. Schill et al., 2017b).

We deploy an instructive cost-minimization model of a DC load flow power system that is analytically solved for two regions $i \in I$ and $I = \{1, 2\}$ as well as an arbitrary number of time slices $t \in T$. In addition to the variable descriptions given in the text, a comprehensive nomenclature is given in Appendix 3.A. The minimal system costs are given by:

$$\min_{g_{i,t}, l_t, s_{i,t}, L, S_i} C = \sum_i \left[\sum_t c_i(g_{i,t}) + \psi S_i \right] + \gamma L, \tag{3.1}$$

subject to the local energy balance constraints

$$\forall t, i : R_{i,t} - g_{i,t} + s_{i,t} - \sigma l_t = 0, \text{ where } \sigma = \begin{cases} 1, \text{ for } i = 1, \\ -1, \text{ for } i = 2, \end{cases} \tag{3.2}$$

capacity constraints on transmission and storage

$$\forall t : |l_t| - L \leq 0, \tag{3.3}$$

$$\forall t, i : s^+_{i,t} + s^-_{i,t} - S_i \leq 0, \tag{3.4}$$

and balance of energy charged and discharged by the storage facilities

$$\forall i : \sum_t s^-_{i,t} - \eta \sum_t s^+_{i,t} = 0, \tag{3.5}$$

Investment is possible in regional storage power capacities $S_i \geq 0$, which can be installed at unit costs ψ, and in transmission line capacity $L \geq 0$ at unit costs γ. The dispatch decision concerns generation $g_{i,t} \geq 0$, which comes at generation costs $c_i(g_{i,t})$, storage charge $s^+_{i,t} \geq 0$, storage discharge $s^-_{i,t} \geq 0$, and transmission throughput l_t, and which has to satisfy the exogenous and inelastic residual demand $R_{i,t}$. A positive sign of l_t indicates that power is transmitted from region 2 to region 1 at time t, while a negative sign indicates the opposite power flow direction. For convenience, we write $c_{i,t} = c_i(g_{i,t})$ and marginal costs $c'_{i,t} = c'_i(g_{i,t})$. We assume that $c'_{i,t} > 0$ and $c''_{i,t} > 0$ (cf. Crampes & Moreaux, 2010). Furthermore, we denote storage net charge as $s_{i,t} = s^+_{i,t} - s^-_{i,t}$ and its round-trip efficiency as $\eta < 1$.

Our theoretical approach has the advantage that we can generalize from currently available technologies and economic conditions. Thus, the model allows us to investigate the implications of both present and possible future costs (e.g., if storage becomes competitive at a large scale). To this end, however, we need to make some common abstractions from technical details such as the reduction to two regions (cf. Höffler & Wambach, 2013, Oliver et al., 2014). However, each of the two regions may be interpreted as an aggregate of a network of multiple generation and load nodes connected via a single transmission line.

We follow Steffen & Weber (2013) in their assumptions about equal charge and discharge capacities as well as inelastic residual demand. Hence, we implicitly account for generation from renewable energies. Assuming an inelastic demand has the benefit that we can abstract from demand response programs and thereby isolate the pure effects of the transmission-storage interdependence. Instead of assuming that charging is a prerequisite for discharging, we impose an energy balance constraint on storage, i.e., storage has some initial energy level that must be restored eventually, and we ignore constraints on energy capacity (cf. Clack et al., 2015). Furthermore, we abstract from investment decisions in conventional generation capacity and assume perfect flexibility of generation (cf. Bertsch et al., 2016, Eisenack & Mier, 2018, Schill et al., 2017a).

3.3 Optimal dispatch and capacities

To obtain more insights and intuition about transmission and storage, in the following, we derive the optimal dispatch and capacity decisions. In Section 3.5, we will make direct use of the obtained conditions to specify our results about interdependence. We set up the Lagrangian for our optimization problem

$$\begin{aligned}\mathcal{L} = &\sum_{i\in I}\left[\sum_{t\in T} c_i(g_{i,t}) + \psi S_i\right] + \gamma L \\ &+ \sum_{i\in I, t\in T} \alpha_{i,t}(R_{i,t} - g_{i,t} + s_{i,t} - \sigma_i l_t) + \sum_{t\in T}\lambda_t(|l_t| - L) \\ &+ \sum_{i\in I, t\in T} \mu_{i,t}(s^+_{i,t} + s^-_{i,t} - S_i) + \sum_{i\in I}\xi_i(\sum_{t\in T} s^-_{i,t} - \eta\sum_{t\in T} s^+_{i,t}), \end{aligned} \tag{3.6}$$

where $\lambda_t, \mu_{i,t} \geq 0$ are the shadow prices for transmission capacity and storage capacity, $\alpha_{i,t}, \xi_i$ the ones for generation and stored electricity. Assuming strict non-negativity for generation, the Karush-Kuhn-Tucker conditions yield:[2]

$\forall i \in I, t \in T:$

$$\frac{\partial \mathcal{L}}{\partial g_{i,t}} = c'_{i,t} - \alpha_{i,t} = 0 \quad \text{for } g_{i,t} > 0, \tag{3.7}$$

$$\frac{\partial \mathcal{L}}{\partial s^+_{i,t}} = c'_{i,t} + \mu_{i,t} - \eta\xi_i \geq 0, \quad s^+_{i,t} \geq 0, \quad \frac{\partial \mathcal{L}}{\partial s^+_{i,t}} s^+_{i,t} = 0, \tag{3.8}$$

$$\frac{\partial \mathcal{L}}{\partial s^-_{i,t}} = -c'_{i,t} + \mu_{i,t} + \xi_i \geq 0, \quad s^-_{i,t} \geq 0, \quad \frac{\partial \mathcal{L}}{\partial s^-_{i,t}} s^-_{i,t} = 0, \tag{3.9}$$

$$\forall t \in T: \frac{\partial \mathcal{L}}{\partial l_t} = \begin{cases} -c'_{1,t} + c'_{2,t} - \lambda_t = 0 & \text{for } l_t < 0, \\ -c'_{1,t} + c'_{2,t} + \lambda_t = 0 & \text{for } l_t \geq 0, \end{cases} \quad \frac{\partial \mathcal{L}}{\partial l_t} l_t = 0. \tag{3.10}$$

Under consideration of complementary slackness, for transmission, one of the following cases holds for each $t \in T$:

$$l_t = -L \quad \text{and} \quad c'_{1,t} \leq c'_{2,t}, \tag{3.11}$$

$$l_t \in (-L, L) \quad \text{and} \quad c'_{1,t} = c'_{2,t}, \tag{3.12}$$

[2] In Eq. (3.8)-Eq. (3.10) we directly use Eq. (3.7) to replace $\alpha_{i,t} = c'_{i,t}$.

$$l_t = L \quad \text{and} \quad c'_{1,t} \geq c'_{2,t}. \tag{3.13}$$

Hence, if flows are chosen optimally, at any point in time, transmission is either used below its capacity, with MGC equalized between the regions, or at its capacity limits (congestion), with a remaining spread of MGC depicted by the shadow prices (Figure 3.1A; also cf. Bohn et al., 1984).

Now let us focus on optimal storage operation. Note that if strictly $s^+_{i,t} > 0, s^-_{i,t} > 0$ for any time and region, then complementary slackness of Eq. (3.8) and Eq. (3.9) implies $\xi_i = \frac{2\mu_{i,t}}{\eta - 1}$. Hence, the value of stored energy ξ_i has to be negative. Abstracting from negative values for power, i.e., $c'_{i,t} > 0$ we can conclude that storage will not charge and discharge simultaneously, i.e., $s^+_{i,t} s^-_{i,t} = 0$. Consequently, for each $i \in I, t \in T$, one of the following cases holds:

$$s^+_{i,t} = S_i,\ s^-_{i,t} = 0 \quad \text{and} \quad c'_{i,t} > \eta\xi_i, \tag{3.14}$$

$$s^+_{i,t} \in (0, S_i),\ s^-_{i,t} = 0 \quad \text{and} \quad c'_{i,t} = \eta\xi_i, \tag{3.15}$$

$$s^+_{i,t} = 0,\ s^-_{i,t} = 0 \quad \text{and} \quad \xi_i > c'_{i,t} > \eta\xi_i, \tag{3.16}$$

$$s^-_{i,t} \in (0, S_i),\ s^+_{i,t} = 0 \quad \text{and} \quad c'_{i,t} = \xi_i, \tag{3.17}$$

$$s^-_{i,t} = S_i,\ s^+_{i,t} = 0 \quad \text{and} \quad c'_{i,t} < \xi_i, \tag{3.18}$$

We can interpret these cases in the following way: For optimal storage operation, there are two specific MGC thresholds for each region. The higher threshold ξ_i depicts the minimum discharge cost, while the lower threshold $\eta\xi_i$ depicts the maximum charge cost. If MGC are between those two levels, storage is idle, as round-trip losses render void the benefits of any kind of operation. Otherwise, at times when MGC strictly exceed these thresholds, storage power plants operate at their maximum capacity (Figure 3.1B). For dispatch, we thus derive the intuitive results that in general, the spread of MGC is reduced locally by transmission and temporally by storage. Finally, we turn to the optimal capacity decisions. The Karush-Kuhn-Tucker conditions for optimal storage and transmission capacities are:

$$\frac{\partial \mathcal{L}}{\partial L} = \gamma - \sum_t \lambda_t \geq 0; \quad L \geq 0, \quad \frac{\partial \mathcal{L}}{\partial L} L = 0, \tag{3.19}$$

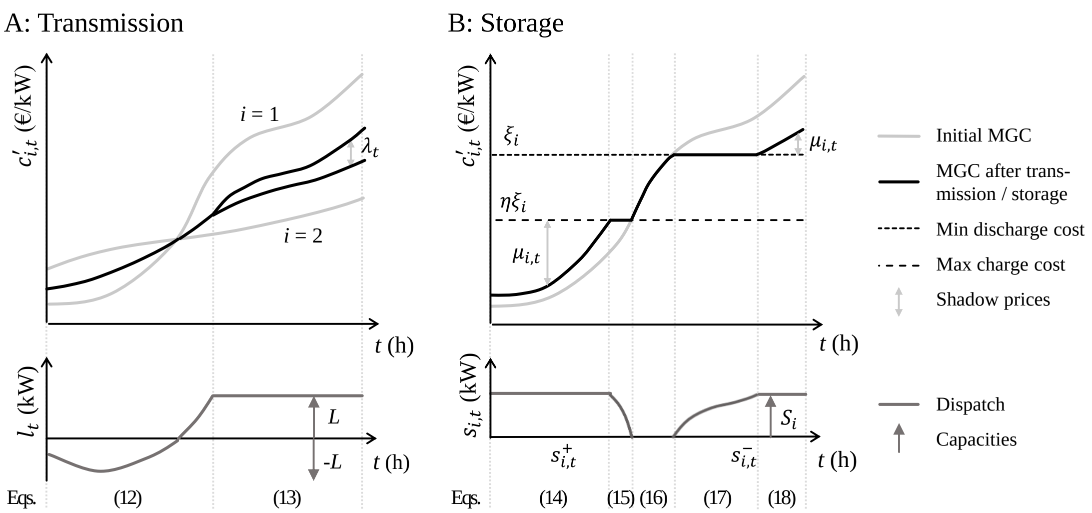

Figure 3.1: Optimal transmission flow (A) and storage operation (B) for exemplified MGC curves. Generally, both technologies cause MGC to converge. If operated at the capacity limit, shadow prices are the difference between regional MGC (transmission) or between the MGC and the respective charge/discharge threshold (storage). Respective equation numbers are given for each operational case.

$$\forall i \in I: \frac{\partial \mathcal{L}}{\partial S_i} = \psi - \sum_t \mu_{i,t} \geq 0, \quad S_i \geq 0, \quad \frac{\partial \mathcal{L}}{\partial S_i} S_i = 0. \tag{3.20}$$

We denote the solutions to this equation system by L^*, S_i^*. If storage is installed at all in region i, then:

$$\psi = \sum_t \mu_{i,t} = \sum_{t \text{ with } s^+_{i,t} = S_i} (\eta\xi_i - c'_{i,t}) - \sum_{t \text{ with } s^-_{i,t} = S_i} (\xi_i - c'_{i,t}). \tag{3.21}$$

For transmission, we obtain the similar result that if there is transmission capacity at all,

$$\gamma = \sum_t \lambda_t = \sum_t |c'_{1,t} - c'_{2,t}|. \tag{3.22}$$

It follows that if storage and transmission capacities are chosen optimally, the costs of additional capacity are in balance with the associated marginal reduction in dispatch costs, represented by the respective shadow prices. Thus, the sum of shadow prices across all time periods must be equal to the respective unit capacity costs. It follows the usual result that capacity constraints need to be binding at least once (cf. Steiner, 1957). Otherwise, there would obviously be excess capacity, which cannot be optimal.

We summarize these findings in the following proposition.

Lemma 3.1. *Given the model described in Section 3.2, we find that optimally deployed and dispatched transmission and storage converge MGC in the local and temporal dimensions. Storage is idle if MGC are within a certain range. All capacities must operate at least once at their capacity limits, such that the cost of a marginal increase in capacity corresponds to the associated marginal dispatch cost savings.*

3.4 General complementarity and substitutability of storage and transmission

We are interested in how a marginal change in storage capacity affects the optimal choice (indicated by $*$) of transmission capacity. Hence, we need to evaluate $sgn(\mathrm{d}L^*/\mathrm{d}S_i)$ for all $i \in I$, which determines complementarity and substitutability of capacities. Our results below also extend to $sgn(\mathrm{d}S_i^*/\mathrm{d}L)$ by symmetry. It is convenient to restate the optimization problem Eq. (3.1) to Eq. (3.5) in the following two-stage formulation to facilitate proofs and interpretation subsequently. It separates consecutive decisions on capacity and dispatch:

$$\min_L C = DC^*(L, S_1, S_2) + \psi \sum_{i \in I} S_i + \gamma L, \tag{3.23}$$

$$\text{s.t. } DC^*(L, S_1, S_2) = \min_{g_{i,t}, s_{i,t}, l_t} \sum_{i \in I, t \in T} c_{i,t}, \tag{3.24}$$

$$\text{s.t. Eq. (3.2) – Eq. (3.5).} \tag{3.25}$$

Here, storage capacities are exogenously given. The solution to the second stage DC^* represents the minimal dispatch cost when generation is at its optimal levels $g^*_{i,t}$. In the first stage, transmission capacity is optimized, while the implications for optimal generation on the second stage are factored in. If storage capacities are chosen optimally, this formulation is equivalent to the original one since the objective to minimize Eq. (3.24) is aligned with Eq. (3.23), the objective to reduce total costs C. If storage capacities marginally deviate from the optimum, we can determine whether optimal transmission rises or falls.

The first-order condition for optimal transmission capacity becomes $\partial DC^*/\partial L = -\gamma$. The total differential then yields:

$$\frac{\mathrm{d}L^*}{\mathrm{d}S_j} = -\frac{\partial^2 DC^*/\partial S_j \partial L}{\partial^2 DC^*/\partial L^2}. \tag{3.26}$$

To obtain information on the kind of interdependence, we thus need to infer the signs of the second derivatives of DC^*. We assume that $\partial^2 DC^*/\partial L^2 \equiv DC^*_{LL} > 0$, i.e., decreasing cost savings for additional capacity. Later we prove this for the special cases of linear MGC (Section 3.5.1) and two periods (Section 3.5.2). Thus, if the cross-derivative $\partial^2 DC^*/\partial S_j \partial L$ is positive, an increase in storage capacity decreases the optimal transmission capacity and the two are substitutes, whereas for negative cross-derivatives, the two are complements.[3] This finding is summarized in the following proposition, which can be used to check for the kind of interdependence.

Proposition 3.1. *Electricity storage at node j complements optimally deployed transmission capacity if*

$$-\frac{\mathrm{d}L^*}{\mathrm{d}S_j} \propto \sum_{i\in I, t\in T} c''_{i,t} \frac{\mathrm{d}g^*_{i,t}}{\mathrm{d}L} \frac{\mathrm{d}g^*_{i,t}}{\mathrm{d}S_j} + c'_{i,t} \frac{\mathrm{d}^2 g^*_{i,t}}{\mathrm{d}L \mathrm{d}S_j} < 0, \tag{3.27}$$

(and substitutes it if this expression is positive), assuming decreasing cost savings for additional transmission capacity, i.e., $DC^*_{LL} > 0$.

Proof. See Appendix 3.B. *Q.E.D.*

For applications, the criterion Eq. (3.27) can be numerically evaluated if sufficient data are available. It has several general implications. Most significantly, storage and transmission are not necessarily always complements or substitutes. Determining factors are the cost functions and the optimal adjustment of generation in response to changes in capacities. As a consequence, the kind of interdependence can be different for storage at different ends of the transmission line. If the optimal generation is independent of one of the capacities at all times and in

[3]Assuming decreasing cost savings for additional storage capacity as well $DC^*_{S_j S_j} > 0$ allows for the same conclusion if storage capacities are optimally adjusted to exogenous transmission capacities.

a given region, storage in that region and transmission are neither substitutes nor complements but independent from one another. This occurs, for instance, if at least one of the two capacities is over-deployed, i.e., is never used at full capacity.

The first term in the sum represents direct effects of the capacities on optimal generation, while the second term represents indirect effects. We will show in the subsequent section that the indirect effects disappear for important special cases. The direct effects imply substitutability between storage and transmission if generation changes in the same direction when (ceteris paribus) more storage or more transmission capacity is supplied. If generation changes in the opposite direction, i.e., if expanding one capacity increases optimal generation while expanding the other reduces it, the direct effects imply complementarity. Consider, for example, a situation in which a transmission line is congested at peak load. If storage is expanded in the region with higher MGC, it could charge cheaply during off-peak periods and discharge during peak periods, leading, ceteris paribus, to lower generation in the peak load periods. If transmission is expanded, there is also less generation during peak load periods in the region with higher MGC due to additional transport into that region. Overall, this situation thus implies reduced generation for both capacities, and hence substitutability.

In the same example, complementarity occurs for storage in the region with lower MGC. First, expansion of transmission capacity leads to more peak-load generation in the cheaper region in order to serve more demand in the more expensive region. Yet, if more storage capacity is installed in that region, it leads to less generation during peak-load: The storage is discharged at peak times to achieve less expensive generation of the electricity that is transported through the congested line.

The indirect effects in Eq. (3.27) express how the deployment of one capacity influences the marginal effect of the other. Obviously, changing one capacity can lead to more or less generation. If the other capacity changes at the same time, this effect might be enhanced or reduced. This might in principle be possible. Consider storage in the region with lower MGC and transmission congestion during peak load. Expanding storage leads to more off-peak generation. Then, if also transmission is expanded and more electricity can be transmitted to the more expensive region during peak-load, even more might be generated during off-peak. Under these circumstances, the indirect effects imply substitutability and oppose the direct effects. Under other conditions, direct and indirect effects may also imply the same kind of interdependence. In general, indirect effects can only stem from non-linear components in the model. We were not able to find simple numerical examples. We thus argue that the indirect effects are of minor importance. For example, it can be shown that they cannot occur for two time periods (cf. Section 3.5).

3.5 Complementarity and substitutability with model specifications

3.5.1 Linear marginal generation cost

Let us now consider MGC that are linear in $g_{i,t}$. By utilizing the optimal dispatch results from Lemma 3.1, our finding from Proposition 3.1 can be specified as follows.

Proposition 3.2. *Electricity storage at node j complements optimally deployed transmission capacity if*

$$-\frac{\mathrm{d}L^*}{\mathrm{d}S_j} \propto \sum_{i\in I, t\in T} c''_{i,t} \frac{\mathrm{d}g^*_{i,t}}{\mathrm{d}L} \frac{\mathrm{d}g^*_{i,t}}{\mathrm{d}S_j} < 0, \tag{3.28}$$

(and substitutes it if this expression is positive), assuming linear MGC, i.e., $\forall i \in I, t \in T : c'''_{i,t} = 0$.

Proof. See Appendix 3.C. *Q.E.D.*

Compared to the previous criterion Eq. (3.27) the cross-derivatives and hence the indirect effects vanish. Thus, the kind of interdependence can be immediately derived from the direct effects if MGC are linear. In Proposition 3.3, we show that Eq. (3.28) also holds for non-linear MGC if we consider two time periods. There might be further conditions that are also sufficient.

3.5.2 Two periods

We introduce the two time periods *peak* and *off-peak*, which we denote by π and ω, respectively (two-period approaches can also be found in Gravelle, 1976, Sioshansi, 2014). By doing so, we can also specify our findings on interdependency (Proposition 3.1) and utilize the results for optimal dispatch and capacity (Lemma 3.1) to obtain the following proposition.

Proposition 3.3. *If $|T| = 2$, then electricity storage at node j complements optimally deployed transmission capacity if*

$$-\frac{\mathrm{d}L^*}{\mathrm{d}S_j} = - \sum_{t \text{ if } l_t = L \vee l_t = -L} \frac{1}{1 + \sum_i c''_{i,t}/c''_{j,t}} \sigma_j \frac{\mathrm{d}l_t^*}{\mathrm{d}L} \frac{\mathrm{d}s_{j,t}^*}{\mathrm{d}S_j} < 0 \tag{3.29}$$

(and substitutes it if this expression is positive). Note that this does not require $c'''_{i,t} = 0$.

Proof. See Appendix 3.D. *Q.E.D.*

Note that due to $c''_{i,t} > 0$, the first fraction to the right of the equals sign is always positive and can thus only influence the magnitude of the effect. For simplification purposes, let us denote this fraction by $\theta_{j,t}$. The kind of interdependence is determined by the consecutive terms, which depict the direct effects in a specified manner. In fact, the term now depends only on the reaction of optimal storage operation and transmission flow to a change in their own respective capacities. As in the case of linear MGC, the indirect effects vanish.

To be able to specifically evaluate Eq. (3.29), we need to insert the solutions for optimal transmission and storage dispatch Eq. (3.11)–Eq. (3.16). Even for two periods, there are several combinatorial possibilities to dispatch storage and transmission. Without a loss of generality, we denote the period and region with the highest MGC as period π (peak) and region 1, such that

$$\forall i, t : c'_{1,\pi} \geq c'_{i,t}. \tag{3.30}$$

Given this definition and assuming strictly positive storage and transmission capacities that are smaller than or equal to their optimum, the following proposition holds:

Proposition 3.4. *For two periods and regions, the feasible combinations of storage and transmission dispatch reduce to exactly seven cases, which are given in Table 3.1.*

Proof. See Appendix 3.E. *Q.E.D.*

Now let us look at the characteristics of these cases. For two periods, storage always charges at the capacity limit and discharges all available energy. Following

Table 3.1: Feasible dispatch cases and their characteristics for two periods and two regions. Only discharge is shown for storage. If MGC are aligned positively storage in region 2 discharges at the peak period. If congestion occurs at both and not only one period, it can be characterized as unidirectional (uni) or bidirectional (bi).

Case	$s^-_{1,\pi}$	$s^-_{2,\pi}$	$s^-_{2,\omega}$	l_π	l_ω	MGC alignment	Transmission congestion at
(i)	ηS_1	ηS_2		L	L	pos.	π, ω (uni)
(ii)	ηS_1	ηS_2		L	$-L$	pos.	π, ω (bi)
(iii)	ηS_1	ηS_2		L	$\in (-L, L)$	pos.	π
(iv)	ηS_1	ηS_2		$\in (-L, L)$	L	pos.	ω
(v)	ηS_1		ηS_2	L	L	neg.	π, ω (uni)
(vi)	ηS_1		ηS_2	L	$-L$	neg.	π, ω (bi)
(vii)	ηS_1		ηS_2	L	$\in (-L, L)$	neg.	π

Eq. (3.30), storage in region 1 always discharges in the peak period, but storage in region 2 may be discharging in the off-peak period if $c'_{2,\omega} > c'_{2,\pi}$. Then we speak of *negatively aligned* MGC (v-vii), and of *positively aligned* MGC if $c'_{2,\pi} > c'_{2,\omega}$ (i-iv). Transmission flow can be characterized by the timing of congestion (e.g., only during peak (iii,vii), only during off-peak (iv), or during both periods), as well as the congestion direction (e.g., bidirectional (ii,vi) or unidirectional (i,v)). Table 3.1 provides an overview of the case characteristics.

Interestingly, Eq. (3.29) can be temporally disaggregated. At any particular time and and in any region, it is only different from zero if the transmission is congested and if the storage operation depends on its own capacity. Hence, the kind of interdependence can be unambiguously determined if, during all times of congestion, the product of the direct effects has the same sign. If that is not the case, it may also depend on the magnitude of the direct effects, and $\theta_{j,t}$. For all cases, we present the solution to Eq. (3.29) in Table 3.2. We obtain that ambiguity occurs only if the transmission is unidirectionally congested during both peak and off-peak periods (i,v). In these cases, for instance, storage in region 1 has a substitutive effect during the peak period and a complementary effect during the off-peak period.

Unambiguous complementarity only exists if MGC are positively aligned (ii-iv). In this case, charge and discharge patterns are equivalent for storage facilities in both regions. Thus, storage in one region has a similar influence on MGC as transmission (e.g., discharging at the outlet of a congested line) while storage of

Table 3.2: Solution of Eq. (3.29) for the dispatch cases. Positive terms imply substitutability, negative terms complementarity of transmission and storage of a particular region.

	Storage at			
Case	Region 1		Region 2	
(i)	$\eta\theta_{1,\pi} - \theta_{1,\omega}$		$-\eta\theta_{2,\pi} + \theta_{2,\omega}$	
(ii)	$\eta\theta_{1,\pi} + \theta_{1,\omega}$	> 0	$-\eta\theta_{2,\pi} - \theta_{2,\omega}$	< 0
(iii)	$\eta\theta_{1,\pi}$	> 0	$-\eta\theta_{2,\pi}$	< 0
(iv)	$-\theta_{1,\omega}$	< 0	$\theta_{2,\omega}$	> 0
(v)	$\eta\theta_{1,\pi} - \theta_{1,\omega}$		$\theta_{2,\pi} - \eta\theta_{2,\omega}$	
(vi)	$\eta\theta_{1,\pi} + \theta_{1,\omega}$	> 0	$\theta_{2,\pi} + \eta\theta_{2,\omega}$	> 0
(vii)	$\eta\theta_{1,\pi}$	> 0	$\theta_{2,\pi}$	> 0

the other region has an opposing effect (e.g., discharging at the inlet of the line). For instance, if congestion occurs during the peak period (iii), storage in region 1 substitutes, while storage in region 2 complements transmission, and vice versa for off-peak congestion (iv). Such a configuration does not occur, however, if MGC are negatively aligned. Here, storage operation is temporally opposing, and storage and transmission are predominantly substitutes (vi, vii).

Elaborating further on $\theta_{j,t}$, the fraction $\sum_i c''_{i,t}/c''_{j,t}$ depicts a relationship between cost function curvatures, which represent the change of marginal cost curves. If this is known or can be closely approximated, the otherwise indistinct cases (i,v) can also be evaluated unambiguously. Furthermore, the influence of storage capacity on optimal transmission deployment at one particular point in time will be greater, the larger $c''_{i,t}$ is in the storage region compared to the other region.

Our last interesting finding involves the aggregate (not regional) interdependence of storage and transmission. For positively aligned MGC (i-iv), we see from Table 3.2 that the effects of the two regions are always exactly opposing. Hence, if generation cost curves in both regions are equivalent and MGC are linear ($\forall i, t : c'''_{i,t} = 0$), the effects cancel each other out and regionally aggregated storage capacity is independent of transmission.

3.6 Model applicability and empirical evidence

3.6.1 General

In the following, we discuss the general applicability of our model approach and provide some supporting evidence from an empirical example. While our approach is not appropriate to evaluate minor loop-flow-induced congestion, it is well suited to consider structural congestion on regional interconnectors. Additionally, it is applicable for dispatchable flows on, e.g., phase-shifter-controlled border connections or long-distance HVDC lines (IEA, 2016). Furthermore, assumptions on inelastic demand and continuous investment come into play. Relaxing the former would induce a price driven load shifting from expensive to cheaper times. Hence, the effects would resemble those of storage. As a consequence, elastic demand could substitute or complement transmission capacities and would thereby reduce the effective implications of storage. One may also consider that investments in the electricity sector, particularly transmission lines are discrete. Then, our results on marginal capacities cannot be directly extended. However, the seven dispatch cases are still valid. If discrete capacity changes do not lead to switching to another case, our results carry over.

For an empirical application, it is convenient to apply the more specific Eq. (3.29) from the two-period case rather than the more general Eq. (3.27). By doing so, we can deduce the kind of interdependency directly from Table 3.2 without the need for much data, given that a two-period case can represent the real-world setup. Even though this neglects indirect effects, it is reasonable to assume that storage operation is primarily affected by storage capacity (this holds, e.g., if the round-trip efficiency is high). We thus conjecture that the two-period approach can be applied appropriately to multi-period setups.

3.6.2 Evidence from Italian price data

To illustrate the applicability of our model, we analyse Italian regional day-ahead electricity price data for one year (11/2016-10/2017) provided online by Gestore dei Mercati Energetici S.p.A (2017), and focus on the price relations between the bidding zones Northern Italy (NO) and Central-Northern Italy (CN), Central-Southern Italy (CS) and Sardinia (SA), as well as Central-Southern Italy and Southern Italy (SU). We assume that the obtained price data depict the temporal and regional MGC. When prices in the connected regions deviate, we can conclude that congestion occurs. Comparing price pairs during congestion with the mean prices of both regions allows us to determine peak and off-peak congestion, to match the data to the theoretical two-period dispatch cases, and to obtain the kind of interdependence between storage and transmission in the case at hand. Related price data scatter plots and descriptive statistics are given in Figure 3.2 and Appendix 3.F. Table 3.3 summarizes the results.

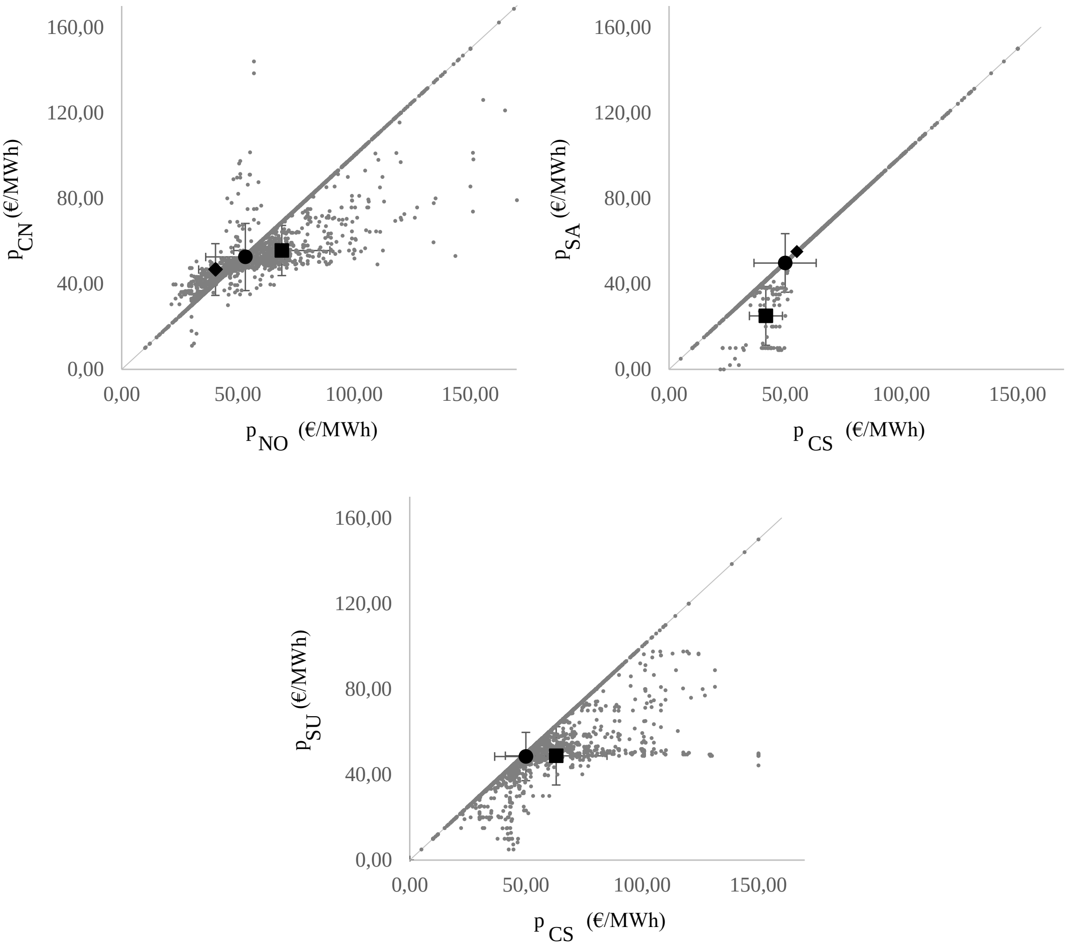

Figure 3.2: Day-ahead electricity price relation between adjacent Italian price zones. The diagonal indicates equal prices in both regions. Data points off the diagonal imply price differentials due to congestion. Bold points depict mean values (see Table 3.4) off all data points (●) as well as for congestion in either direction (■, ⧫). Data source: Gestore dei Mercati Energetici S.p.A (2017).

The transmission between NO and CN is congested bidirectionally at about 7 % of all times with a power flow from CN to NO and 5 % in the opposite direction. In the former congestion case, prices are predominantly above the total mean, while in the latter, they are below. In addition, there exists a mostly positive alignment of regional prices, resembling the dispatch case (ii), characterized by bidirectional congestion. Hence, our model suggests that storage in NO substitutes, while storage in CN complements the transmission capacities between the two regions. The intuition is that in CN, charging during off-peak as well as discharging during peak times increases the regional price spread, while storage operation in NO reduces it. Higher (lower) price differentials, in turn, raise (reduce) the economic viability of interconnectors.

Transmission between regions CS and SA is congested at about 1 % of all times, resembling case (iv). Our model thus suggests that additional storage at CS would complement the interconnector of these regions, whereas storage at SA would substitute it. Between CS and SU, congestion occurs at around 11 % of all times. Prices in CS are always higher than in SU, and during congestion, both prices are generally either higher or lower than the mean, which indicates a positive alignment between them. These empirical findings resemble case (i), where during peak as well as off-peak times, the flow from SU to CS is congested. Hence, no clear conclusion about the complementarity of storage and transmission can be drawn from our model. In CS, storage substitutes transmission during peak times and complements it at off-peak times (and vice versa in SU). As we observe a substantially higher congestion mean price in CS relative to the mean of all times, which indicates congestion at predominantly peak times, substitutability of storage in CS and complementarity of storage in SU is implied.

Table 3.3: Summary of properties and model predictions for the empirical analysis. The MGC alignment and congestion characterization translate into respective cases. From those, our model predicts the kind of interdependence (S – substitutes, C – complements) between the inter-regional transmission and storage at either region.

Regions	MGC alignment	Congestion characteristic	Case resembled	Model prediction (storage at) NO	CN	CS	SA	SU
NO–CN	pos.	bi	(ii)	S	C			
CS–SA	pos.	off-peak	(iv)			C	S	
CS–SU	pos.	uni	(i)			S[a]		C[a]

[a] Kind of interdependence deducted from the dominance of peak time congestion.

In addition to the insight that storage on either end of a transmission line may induce different kinds of interdependence (cases ii-iv), we thus also find empirical evidence that storage in a single region can complement one transmission line and substitute another, which is the case for storage in CS and the lines to SA and SU. Such phenomena may occur if the congestion characteristics are different for the two lines. As a consequence, no general statements about the induced kind if interdependence can be made by just looking at one capacity. Instead, it is crucial to determine which particular pair of capacities is being analysed.

3.7 Conclusion and outlook

Despite the rise in public interest and increased number of pilot projects in recent years using storage to cope with transmission challenges, scientific literature on the true nature of the interdependence of storage and transmission is still scarce. Often, the substitutability of transmission by storage is even assumed without rigorous analysis. This can lead to the conclusion that recent transmission network challenges simply solve themselves once sufficient storage capacity is being constructed.

Our study highlights the need for sensitivity towards the complex interdependence of the electricity grid and storage. The results obtained here show that storage and transmission are not generally substitutes or complements, but that their kind of interdependence differs between regions. Hence, an increased availability of storage may imply a higher transmission requirement. This may occur if loads between regions are positively aligned or if, more generally, storage and transmission have opposing effects on optimal generation. In addition to the storage location, the timing of and flow direction during transmission congestion as well as the alignment of MGC are found to be key factors in determining the kind of interdependence. Furthermore, if storage capacities are deployed in two adjacent regions with similar and positively aligned cost structures, they are likely to exert opposing effects on the connecting transmission line, such that the overall effect on transmission is small.

The two-period model can be successfully applied to empirical price data to derive initial indications as to the effects of additional storage capacity on transmission requirements. However, the more general equation we provided here may also be utilized if comprehensive data are available. Our insights about the interactions of storage and transmission capacities may be used for future infrastructure planning and in considering various options for the development of power systems.

For example, projections on the value of storage can be adjusted in accordance to transmission network planning or assumptions on future transmission requirement can be adjusted according to storage deployment predictions. This paves the way for more efficient planning of capacities and policies. Future research should attempt to validate our findings with a more complex empirical analysis, i.e., by evaluating the impact of complex networks and additional arrangement options for storage. Of further interest are second-best approaches that take into account different storage operation objectives and regulatory aspects such as incentives for a storage operation that benefits the system. Enhancing our understanding of spatio-temporal phenomena will improve the integration of renewable energies and thus help to guide a more efficient transition towards a resilient low-carbon society.

Appendices

3.A Nomenclature

$t \in T$	Time index
$\pi,\ \omega$	Two-period time indices for peak and off-peak
$i \in I = \{1, 2\}$	Region index
$g_{i,t}$	Generation (net of storage and transmission, kW)
$s_{i,t} = s^+_{i,t} - s^-_{i,t}$	Net storage operation (charge minus discharge, kW)
l_t	Transmission flow at time t, $l_t > 0$ for flow from region 1 to 2 (kW)
S_i	Storage power capacity (kW)
L	Transmission capacity (kW)
C	Electricity system cost (€)
DC	Dispatch cost (€)
c_i	Generation cost functions (€)
ψ	Unit costs for storage power capacity (€/kW)
γ	Unit costs for transmission capacity (€/kW)
$R_{i,t}$	Residual load (kW)
η	Storage round-trip efficiency

3.B Proof of Proposition 3.1

From Eq. (3.24) we obtain the derivatives

$$\frac{\partial DC^*}{\partial S_j} = \sum_{i \in I, t \in T} c'_{i,t}(g^*_{i,t}) \frac{\mathrm{d}g^*_{i,t}}{\mathrm{d}S_j}, \tag{3.31}$$

$$\frac{\partial DC^*}{\partial L} = \sum_{i \in I, t \in T} c'_{i,t}(g^*_{i,t}) \frac{\mathrm{d}g^*_{i,t}}{\mathrm{d}L}, \tag{3.32}$$

$$\frac{\partial^2 DC^*}{\partial L^2} = \sum_{i \in I, t \in T} c''_{i,t} \left(\frac{\mathrm{d}g^*_{i,t}}{\mathrm{d}L}\right)^2 + c'_{i,t} \frac{\mathrm{d}^2 g^*_{i,t}}{\mathrm{d}L^2}, \tag{3.33}$$

$$\frac{\partial^2 DC^*}{\partial L \partial S_j} = \sum_{i \in I, t \in T} c''_{i,t} \frac{\mathrm{d}g^*_{i,t}}{\mathrm{d}L} \frac{\mathrm{d}g^*_{i,t}}{\mathrm{d}S_j} + c'_{i,t} \frac{\mathrm{d}^2 g^*_{i,t}}{\mathrm{d}L \mathrm{d}S_j}. \tag{3.34}$$

Eq. (3.34) together with Eq. (3.26) yields the relation we want to show.

3.C Proof of Proposition 3.2

If MGC are linear, i.e., $c'''_{i,t} = 0$, the second derivative with respect to the capacities vanishes in Eq. (3.33) and Eq. (3.34) due to the following argument. The optimal dispatch decision is determined from the KKT conditions Eq. (3.2) – Eq. (3.5), Eq. (3.11) – Eq. (3.18). This equation system, which determines all dispatch decision variables, is generally linear, except Eq. (3.12), Eq. (3.15), and Eq. (3.17). Yet, for linear MGC, the latter three equations also become linear. If re-arranged, this right-hand-side vector of the equation system has, inter alia, the capacities L, S_1, S_2 as coefficients. Thus, the solution of the equation systems depends linearly on the capacities, so the second derivatives vanish. Furthermore, for Eq. (3.33) the remaining quadratic term thus induces $DC^*_{LL} \geq 0$. However, it can only be $DC^*_{LL} = 0$ if the optimal generation is independent of the transmission capacity. In this case, storage and transmission capacities are also independent and we can ignore this case for our analysis, reducing our focus to $DC^*_{LL} > 0$. Thus Eq. (3.26) can be rewritten as Eq. (3.28).

3.D Proof of Proposition 3.3

First, determine how $s^*_{i,t}$ depends on capacities. Due to $T = \{\pi, \omega\}$, we have $\forall i \in I : s^+_{i,\omega} = S_i, s^-_{i,\pi} = \eta S_i$ or $s^+_{i,\pi} = S_i, s^-_{i,\omega} = \eta S_i$. Thus, obviously $\forall i \neq j : \frac{\mathrm{d}s^*_{i,t}}{\mathrm{d}S_j} = 0$ and $\frac{\mathrm{d}s^*_{i,t}}{\mathrm{d}L} = 0$ and $\frac{\mathrm{d}s^*_{j,t}}{\mathrm{d}S_j} \in \{1, \eta\}$. Now let us turn to the derivatives of l^*_t. In cases in which transmission is constrained by capacity, $l^*_t = L$ or $l^*_t = -L$, with obvious derivatives. In the other cases with $l^*_t \in (-L, L)$, MGC are identical in both regions, resulting in the equation $c'_1(R_{1,t} + s^*_{1,t} - \sigma_1 l^*_t) = c'_2(R_{2,t} + s^*_{2,t} - \sigma_2 l^*_t)$. This can be rearranged such that l^*_t is a function of $R_{i,t}, S_i, \eta$, but not of L. Thus, for $l_t \in (-L, L) : \frac{\mathrm{d}l_t}{\mathrm{d}L} = 0$. As one consequence, we can write each $g^*_{i,t} = R_{i,t} + s^*_{i,t} - \sigma l^*_t$ alternatively as an additive separable function of S_i, S_j, L, which results in $\frac{\mathrm{d}^2 g^*_{i,t}}{\mathrm{d}L \mathrm{d}S_j} = 0$. Furthermore, we can simplify:

$$\frac{\mathrm{d}g^*_{i,t}}{\mathrm{d}L} = \frac{\mathrm{d}s^*_{i,t}}{\mathrm{d}L} - \sigma \frac{\mathrm{d}l^*_t}{\mathrm{d}L} = \begin{cases} -\sigma, & \text{if } l^*_t = L, \\ \sigma, & \text{if } l^*_t = -L, \\ 0, & \text{if } l^*_t \in (-L, L), \end{cases} \tag{3.35}$$

this directly yields

$$\left(\frac{\mathrm{d}g^*_{i,t}}{\mathrm{d}L}\right)^2 = \begin{cases} 1, & \text{if } l_t = L \vee l_t = -L, \\ 0, & \text{if } l^*_t \in (-L, L), \end{cases} \tag{3.36}$$

$$DC^*_{LL} = \sum_{i\in I, t\in T} c''_{i,t} \left(\frac{\mathrm{d}g^*_{i,t}}{\mathrm{d}L}\right)^2 = \sum_{i\in I, t \text{ if } l_t = L \vee l_t = -L} c''_{i,t}, \tag{3.37}$$

so that $DC^*_{LL} > 0$ follows from $c''_{i,t} > 0$ given that transmission capacities are binding at least once.

We can now rewrite Eq. (3.27) with vanishing cross-derivatives and distinguish terms by the cases for optimal flow:

$$-\frac{\mathrm{d}L^*}{\mathrm{d}S_j} = \frac{1}{\sum\limits_{i,t \text{ if } l_t = L \vee l_t = -L} c''_{i,t}} \left(- \sum_{i,t \text{ if } l_t = L} c''_{i,t} \frac{\mathrm{d}g^*_{i,t}}{\mathrm{d}L} \sigma \frac{\mathrm{d}L^*}{\mathrm{d}S_j} - \sum_{i,t \text{ if } l_t = -L} c''_{i,t} \frac{\mathrm{d}g^*_{i,t}}{\mathrm{d}L} \sigma \frac{\mathrm{d}(-L^*)}{\mathrm{d}S_j} \right.$$
$$\left. - \sum_{i,t \text{ if } l_t = \in(-L,L)} c''_{i,t} \frac{\mathrm{d}g^*_{i,t}}{\mathrm{d}L} \sigma \frac{\mathrm{d}l^*_t}{\mathrm{d}S_j} + \sum_{i,t} c''_{i,t} \frac{\mathrm{d}g^*_{i,t}}{\mathrm{d}L} \frac{\mathrm{d}s^*_{i,t}}{\mathrm{d}S_j} \right). \tag{3.38}$$

Making use of Eq. (3.35), this simplifies to:

$$-\frac{\mathrm{d}L^*}{\mathrm{d}S_j} = \frac{1}{\sum\limits_{i,t \text{ if } l_t = L \vee l_t = -L} c''_{i,t}} \left(\sum_{t \text{ if } l_t = L} \sigma^2 c''_{j,t} \frac{\mathrm{d}L^*}{\mathrm{d}S_j} + \sum_{t \text{ if } l_t = -L} \sigma^2 c''_{j,t} \frac{\mathrm{d}L^*}{\mathrm{d}S_j} \right.$$
$$\left. - \sum_{t \text{ if } l_t = L \vee l_t = -L} c''_{j,t} \sigma \frac{\mathrm{d}l^*_t}{\mathrm{d}L} \frac{\mathrm{d}s^*_{j,t}}{\mathrm{d}S_j} \right). \tag{3.39}$$

Since the sums over t for $l_t = L$ and $l_t = -L$ are equivalent, we can rearrange and solve for $\frac{\mathrm{d}L^*}{\mathrm{d}S_j}$ to obtain

$$-\frac{\mathrm{d}L^*}{\mathrm{d}S_j} = - \sum_{t \text{ if } l_t = L \vee l_t = -L} \frac{1}{1 + \sum_i c''_{i,t} / c''_{j,t}} \sigma_j \frac{\mathrm{d}l^*_t}{\mathrm{d}L} \frac{\mathrm{d}s^*_{j,t}}{\mathrm{d}S_j}, \tag{3.40}$$

the relation we want to show.

3.E Proof of Proposition 3.4

From the optimal storage operation, it follows that storage charges at the capacity limit during the period of the lower price. Since we consider only two periods and $\eta < 1$, it cannot reach the capacity limit while discharging. For region 1 it follows from Eq. (3.30) that $s^-_{1,\pi} = \eta S_1, s^+_{1,\omega} = S_1$. However, the charge and discharge timing is less straightforward for region 2, because the period of higher MGC is not determined. Hence, we can have $s^-_{2,\pi} = \eta S_2, s^+_{2,\omega} = S_2$, i.e., a discharge at π, or $s^-_{2,\omega} = \eta S_2, s^+_{2,\pi} = S_2$, i.e., a discharge at ω. Thus, we obtain two possible cases with respect to optimal storage dispatch. For the former, it means that marginal costs between regions are positively, for the latter negatively aligned ($c'_{2,\pi} > c'_{2,\omega}$ or $c'_{2,\pi} < c'_{2,\omega}$). Note that for the marginal case $c'_{i,\pi} = c'_{i,\omega}$, optimally no storage capacity would be deployed, i.e., $S_i = 0$ and hence there would also be no storage operation, i.e., $\forall t : s^*_{i,t} = 0$. We can therefore ignore this case.

We now turn our attention to the transmission flow. From Eq. (3.11)– Eq. (3.13) we know that there are three possible flows for each time period and hence nine combinatorial solutions. Yet, optimality excludes a flow from a region with higher to one with lower MGC, and hence $l_\pi \neq -L$. Furthermore, we have shown above that the capacity must be binding at least once. We can thus drop the combination $l_\pi \in (-L, L), l_\omega \in (-L, L)$. Also, if the transmission is uncongested for $t = \pi$, region 1 is not clearly defined from Eq. (3.30) because MGC are the same in both regions. Again, without loss of generality, we can define region 1 such that $l_\omega = L$. By doing so we omit the case of $l_\pi \in (-L, L), l_\omega = -L$, which is equal to the case $l_\pi \in (-L, L), l_\omega = L$ with a reverse region definition. Four cases remain with respect to optimal flow: $l_\pi = L$ together with $l_\omega = L$ or $l_\omega \in (-L, L)$ or $l_\omega = -L$ and $l_\pi \in (-L, L)$ with $l_\omega = L$.

Finally, we can combine two cases for storage operation and four cases for transmission flow. Yet, one of the eight combinations can still be excluded. In fact, $l_\pi \in (-L, L)$ implies that $c'_{1,\pi} = c'_{2,\pi} \geq c'_{2,\omega}$. Hence, an optimally operated storage facility can only charge at $t = \omega$ and discharge at $t = \pi$, such that the flow $l_\pi \in (-L, L)$ is not feasible with storage operation $s^-_{2,\omega} = \eta S_2, s^+_{2,\pi} = S_2$. This leaves us with the seven dispatch cases given in Table 3.1.

3.F Descriptive statistics for Italian regional prices

Table 3.4: Mean day-ahead prices (p_i) and standard deviations (sd) (€ /MWh) for Italian regions North (NO), Central North (CN), Central South (CS), South (SU), and Sardinia (SA). Values are computed for all hours of one year (11/2016-10/2017) and for hours with transmission congestion, i.e., $p_1 \neq p_2$. Data source: Gestore dei Mercati Energetici S.p.A (2017).

Regions i	All			$p_1 > p_2$			$p_2 > p_1$		
	N	$p_1 \pm sd$	$p_2 \pm sd$	N	$p_1 \pm sd$	$p_2 \pm sd$	N	$p_1 \pm sd$	$p_2 \pm sd$
1–NO, 2–CN	8760	53,22 ± 17,01	52,56 ± 15,74	653	68,91 ± 20,69	55,6 ± 11,7	461	40,33 ± 7,21	46,7 ± 12,07
1–CS, 2–SA	8760	49,97 ± 13,38	49,78 ± 13,67	100	41,67 ± 7,1	25 ± 13,75	1	55	55,08
1–CS, 2–SU	8760	49,97 ± 13,38	48,44 ± 11,28	944	63,02 ± 21,85	48,81 ± 13,66	0		

4

Renewable energy policies in federal government systems

Abstract
Renewable energy (RE) policies are widely used to decarbonize power generation and implemented at various governance levels. We use an analytically tractable two-level model to study the effects of overlapping RE policies from the federal and state governments. We find that there are contrasting incentives for states to support RE deployment, depending on whether the federal government implements a feed-in tariff (FIT) or an auction system. Under federal FIT, states that bear a greater burden in financing the federal policy under-subsidize RE in order to reduce nationwide RE deployment and thereby lower their costs. Under federal auction, states that bear a greater burden to finance federal policy over-subsidize RE to drive down the quota price, and thereby also their costs. In an application to Germany, we illustrate that the recent shift from FIT to auctions increases incentives for state governments to support RE in the demand-intensive south, while decreasing them in the wind-abundant north.
Keywords: Auction, feed-in tariff, multi-level governance, federalism, overlapping regulation, energy transition
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4.1 Introduction

Enormous efforts are necessary to limit global warming to "well below two degrees" as agreed upon in Paris (IPCC, 2018). While carbon pricing is considered to be the most cost-effective way to reduce carbon emissions, it is often politically infeasible (e.g. Aldy & Stavins, 2012). At present, RE support policies are the instrument most widely used to decarbonize the power sector (Meckling et al., 2017) and many governments have set RE targets in addition to greenhouse gas (GHG) mitigation targets. In this context, RE support policies should not necessarily be seen as a second-best option, but may closely approximate to the social optimum (Abrell et al., 2019, Helm & Mier, 2018). Additional rationales for RE policies include that they provide support for infant industries and other co-benefits for the local economy, as well as promoting energy sovereignty by reducing dependency on imported fossil fuels.

A central challenge for the efficient design of RE support policies is that they are usually implemented in multi-level governance systems. In most jurisdictions, there are several nested levels of governance,[1] whose RE targets and support instruments may differ.[2] In setting targets, lower-level governments might be particularly interested in co-benefits and economic development within their jurisdiction while upper-level governments are likely to focus on overall national welfare. RE support may be explicit, e.g. by means of direct subsidies (tariffs or premiums), quotas or renewable portfolio standards; or more implicit, e.g. through infrastructure provision, the designation of suitable or unsuitable areas, tax incentives and loans. In fact, all countries of the European Union use between two and six RE support instruments and are characterized by overlapping national and lower-level RE policies (del Río & Mir-Artigues, 2014). As RE support policies often involve large financial outlays, it is important that they are spent efficiently. For this reason, in many countries there has been a recent shift from lump-sum subsidies to more competitive schemes like auctions (REN21, 2019).

In this paper we study the design of RE policies in multi-level governance systems and assess their efficiency. In particular, we ask: (i) How are incentives for

[1] Governance levels may include (but are not restricted to) municipal, regional, state, federal and supranational.

[2] For instance, in Germany the RE targets of the state governments and the federal government differ widely. Aggregated state targets were for RE to contribute 50-55 % of total power generation by 2020, while the federal target was only 35 % (Goetzke & Rave, 2016).

lower-level governments to support RE affected by the upper-level policy instrument(s) in place? (ii) In which circumstances can overlapping provision of RE support by 'upper' and 'lower' governance levels be efficient?

To this end, we develop a formal analytical model of optimal RE policy design in which an upper-level federal government and multiple lower-level state governments simultaneously choose their level of RE support. On the federal level, we analyze the two most prominent RE policy instruments: a price instrument (feed-in tariffs; FIT) and a quantity instrument (an auction of a RE capacity quota). On the state level, we consider a multitude of implicit RE support measures, equivalent to and expressed by a single financial subsidy per unit of capacity. The costs of the federal RE policy are distributed among all states. In the context of federal and state-level policies, competitive suppliers decide on the deployment of RE capacity. RE deployment in one state can cause positive externalities for other states (spillover benefits); as well as negative (cost) externalities, by affecting the distribution of the burden of financing federal RE policy. We compute the equilibrium outcome for overlapping federal and state policies in a one-shot game. In particular, we study a second-best setting, where the federal government can only implement a nationwide (not state-specific) FIT or auctioned quota while state governments provide local subsidies.

We find that the selection by the federal government of either a price or a quantity instrument substantially affects the incentives for states to implement their own RE support measures, as well as the circumstances under which overlapping RE policies are efficient. While price and quantity instruments are equivalent if the upper-level government implements a single nationwide policy, this does not hold if lower-level governments implement additional RE support. Our key results are: (i) Under a combination of nationwide FIT and state subsidies, a state's subsidy is inefficiently high (low) if and only if its share in the marginal benefits from nationwide RE deployment is larger (smaller) than the state's relative burden share. (ii) Under a combination of a nationwide auction and state subsidies, a state's subsidy is inefficiently high (low) if and only if its RE capacity share is smaller (larger) than its relative burden share.[3] (iii) Depending on the characteristics of states' marginal cost and benefit functions national RE capacity is either inefficiently high under FIT and inefficiently low under auction or vice

[3]We use the term 'burden share' for the absolute payments of a state incurred by financing the federal RE policy and add 'relative' to denote the state's fraction of all states' payments. We use the term 'capacity share' for a state's share of the nation's total RE capacity.

versa.

The differences between price and quantity instruments for RE support in multi-level governance systems merit some attention. Where there are overlapping policies, a first-best allocation of RE capacities is achieved only if all states' shares in the marginal benefit (under FIT) or in nationwide RE capacity (under auction) are equal to their relative burden share. Otherwise, certain states have incentives to offer subsidies that are too high or low, leading to surplus or deficit RE capacity, respectively. Under FIT, a state can reduce its burden share by reducing its subsidies, as this will cause a reduction in nationwide RE capacity. This strategy does not work under an auction system as capacity is fixed. Here, however, a state can reduce its burden share by increasing state subsidies, thereby reducing the national quota price. As a consequence, national-level FIT or auction-based policies give rise to opposing policy-setting incentives at the state level.

These novel theoretical results are directly relevant for the efficient design of RE support schemes in multi-level governance systems. In any real-world application, the efficiency of a price or quantity instrument and the incentives for state RE policies will depend on how the burden share is distributed among states. In applying the model to Germany, we find that the recent shift from FIT to a national auction likely increased the incentives for state support for wind energy in the demand-intensive southern states while reducing it in the wind-abundant northern states.

Our paper contributes to the analytical literature on public good provision in general and RE support in particular in multi-level governance systems. To the best of our knowledge, it is the first theoretical analysis of how the incentives of state governments to support RE depend on whether the federal government adopts a price or quantity instrument. Our work adds to seminal contributions on public good provision in federal systems. Myers (1990) showed that with labor mobility, state governments will provide efficient amounts of a public good without federal policies. In the case of imperfect mobility, interregional transfers from the federal government induce efficiency if the states' decisions precede the federal decision (Caplan et al., 2000). This also holds for correlated local and national externalities (Caplan & Silva, 2005). Contrary to those approaches, where lower-level governments decide directly on their provisions to the public good, in our setup they can only incentivize public good provision from respective suppliers. Furthermore, we consider additional incentives for public good provision created by the upper-level government via a price or quantity instrument and a Nash game between all governments.

Our approach is inspired by Williams III (2012), who develops a stylized model in which the federal and state governments use the same instrument to regulate environmental pollution. He finds that the incentive for the state governments to override federal regulations depends on whether they implement pollution caps, taxes or tradable permits. Coria et al. (2018) extend this literature by considering a tax on the federal level and command-and-control regulation from the states and test the effectiveness of this policy for a Swedish example. We extend this literature by analyzing the efficiency of combined policies where the upper-level government employs a quantity instrument and the lower-level governments price instruments. Ambec & Coria (2018) analyse regulation of a local and a global pollutant, respectively, by local and national governments.

There is an extensive literature on the efficient design of RE support. Menanteau et al. (2003), Palmer & Burtraw (2005) discuss the efficiency of different price and quantity instruments. The design of auctions was further investigated by del Río & Linares (2014), Kreiss et al. (2017). Ambec & Crampes (2019), as well as Abrell et al. (2019) evaluate the efficiency of different policy instruments for RE support in analytic and numerical modeling settings. Helm & Mier (2018) additionally consider policies for power storage, while Pechan (2017) shows that the RE support scheme drives the spatial distribution of wind turbines. Lancker & Quaas (2019) show that optimal RE support differs across technologies when inter-temporal learning spillovers are considered. None of these studies consider overlapping regulation from different governance levels.

Overlapping regulations are principal focus of the study by Fischer & Preonas (2010), who review economic literature and develop a stylized theoretical model. In contrast to our study, these authors focus on the interactions between RE support policies and (non-RE) climate policies like emission caps. Similarly, Goulder & Stavins (2011) analyze nested state–federal regulations. Based on a qualitative analysis, they hypothesize that price instruments for RE support may be able to avoid problems arising from overlapping regulations. Finally, in a complementary analysis to ours, Meier & Lehmann (2019) evaluate different RE regulation policies in a federal system. They study a nation that consists of two states. In their model, the federal government supports RE with a subsidy, while state governments implement subsidies or expansion caps. In comparison, we allow for the more general case of n states, compare federal FIT and auctions as instruments for RE support and consider not only their efficiency but also the conditions giving rise to under- or over-support for RE at both state and national level.

The remainder of the paper is structured as follows: First, in Section 4.2, we introduce the theoretical model. In Section 4.3 we solve the model for different configurations of RE support schemes and present results. Then in Section 4.4, we apply our theoretical findings to German data. We discuss implications of the model and its application in Section 4.5 and present an outlook and conclusions in Section 4.6. The Appendices contain a nomenclature and all formal proofs.

4.2 Model

Consider a two-level governance system with one upper-level government and n lower-level governments labelled $i = 1, ..., n$. For convenience, we call the upper level a nation and refer to its government as the 'federal government'; while at the lower-level governance units are called states, and their governments 'state governments'. Both governance levels decide on their RE policy. Consecutively, in each state competitive RE suppliers choose their investments in RE capacity r_i taking account of the RE support provided by state and federal governments. The nation's total RE capacity, R, is then

$$R := \sum_{i=1}^{n} r_i. \tag{4.1}$$

On the federal level, we study two prominent types of RE support schemes: feed-in tariff (FIT) and auction. In the case of a FIT, the federal government chooses the tariff T_i to be paid per unit of installed RE capacity[4] to the suppliers in state i. When the federal government uses a nationwide FIT – as opposed to a state-specific FIT – we denote this by suppressing the index i, i.e. $\forall i : T_i = T$. Note that under a FIT the RE suppliers only receive policy support for the supplied electricity and cannot additionally sell electricity on the market as would be the case under a feed-in premium. In the case of an auction, the federal government chooses state-specific quotas Q_i for auctioned RE capacity. RE suppliers bid a quota price P_i, which they receive as a subsidy per unit of RE capacity installed. The highest accepted bid for RE capacity in an auction defines the uniform (non-

[4]Typically, a FIT is paid per unit of RE generation. As RE generation is approximately linear in capacity, both option are about equivalent and we consider capacity for parsimony.

discriminatory) quota price that is guaranteed to all suppliers of the state in question.[5] Analogous to FIT, we consider that RE suppliers receive revenues only from the policy and not through additional market sales. When the federal government uses a nationwide RE capacity quota we denote this by $Q := \sum_{i=1}^{n} Q_i$. Empirically, a nationwide quota is for instance auctioned from a federal level in Germany. To the contrary, in the US most states have binding RE quantity targets in the form of renewable portfolio standards (Upton & Snyder, 2017).

On the state level, we consider a subsidy s_i paid per unit of deployed RE capacity r_i. The subsidy is the financial equivalent of all kinds of measures with which a state supports the deployment of RE, e.g. by offering land, information on geophysical conditions or RE-friendly regulation.

We consider the total cost of providing and operating RE capacity to be $C_i(r_i)$, which is twice-differentiable with $\frac{\partial C_i(r_i)}{\partial r_i} > 0$ and $\frac{\partial^2 C_i(r_i)}{\partial r_i^2} = b \geq 0$. Costs are the net present value of all costs incurred in providing a certain capacity, including investment and maintenance. We assume that there are benefits to a state i from local and national RE capacity deployment, which are denoted $B_i(r_i, R)$. The benefit function is twice-differentiable, with respect to r_i as well as R, increases in both arguments, i.e., $\frac{\partial B_i(r_i,R)}{\partial r_i} > 0$, $\frac{\partial B_i(r_i,R)}{\partial R} > 0$ and is concave, i.e., $\frac{\partial^2 B_i(r_i,R)}{\partial r_i^2} \leq 0$, $\frac{\partial^2 B_i(r_i,R)}{\partial R^2} \leq 0$. Due to positive spillover benefits, RE deployment is an impure public good from the states' perspectives (e.g. Cornes & Sandler, 1994, Kotchen, 2005). Moreover, a state's marginal benefit from any additional RE deployment is weakly decreasing in the national RE capacity, i.e. $\frac{\partial^2 B_j(r_j,R)}{\partial R \partial r_i} \leq 0$. Benefits are the net present value of all future benefits. The setup allows us to study *local benefits* in a state, e.g. from increased economic activity in the state or local environmental improvements from substitution of fossil fuels by RE, as well as inter-state *spillover benefits* ('national benefits') such as the contribution to the nation's international climate mitigation commitments, or nationwide decreases in electricity prices.

Federal costs of RE support may be distributed differently among states. This could be because federal RE policies are financed through the federal budget and tax payments differ among states; or because federal RE policies are financed by a levy on the electricity price and states' electricity consumption is not proportional to their RE capacity. To take account of this, we introduce $e_i \in [0, 1]$ as the relative

[5] For risk-neutral bidders, discriminatory and non-discriminatory auctions are equivalent (cf. Holt, 1980).

burden share of federal RE support (FIT or auctions) incurred by residents in state i. The (non-relative) burden share is thus $e_i \sum_{j=1}^{n} \Phi_j r_j$, with $\Phi_i \in \{T_i, P_i\}$ denoting the respective federal payments per unit of RE capacity under FIT and auction. As all costs must be refinanced, it is

$$\sum_{i=1}^{n} e_i = 1. \tag{4.2}$$

In general, we assume that for political reasons the federal government is not able to freely choose e_i. However, we access the implications of (un)restricting the choice of e_i in the Discussion.

We are now able to specify the players' objectives. The federal government takes a social planner perspective. Its objective is to maximize the nation's net benefit of RE support, calculated as the sum of all costs and benefits.

$$\Pi^{FED}(r_i, R) = \sum_{i=1}^{n} \left[-C_i(r_i) + B_i(r_i, R)\right]. \tag{4.3}$$

Note that RE support payments do not appear in the federal government's objective as they remain within the nation.

Each state government aims to maximize welfare in its jurisdiction. States' net benefits are given by the sum of state-level costs and benefits. The states' objectives can be written as

$$\forall i: \; \Pi_i^{ST}(r_i, R, \Phi_i, e_i) = -C_i(r_i) + B_i(r_i, R) - e_i \sum_{j=1}^{n} \Phi_j \, r_j + \Phi_i \, r_i. \tag{4.4}$$

While a state's own subsidy does not appear in its government's objective function, a state considers support given by the federal government $\Phi_i \, r_i$ as well as its burden share. Thus, we consider a situation where governments at both levels aim at maximizing their residents' welfare and state residents are a subset of national residents.

Finally, we consider a representative supplier of RE capacity in each state. The supplier in state i obtains revenues $s_i \, r_i$ through the state subsidy and revenues $\Phi_i \, r_i$ from the federal policy and faces deployment costs C_i. The supplier's objective is then:

$$\forall i: \; \Pi_i^{SUP}(r_i, s_i, \Phi_i) = -C_i(r_i) + (s_i + \Phi_i)\, r_i. \tag{4.5}$$

Recall that suppliers only receive policy support. Hence, market prices are irrelevant for the suppliers' choice of RE deployment.

The game is set up as a two-stage decision-making process. The first stage is a one-shot, simultaneous move game between the federal and all state governments, i.e. a Nash equilibrium. This setup is especially appropriate if both governance levels can adjust policies equally easily (Williams III, 2012). After all policies are announced, suppliers decide on their state-specific investments in RE capacity, i.e. they are Stackelberg followers.

4.3 Results

In the following, we first analyze the efficiency of unilateral RE support at only one government level, i.e. state or federal (Section 4.3.1). Then we consider the case of combined support at both state and federal level. We first consider nationwide FIT (Section 4.3.2), then nationwide auctions (Section 4.3.3) and, finally, compare the incentives for states to support RE deployment under both federal policy instruments (Section 4.3.4). We denote the total RE support in state i as $\Psi_i := \Phi_i + s_i$ and the first-best level of RE support as Ψ_i^*.

4.3.1 Unilateral support from federal or state governments

State-specific RE policies implemented only by the federal government define the benchmark for the first-best allocation of RE capacity. The federal government faces the decision problem

$$\max_{T_1,\ldots,T_n \vee Q_1,\ldots,Q_n} \Pi^{FED} = \sum_{i=1}^{n} \left[-C_i(r_i) + B_i(r_i, R)\right], \tag{4.6}$$

$$\text{s.t. } \forall i: \; \max_{r_i} \Pi_i^{SUP} = -\, C_i(r_i) + T_i\, r_i. \tag{4.7}$$

The solution of this problem establishes Lemma 4.1.

Lemma 4.1. *A first-best allocation of RE capacity with federal support only* ($s_i = 0, \Phi_i > 0$) *is achievable with both state-specific FIT,* $\Phi_i = T_i$, *and state-specific* *quotas,* $\Phi_i = P_i$*. The efficient level of RE support is*

$$\forall i: \ \Psi_i^* := \frac{\partial B_i}{\partial r_i} + \sum_{j=1}^{n} \frac{\partial B_j}{\partial R}. \tag{4.8}$$

Proof. See Appendix 4.B. *Q.E.D.*

Lemma 4.1 defines the first-best RE policy, against which the structurally more complex support schemes considered in the next section can be compared. It shows that the federal government can use either policy instrument for RE support to obtain the welfare optimum, by setting state-specific FIT or quotas so that marginal costs of an additional unit of RE capacity in a state i equal the local marginal benefits in state i plus the marginal national benefits enjoyed by all states.

By contrast, when support is provided at state level only, a first-best allocation is not achieved, due to the inter-state spillover benefits of RE. In the absence of a federal policy, state subsidies result in insufficient RE support and hence deficit RE capacity, except for the trivial case of no inter-state externalities, $\forall i: \frac{\partial B_i}{\partial R} = 0$. Hence, the spillover benefits of RE provide a rationale for a federal RE policy.

Lemma 4.1 only holds if the federal government can set *state-specific* FITs or quotas such that the support equals total marginal benefits. However, in practice, a federal government will often be restricted to setting up a single, *nationwide* FIT or quota system. We directly observe from Eq. (4.8) that a nationwide FIT, $\forall i: T_i = T$, or a nationwide quota Q with $\forall i: P_i = P$, will only yield the first-best allocation in the special case where all marginal local benefits are identical, i.e., $\forall i, j: \frac{\partial B_i}{\partial r_i} = \frac{\partial B_j}{\partial r_j}$.

4.3.2 State subsidies and federal FIT

We now turn to the case of combined support by federal nationwide FIT and state subsidies (the following is formally proven in Appendix 4.C). The decision problem reads

$$\max_T \Pi^{FED} = \sum_{i=1}^{n} \left[-C_i(r_i) + B_i(r_i, R)\right], \tag{4.9}$$

$$\forall i: \max_{s_i} \Pi_i^{ST} = -C_i(r_i) + B_i(r_i, R) - e_i \sum_{j=1}^{n} T\, r_j + T\, r_i, \tag{4.10}$$

$$\text{s.t. } \forall i: \max_{r_i} \Pi_i^{SUP} = -C_i(r_i) + (s_i + T)\, r_i. \tag{4.11}$$

For given state subsidies, the federal government sets the nationwide FIT such that the marginal costs equal the average difference between state subsidies and marginal local benefits plus the sum of the inter-state externalities:

$$T(s_1, ..., s_n) = \frac{1}{n} \sum_{i=1}^{n} \left[\frac{\partial B_i}{\partial r_i} - s_i \right] + \sum_{j=1}^{n} \frac{\partial B_j}{\partial R}. \tag{4.12}$$

Thus, the federal government's RE support decreases as state subsidies increase, as this implies that RE suppliers are already operating at higher marginal costs.

For a given nationwide FIT, each state government sets its subsidy to equal the received marginal benefits of RE deployment minus its marginal burden share:

$$\forall i: s_i(T) = \frac{\partial B_i}{\partial r_i} + \frac{\partial B_i}{\partial R} - e_i T. \tag{4.13}$$

Note, that in general a state only partly finances the federal RE support it receives back, while the remainder of the cost is borne by the other states. For a state's optimal choice of RE subsidy only its burden share is directly relevant but not the received FIT. RE is supplied such that for each change in FIT, there is an identical change in marginal costs of RE deployment. Hence, an increase in FIT results in higher capacities and thus higher state benefits. Consequently, subsidies only depend on the marginal benefits of RE deployment and the state's marginal burden share.

We denote the associated Nash equilibrium between federal FIT and states' subsidies by $\tilde{T}, \tilde{s_1}, ..., \tilde{s_n}$. The equilibrium RE support is

$$\tilde{T} = \sum_{j=1}^{n} \frac{\partial B_j}{\partial R}, \tag{4.14}$$

$$\forall i: \tilde{s_i} = \frac{\partial B_i}{\partial r_i} + \frac{\partial B_i}{\partial R} - e_i \sum_{j=1}^{n} \frac{\partial B_j}{\partial R}. \tag{4.15}$$

In equilibrium, the nationwide FIT exactly corresponds to the inter-state spillover benefits and does not depend on the local benefits. For positive marginal national benefits of RE, the FIT is always positive. A state's subsidy equals the state's marginal benefits from RE deployment minus its marginal burden share. The equilibrium state subsidy is first-best if it corresponds to the amount of the state's own local benefits of RE deployment, $\tilde{s}_i = \frac{\partial B_i}{\partial r_i}$ (cf. Eq. 4.29).

Comparing the total RE support provided by the nationwide FIT and the state subsidies with the first-best allocation derived in Lemma 4.1 establishes Proposition 4.1.

Proposition 4.1. *Under a combination of nationwide FIT and state subsidies* $(\tilde{s}_i > 0, \Phi_i = \tilde{T} > 0)$, *a state's subsidy is too high (too low) if and only if its share in the marginal benefits from nationwide RE deployment is larger (smaller) than its relative burden share. The combined support is efficient if and only if both shares are equal:*

$$\forall i: \; \tilde{T} + \tilde{s}_i \gtreqless \Psi_i^* \iff \frac{\frac{\partial B_i}{\partial R}}{\sum_{j=1}^{n} \frac{\partial B_j}{\partial R}} \gtreqless e_i. \tag{4.16}$$

Proof. See Appendix 4.C. *Q.E.D.*

Proposition 4.1 shows that whether or not the combination of a nationwide FIT and state subsidies is efficient is determined by the relation of each state's share of marginal benefits of nationwide RE deployment to its relative burden share. Support is too high (low) in a state if its share of the marginal benefits of nationwide RE deployment exceeds (is less than) its relative burden share. As a state's RE capacity r_i increases in line with its policy support, $T + s_i$, it follows directly that RE capacity in a state is too high (low) if and only if a state's share of marginal benefits from national RE is larger (smaller) than its relative burden share. Thus, Proposition 4.1 shows that the efficiency condition for combined pollution control with a price instrument from both the federal and state levels extends to public goods as RE (cf. Williams III, 2012).

Intuitively, state subsidies directly affect the amount of national RE capacity. If a state's marginal benefits from federal policy are higher than its relative burden share, than the state will favor increasing capacity. By contrast, if a state's relative burden share exceeds the benefits it derives from federal policy it can improve the welfare of its citizens by reducing RE subsidies and thereby also reducing the overall national RE capacity.

Furthermore, it follows from Eq. (4.16) that the occurrence of structural under- or over-support in all states simultaneously is impossible. Instead, if one or more states provide too little support for RE, there must also be at least one state that is providing too much RE support. As a consequence, RE deployment might be regionally skewed and, at a national level, deviate from optimal amount.

In Proposition 4.2, we compare nationwide RE deployment with the first-best level for cases where the efficiency condition given in Proposition 4.1 is not met and hence the RE allocation is not first-best.

Proposition 4.2. *Consider that e_i deviates from the condition required for optimal RE support (Eq. 4.16) by some Δe_i and, as a consequence, there are $\mu = 1, ..., m$ under- and $\nu = 1, ..., k$ over-burdened states such that $\Delta e_\mu < 0, \Delta e_\nu > 0$. Under a combination of federal nationwide FIT and state subsidies, nationwide RE capacity is larger (smaller) than optimal if and only if the sum of the burden-weighted reciprocal difference between the sensitivities of marginal cost and benefit functions is larger (smaller) in the under-burdened states than in the over-burdened states. Nationwide capacity is the same as under a first-best allocation if both are equal:*

$$R \gtreqless R^* \iff$$
$$-\sum_{\mu=1}^{m} \Delta e_\mu \left[\frac{\partial^2 C_\mu}{\partial r_\mu^2} - \frac{\partial^2 B_\mu}{\partial r_\mu^2} - \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_\mu} \right]^{-1} \gtreqless \sum_{\nu=1}^{k} \Delta e_\nu \left[\frac{\partial^2 C_\nu}{\partial r_\nu^2} - \frac{\partial^2 B_\nu}{\partial r_\nu^2} - \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_\nu} \right]^{-1}. \tag{4.17}$$

Proof. See Appendix 4.D. *Q.E.D.*

Proposition 4.2 states under which conditions the level of nationwide RE capacity is higher or lower than under the first-best allocation given that RE support is non-optimal in at least some states. The amount of nationwide RE capacity is equal to the efficient level only in the very specific case when overcapacity in the under-burdened states exactly compensates for the undercapacity in the over-burdened states. However even though, in this case, nationwide RE capacity is efficient, its distribution is not.

4.3.3 State subsidies and federal quota

Next, we turn to combined support by means of a federal nationwide auction and state subsidies (the following is formally proven in Appendix 4.E). The decision problem reads

$$\max_{Q} \Pi^{FED} = \sum_{i=1}^{n} \left[-C_i(r_i) + B_i(r_i, R)\right], \tag{4.18}$$

$$\forall i: \max_{s_i} \Pi_i^{ST} = -C_i(r_i) + B_i(r_i, R) - e_i R P + r_i P, \tag{4.19}$$

$$\text{s.t. } \forall i: \max_{r_i} \Pi_i^{SUP} = -C_i(r_i) + (s_i + P)\, r_i. \tag{4.20}$$

For given state subsidies, the federal government sets the nationwide quota so that the quota price P equals the sum of marginal benefits of national RE deployment and is thus identical to a nationwide FIT (cf. Eq. 4.14). However, the incentives for states to subsidize RE are different from under FIT. For a given quota each state sets its subsidy equal to its marginal local benefit plus its net benefit from a marginal quota price change:

$$s_i(P) = \frac{\partial B_i}{\partial r_i} + \left[r_i - e_i Q\right] \frac{\partial P}{\partial r_i}. \tag{4.21}$$

Note that states now internalize some of the cost externality from the burden share as they consider the impact of their choice of r_i on the quota price their suppliers receive.

It follows that in Nash equilibrium, which we denote by $\bar{P}, \bar{s_1}, ..., \bar{s_n}$, a state's subsidy is determined by the marginal local benefits and by the effect of the state's RE capacity on the marginal spillover benefits received by all states:

$$\bar{P} = \sum_{j=1}^{n} \frac{\partial B_j}{\partial R}, \tag{4.22}$$

$$\forall i: \bar{s_i} = \frac{\partial B_i}{\partial r_i} + \left[r_i - e_i Q\right] \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_i}. \tag{4.23}$$

Hence, for negative cross derivatives, in equilibrium a state's subsidy decreases in its RE capacity, r_i, and increases in its burden share. Whereas under a nationwide FIT a state increases its subsidy in response to a decrease in its burden share, under a nationwide quota a state responds to a decrease in its burden share by decreasing its subsidy.

Comparing the total RE support in equilibrium for a nationwide quota with the first-best allocation (Lemma 4.1) establishes Proposition 4.3.

Proposition 4.3. *For* $\sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial r_i \partial R} < 0$*, under a combination of a nationwide auction and state subsidies* $(\bar{s}_i > 0, \Phi_i = \bar{P} > 0)$*, a state's subsidy is too high (too low) if and only if its capacity share is smaller (larger) than its relative burden share. The combined support is efficient if and only if both shares are equal:*

$$\forall i: \ \bar{P} + \bar{s}_i \gtreqless \Psi_i^* \iff r_i \gtreqless r_i^* \iff \frac{r_i}{Q} \lesseqgtr e_i. \tag{4.24}$$

For $\sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial r_i \partial R} = 0$*, combined support by federal nationwide auction and state subsidies yields the first-best outcome.*

Proof. See Appendix 4.E. *Q.E.D.*

Proposition 4.3 shows that optimal RE support is achieved if and only if states' RE capacities are distributed proportionally to their burden shares.[6] If that is the case in a state, the federal RE support cancels out to zero in the state's objective (Eq. 4.19) and consequently in its equilibrium subsidy decision (Eq. 4.23). While state governments then only support RE for their local benefits, the federal government supports for all spillover benefits, thus inducing a first-best allocation.

If equilibrium RE deployment is distributed disproportionally to the policy costs, the combined RE support will be inefficiently high in some states and inefficiently low in others. RE deployment is over-supported in a particular state if the state's relative burden share of the federal RE policy is higher than its capacity share. Intuitively, since there is a fixed RE quota, lower state subsidies cannot lead to lower national RE capacity and thus a state cannot reduce its burden share by reducing its subsidy. However, when an individual state increases its support for RE this will lead to a reduced nationwide quota price. Thus, on the

[6] Assuming a state's RE capacity affects some states' marginal national benefits, $\sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial r_i \partial R} < 0$.

one hand, the state's suppliers will receive less support from the federal government, on the other hand, the state reduces its burden share. The net effect for the state is positive if its relative burden share is larger than its capacity share. In this case, the loss in federal support is outweighed by the reduction in the state's burden share. Consequently, the state's suppliers deploy RE capacity at marginal costs that exceed the marginal benefits. As opposed to that, if a state whose relative burden share is lower than its capacity share decreases its RE support, the additional support its suppliers receive will exceed that state's additional burden share resulting from a higher quota price. In this case, the state's suppliers deploy RE capacity at marginal costs that are lower than the marginal benefits. As a summary, over-burdened states have an incentive to increase their subsidies, while under-burdened states have an incentive to decrease them.

A quota-based system thus exerts a mediating effect on RE capacity: If a state's capacity share is lower than its relative burden share, subsidies and RE deployment in the state are higher than welfare-optimal. Hence, this situation can only occur if the state's relative burden share was higher than its welfare-optimal capacity share in the first place. This effectively bounds RE capacity between the welfare-optimal capacity and its allocation in accordance with the given relative burden share: $r_i^* \leq r_i \leq e_i Q$ or $r_i^* \geq r_i \geq e_i Q$, which also follows directly from Eq. (4.24).

As for a nationwide FIT the combined RE support will never be too high or too low for all states. In the following, we compare nationwide RE deployment with the first-best level for cases where the efficiency condition given in Proposition 4.3 is not met and hence the RE allocation is not first-best.

Proposition 4.4. *Consider that e_i deviates from the efficiency condition in Eq. (4.24) by some Δe_i. As a consequence, there are $\mu = 1, ..., m$ under- and $\nu = 1, ..., k$ over-burdened states such that $\Delta e_\mu < 0, \Delta e_\nu > 0$. Under combined support by a federal nationwide auction and state subsidies, nationwide RE capacity is larger (smaller) than optimal if and only if the sum of the burden-weighted reciprocal difference between the sensitivity of marginal cost and marginal benefit functions is smaller (larger) in the under-burdened states than in the over-burdened states. Nationwide RE capacity is the same as under a first-best allocation if both are equal:*

$$R \gtreqless R^* \iff$$

$$-\sum_{\mu=1}^{m} \Delta e_{\mu} \left[\frac{\partial^2 C_{\mu}}{\partial r_{\mu}^2} - \frac{\partial^2 B_{\mu}}{\partial r_{\mu}^2} - \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_{\mu}} \right]^{-1} \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_{\mu}} \gtreqless$$

$$\sum_{\nu=1}^{k} \Delta e_{\nu} \left[\frac{\partial^2 C_{\nu}}{\partial r_{\nu}^2} - \frac{\partial^2 B_{\nu}}{\partial r_{\nu}^2} - \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_{\nu}} \right]^{-1} \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_{\nu}}. \tag{4.25}$$

Proof. See Appendix 4.F. *Q.E.D.*

Proposition 4.4 states under which conditions the level of nationwide RE capacity is higher or lower than under the first-best allocation given that RE support is non-optimal in at least some states. Compared to the result for a nationwide FIT (Eq. 4.17), the sum of the cross derivatives $\sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_i}$ is an additional term. As the cross derivatives are strictly negative, the resulting relations between capacities, relative burden shares and the sensitivities of marginal cost and marginal benefit curves under an auction system are switched compared to under FIT. As for FIT, the resulting nationwide capacity is only equal to the first-best capacity under very specific combinations of parameters – except in the trivial case where all cross derivatives are zero, which directly induces the first-best allocation.

4.3.4 Comparing state subsidies under FIT and auction

Comparing nationwide FIT and nationwide auctions, we find identical support at the federal level. However, the incentives for states to support RE substantially differ: For both FIT and auctions, state governments grant subsidies in the amount of the local marginal benefits from RE in their state, which are than raised or decreased, depending on the distribution of the federal instrument's costs. If a FIT is implemented by the federal government, a state will increase its subsidy if its share of marginal benefit from national REs is higher than its relative burden share (and vice versa). If the federal government implements an auction, a state will raise its subsidy if its capacity share is lower than its relative burden share (and vice versa).

As a consequence, a high burden share leads to state RE support that is lower than the efficient level under federal FIT and higher than the efficient level under an federal auction system. Under FIT, there is a quantity effect: Reducing the subsidy in a state will also decrease the nationwide RE capacity and thus the state's burden share. In contrast, if the nationwide RE capacity is set by the federal quota, reducing the subsidy and thus the capacity in one state would fully be substituted from capacity in other states. Thus, a state cannot lower its burden share by lowering capacity. However, under an auction system, there is a price effect: If the national quota price falls as a result of one state increasing RE support and hence demand for quotas, this also reduces the burden share for all states. Hence, in contrast to FIT, there is an incentive for an over-burdened state to increase capacity by over-supporting RE (in comparison with welfare-optimal levels of support).

Table 4.1 summarizes our results on the efficiency of different single- and two-level RE support schemes and Proposition 4.5 provides the formal condition under which RE support in a state is higher under an auction scheme than under FIT and vice versa.

Table 4.1: Results summary on efficiency of RE support schemes.

		State policy	
		none	subsidy
Federal policy	none	-	never$^{(b)}$
	state-specific FIT	always	-
	state-specific auction	always	-
	nationwide FIT	never$^{(a)}$	if$^{(b)}$ $\frac{\frac{\partial B_i}{\partial R}}{\sum_{j=1}^{n} \frac{\partial B_j}{\partial R}} = e_i$
	nationwide auction	never$^{(a)}$	if$^{(c)}$ $\frac{r_i}{R} = e_i$

In addition, efficiency is achieved in the following special cases: (a) if marginal local benefits are identical for all states; and (b) if interstate externalities are absent, i.e. marginal national benefits are zero; and (c) if all cross derivatives are zero.

Proposition 4.5. *A state's subsidy is higher (lower) under a nationwide auction ($\bar{s}_i$) than under a nationwide FIT ($\tilde{s}_i$) if and only if the state's share of marginal national benefits, minus the marginal change in federal support received by the state's suppliers is smaller (larger) than its relative burden share:*

$$\bar{s}_i \gtrless \tilde{s}_i \iff \frac{\frac{\partial B_i}{\partial R} - r_i \frac{\partial P}{\partial r_i}}{\sum_{j=1}^{n} \left[\frac{\partial B_j}{\partial R} - r_j \frac{\partial P}{\partial r_i} \right]} \lessgtr e_i. \tag{4.26}$$

Proof. See Appendix 4.G. *Q.E.D.*

Proposition 4.5 shows that a state's incentive to provide RE support varies, depending on whether the federal government implements a FIT or an auction system. Whether a state's subsidy is higher or lower under FIT or an auction system depends on how marginal benefits of nationwide RE deployment are distributed among states, on how the quota price reacts to capacity changes, and on the state's relative burden share. A state will set its subsidy higher (lower) under a federal auction than under FIT if and only if the marginal spillover benefits minus the change in the amount of federal support the suppliers receive in that state relative to all states is lower (higher) than its relative burden share.

Under an auction system, in the special case where the sum of all cross derivatives is zero ($\frac{\partial P}{\partial r_i} = \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_i} = 0$), the level of state subsidy is always first-best (cf. Proposition 4.3). Under FIT, it follows from Eq. (4.26) that the efficiency of the state subsidies is directly determined by how the state's share of marginal national benefits relates to its relative burden share. Thus, the result resembles our finding from Proposition 4.1 (cf. Eq 4.16). Consequently, in this case, a state subsidy under FIT is larger (smaller) than under an auction system if and only if a state's share of marginal benefits from nationwide RE deployment is higher (lower) than its relative burden share.

4.4 Empirical application

We illustrate our findings for Germany using state-wise data for 2015 on onshore wind deployment. In Germany states have played an active role in the ongoing energy transition (Schönberger & Reiche, 2016). After applying a nationwide FIT from 1991 to 2014, the federal government started setting nationwide quotas and holding a discriminatory price auction to determine the level of federal RE support in 2017 (Meya et al., 2016).[7] The federal RE policy is financed by a surcharge on the electricity price and thus proportional to consumption.

It is thus straightforward to approximate a state's relative burden share e_i using power demand data (Kunz et al., 2017).[8] Furthermore, as support is granted for generation rather than capacity, we use RE capacity data (Kunz et al., 2017)

[7] In Germany, RE suppliers bid on a premium on the market price in repeated discriminatory price auctions. Assuming perfect information, this is equivalent to our setup of a single, non-discriminatory price auction for the net present value of a tariff. 2014 to 2017 was a transition phase.

[8] In Germany, large electricity consumers may be exempted from the renewable energy surcharge. This is ignored in our analysis.

together with state-specific full load hours (Koch et al., 2016) to obtain the average capacity available for generation, r_i. The resulting cost shares, e_i, and corrected capacity shares, $\frac{r_i}{R}$, are shown for the sixteen German states in Table 4.2.

Table 4.2: Incentives for state subsidies compared to the efficient amount under nationwide auctions in Germany.

State	**Rel. burden share**, e_i	**Capacity share**, $\frac{r_i}{R}$	**Incent. for subsidies**
NRW	0.200	0.086	$\nearrow$
BY	0.182	0.026	$\uparrow$
BW	0.165	0.014	$\uparrow$
NI	0.092	0.249	$\searrow$
RP	0.068	0.062	$\rightarrow$
HE	0.064	0.018	$\nearrow$
SN	0.042	0.026	$\nearrow$
BE	0.037	0.003	$\uparrow$
HH	0.032	0.003	$\uparrow$
SH	0.024	0.197	$\downarrow$
BB	0.022	0.121	$\searrow$
TH	0.021	0.029	$\rightarrow$
ST	0.020	0.102	$\searrow$
SL	0.015	0.005	$\nearrow$
MV	0.013	0.057	$\searrow$
HB	0.004	0.001	$\nearrow$

Legend: Northrhine-Westphalia (NRW), Bavaria (BY), Baden-Wuerttemberg (BW), Lower Saxony (NI), Rhineland Palatinate (RP), Hesse (HE), Saxony (SN), Berlin (BE), Hamburg (HH), Schleswig Holstein (SH), Brandenburg (BB), Thuringia (TH), Saxony-Anhalt (ST), Saarland (SL), Mecklenburg Western Pomerania (MV), Bremen (HB).
Data sources: Kunz et al. 2017, Koch et al. 2016.

We find that under an auction system (Proposition 4.3), the southern states Bavaria (BY) and Baden-Wuerttemberg (BW), with low wind generation capacity, have an incentive to provide too much support for RE which leads to higher than optimal capacity deployment. In contrast, northern states like Lower-Saxony (NI) or Schleswig-Holstein (SH) with high wind generation capacity are incentivized to offer lower than optimal RE support.

The state incentives arising from the burden share of the nationwide auctions are the reverse of those under the previously prevailing nationwide FIT (see Proposition 4.1).[9] Before 2014, states with abundant wind in the north likely over-

[9] It is certainly more difficult to specify marginal national benefits with empirical data under

supported RE while states with a relative scarcity of wind in the south under-supported it. Our model suggests that these incentives were reversed due to the change in the federal RE policy instrument. As a consequence, in future, RE support and deployment might shift from the north to the south of the country. This would be beneficial for the German power system as currently the transmission of RE generated in the north to consumers in the south is often limited by scarce grid capacity. In fact, harmonization of RE deployment and grid capacity expansion was one of the principal motivations for implementing federal auctions (German Federal Ministry for Economic Affairs and Energy, 2015).

4.5 Discussion

In this section, we discuss several critical assumptions and the extent to which these might limit the generality of our results. These include (i) the static setting, (ii) the assumption that suppliers have perfect information, (iii) the focus on RE capacity rather than generation, (iv) the exogenous distribution of policy costs, (v) the focus on positive inter-state spillovers, (vi) the neglect of non-local RE deployment costs, (vii) the empirical application to Germany, and (viii) the choice of the policy mixes.

First, we consider a static setting only and a one-shot game between both governance levels and suppliers. We thus ignore complex dynamics, such as cost changes due to technological progress. Moreover, in practice, the regulations governing financial support for RE are frequently adjusted. This might give rise to dynamic strategic interactions between governments. However, when both levels of government have the same opportunities to adjust their support for RE, a repeated game will yield results identical to the Nash equilibrium (Williams III, 2012). A dynamic setup would hence increase complexity without yielding additional insights.

Second, we assume that suppliers have perfect information on the maximum acceptable quota price and thus all suppliers (nationally, or in each state if quota prices are state-specific) receive the same quota price. In practice, this is not necessarily the case. In fact, information asymmetries are a main reason for the introduction of auctions. Also, pay-as-bid auctions, where the price paid to each supplier is commensurate with its bid, are gaining in popularity. However,

FIT, which would be necessary to evaluate its efficiency (Proposition 4.1).

uncertainty due to imperfect information is reduced when repeated auctions are held, as is typical for RE (assuming that the quota market is sufficiently liquid). Even under information asymmetry, implementing pay-as-bid remuneration would affect the distribution of rents between governments and suppliers, but would not change the rationale of the marginal supplier and hence not influence the efficient amount of capacity.

Third, by computing tariffs and quota prices on the basis of capacity, we implicitly assume proportionality of RE capacity and generation, because usually support is paid in proportion to generation. As a consequence, in order to translate our model into a real-world setting using numerical simulations it would be necessary to correct for regional heterogeneity in the efficiency of RE capacity use. This could be done using data from each state on full load hours. This would also make it possible to take account of some operational costs of RE instead of just focusing on capacities. However, capacity deployment costs of RE far exceed operational costs and thus the general results would not be affected.

Fourth, we assume an exogenously given burden sharing e_i. This assumption is appropriate in the context of current policy alternatives or for a given burden sharing rule (cf. Böhringer et al., 2015). For instance, if national RE policy is financed out of the central budget, costs are distributed in accordance with general taxation structure, which is fixed from the perspective of the energy agency or energy policymaker. Similarly, if federal RE policy is financed by a premium on the electricity price, then the distribution of costs corresponds to the distribution of energy consumption among states. Nevertheless, future work could include the distribution of costs as a decision variable in the federal government's decision problem, which might be a reasonable assumption for the long run. The literature on federal transfers and Lindahl prices (cf. e.g. Caplan et al., 2000) indicates that this might allow the first-best allocation to be achieved even with a nationwide policy instrument.

Fifth, we focus exclusively on positive inter-state spillover benefits of RE and negative cost externalities incurred in financing federal policies. Positive inter-state spillovers include contributions to national climate targets, lower electricity prices and increased security of supply. These constitute a major rationale for federal RE policy. However, in principle, negative externalities of RE deployment are also possible and it would be straightforward to include these in our analysis by assuming $\frac{\partial B_i(r_i,R)}{\partial R} < 0$. Negative RE externalities could include effects on biodiversity, landscape aesthetics (Meyerhoff et al., 2010), well-being of residents (due to exposure to noise and visual impacts) (von Möllendorff & Welsch, 2017, Krekel & Zerrahn, 2017), house prices (Dröes & Koster, 2016) or grid stability (Zerrahn, 2017). However, as these occur mostly on local scales, net negative inter-state spillovers of RE are rather unlikely and we therefore exclude these secondary effects from the analysis, in the interests of readability.

Sixth, we assume that costs of installing RE capacity are entirely local. While this is accurate with regards to the land area needed for RE capacity development, provision of the necessary (grid) infrastructure may be wholly or partly financed by the federal government. Furthermore, since many RE suppliers operate nationally, it is unlikely that their costs can be allocated perfectly to a single state. This could be taken into account by incorporating spillover costs – or equivalently negative spillover benefits (see above) – into the model. For now, however, we assume that the majority of costs are incurred locally and leave consideration of these spillovers for future research.

Seventh the application of our results to the case of Germany could be criticized as being over-simplistic. While this case study analysis is intended only as an illustration, it still reveals substantial differences between the cost shares and capacity shares across states. The regional distribution of incentives under nationwide quota or FIT suggested by our theoretical analysis seems to be in line with the federal government's motive for the policy instrument change implemented in 2017. And indeed, there have been shifts in some states' policies and RE deployments that tend to support our model predictions. For instance, installation of RE capacity has increased recently in BW and declined sharply in SH (Bundesverband Windenergie, 2019). Nevertheless, our analysis ignores several factors that might in practice determine state subsidies, such as the geophysical conditions or the party-political composition of the state government. We leave a systematic consideration of these heterogeneities and thorough empirical investigation for future work.

Finally, we analyze a particular mix of policies: state subsidies with federal FIT or federal auctions. However, most other RE policies are similar to these as they provide either quantity-based (e.g. renewable portfolio standards) or a price-based (e.g. market premium) support. For instance, if regulators have perfect information on prices, RE support by optimal FIT or market premium will give rise to the same outcome (Abrell et al., 2019). We are thus confident that our general findings also hold for other combinations of price and quantity-based RE support policies. A limitation of the model is that it incorporates both a price and quantity instrument only at the federal level. It would be worthwhile to extend the model to incorporate a quantity instrument on the state level as well. This would be suitable for the US energy system in particular, where many states have implemented portfolio standards (Upton & Snyder, 2017).

4.6 Conclusion

In this paper, we have shown that the incentives for state governments to subsidize RE substantially depend on whether the federal government implements a price or quantity instrument, i.e. a nationwide FIT or a nationwide auction, and on how the costs of this federal RE policy are distributed among states. Under FIT, states that bear a higher (lower) burden in financing the federal policy tend to reduce (increase) their subsidies while under an auction system they tend to increase (reduce) them. In all cases this likely leads to RE subsidies that are either too low or too high compared to first-best levels and, correspondingly, to deficit or surplus RE capacity.

Furthermore, whether or not the level of national RE capacity is efficient depends on the characteristics of the over- and under-burdened states. Under FIT, the national capacity is greater than optimal if the differences between sensitivities of marginal cost and marginal benefit functions are smaller in the under-burdened states than in over-burdened states and vice versa. Under nationwide auctions, this relation is reversed such that the national capacity is lower than optimal if the differences between sensitivities of marginal cost and marginal benefit functions are lower in the under-burdened states than in over-burdened states and vice versa.

Our results offer conceptual guidance for the selection of instruments to support RE in federal government systems: As RE deployment creates benefits on different spatial scales, actions at a single government level will generally not attain an optimal level of RE support. However, due to interaction between national-level and state-level strategies, implementing state-level RE support in addition to a nationwide federal policy does not necessarily lead to a first-best allocation of RE capacities either. A nationwide FIT creates incentives for efficient state policies whenever marginal national benefits of RE are distributed in proportion to the burden share incurred by national RE policy. A nationwide auction creates incentives for efficient RE policies when RE capacities are distributed proportionally to the distribution of the burden share. Moreover, a nationwide auction system will always be efficient if states' marginal national benefits do not depend on other states' RE capacities, which is not the case for FIT. In particular, the derived efficiency condition for an auction system is easy to specify using empirical data on RE capacity. Circumstances in which state support under an auction system might be inefficient are illustrated by the case of Germany, where wind capacity is greatest in the sparsely populated north, while private energy consumption is highest in the densely populated west and south, and federal RE policy is refinanced by a surcharge on consumption.

In addition to RE, our model could also be applied to analyze any policy setup where two government levels provide financial support for the provision of impure public goods. This could include, for example, the deployment of transport and communication infrastructure, or finance for research and development. Overall, in a second-best setting, where the federal government can only implement a nationwide policy, state governments have an incentive to implement their own policies. The efficiency of these state policies substantially depends on whether the federal government uses a price or a quantity instrument and how the cost of federal policy is distributed.

Appendices

4.A Nomenclature

$i = 1, ..., n$	Index for states
$\mu = 1, ..., m$	Index for under-burdened states
$\nu = 1, ..., k$	Index for over-burdened states
r_i	RE deployment in state i
Δr_i	Deviation of RE deployment from optimum
R	RE deployment in the whole nation
s_i	RE subsidy in state i
$T_{(i)}$	(State-specific) feed-in tariff
$Q_{(i)}$	(State-specific) auctioned quota
$P_{(i)}$	(State-specific) quota price for all suppliers defined by last acceptable bid under auction
$\Phi_{(i)} \in \{T_{(i)}, P_{(i)}\}$	(State-specific) federal RE support
Ψ_i	Total RE support in state i
$C_i(r_i)$	Cost of RE deployment in state i
$B_i(r_i, R)$	Benefit of RE deployment in state i
e_i	State i's relative burden share of federal RE support
Δe_i	Deviation of relative burden share from optimum
$\Pi_i^{SUP}, \Pi_i^{ST}, \Pi^{FED}$	Objectives of RE supplier i, state i, and nation

4.B Proof of Lemma 4.1

Consider a *state-specific FIT*. The decision problem of the federal government is given by Eq. (4.6), Eq. (4.7) with choice variables $T_1, ..., T_n$. It follows from the first order condition of the suppliers' maximization problem (Eq. 4.7) that in equilibrium in each state the FIT equals marginal costs

$$\forall i : \frac{\partial C_i(r_i)}{\partial r_i} - T_i = 0. \tag{4.27}$$

Let $r_i(T)$ be the reaction function of the supplier satisfying Eq. (4.27). Inserting this in Eq. (4.6), using $R = \sum_{i=1}^{n} r_i$ and differentiating with respect to T_i gives

$$\forall i : \frac{\partial \Pi^{FED}}{\partial T_i} = - \frac{\partial C_i(r_i)}{\partial r_i} \frac{\mathrm{d}r_i}{\mathrm{d}T_i} + \frac{\partial B_i(r_i, R)}{\partial r_i} \frac{\mathrm{d}r_i}{\mathrm{d}T_i}$$

$$+\sum_{j=1}^{n}\frac{\partial B_j(r_j,R)}{\partial R}\frac{\partial R}{\partial r_i}\frac{\mathrm{d}r_i}{\mathrm{d}T_i}.$$

Setting $\frac{\partial \Pi^{FED}}{\partial T_i}=0$ for all i yields n first order conditions. Dividing by $\frac{\mathrm{d}r_i}{\mathrm{d}T_i}$ and recognizing that $\frac{\partial R}{\partial r_i}=1$ these simplify to

$$\forall i:\frac{\partial C_i(r_i)}{\partial r_i}=\frac{\partial B_i(r_i,R)}{\partial r_i}+\sum_{j=1}^{n}\frac{\partial B_j(r_j,R)}{\partial R}. \tag{4.28}$$

Using Eq. (4.27) in Eq. (4.28) yields the optimal state-specific FIT:

$$\forall i:T_i=\frac{\partial B_i(r_i,R)}{\partial r_i}+\sum_{j=1}^{n}\frac{\partial B_j(r_j,R)}{\partial R}. \tag{4.29}$$

Next, we consider *state-specific quotas*. The decision problem of the federal government is given by Eq. (4.6), Eq. (4.7) with choice variables $Q_1,...,Q_n$. Assuming that P_i is unbound and chosen competitively by the suppliers in each state, it follows directly from the supplier profit maximization and the market clearing (cf. Helm 2003) that

$$\forall i:\frac{\partial C_i(r_i)}{\partial r_i}=P_i, \tag{4.30}$$

$$\forall i:r_i=Q_i, \tag{4.31}$$

$$Q:=\sum_{i=1}^{n}Q_i=R. \tag{4.32}$$

Substituting Eqs. (4.31) and (4.32) in Eq. (4.3) and differentiating with respect to Q_i yields the first order conditions of the federal government:

$$\forall i:\frac{\partial C_i(Q_i)}{\partial Q_i}=\frac{\partial B_i(Q_i,Q)}{\partial Q_i}+\sum_{j=1}^{n}\frac{\partial B_j(Q_i,Q)}{\partial Q}. \tag{4.33}$$

Eq. (4.31) allows to rewrite the suppliers' first order conditions (Eq. 4.30) as $\forall i:P_i=\frac{\partial C_i(Q_i)}{\partial Q_i}$. Inserting this into Eq. (4.33) gives the optimal state-specific quota price

$$\forall i : P_i = \frac{\partial B_i(Q_i, Q)}{\partial Q_i} + \sum_{j=1}^{n} \frac{\partial B_j(Q_i, Q)}{\partial Q}, \tag{4.34}$$

which is identical to the support with a state-specific FIT (cf. Eq. 4.29).

4.C Proof of Proposition 4.1

Consider a situation of combined *nationwide FIT* and *state subsidies*. The decision problem is given by Eq. (4.9) – Eq. (4.11). The first order conditions of the suppliers' profit maximization problem are

$$\forall i : \frac{\partial C_i}{\partial r_i} = s_i + T. \tag{4.35}$$

In the following, let $r_i(T, s_i)$ denote the amount of capacity that satisfies Eq. (4.35).

For a given federal tariff, T, and given subsidies, s_{-i}, a state i's maximization problem reads

$$\forall i : \max_{s_i(T, s_{-i})} \Pi_i^{ST} = -C_i(r_i) + B_i(r_i, R) - e_i \sum_{j=1}^{n} T\, r_j + T\, r_i. \tag{4.36}$$

Differentiating each state's objective function with respect to the state's subsidy, we obtain the first order conditions[10]

$$\forall i : \frac{\partial \Pi_i^{ST}}{\partial s_i} = -\frac{\partial C_i}{\partial r_i} \frac{\mathrm{d}r_i}{\mathrm{d}s_i} + \frac{\partial B_i}{\partial r_i} \frac{\mathrm{d}r_i}{\mathrm{d}s_i} + \frac{\partial B_i}{\partial R} \frac{\partial R}{\partial r_i} \frac{\mathrm{d}r_i}{\mathrm{d}s_i} - e_i T \frac{\mathrm{d}r_i}{\mathrm{d}s_i} + T \frac{\mathrm{d}r_i}{\mathrm{d}s_i} = 0.$$

Dividing by $\frac{\mathrm{d}r_i}{\mathrm{d}s_i}$ and recognizing $\frac{\partial R}{\partial r_i} = 1$ yields

$$\forall i : 0 = -\frac{\partial C_i}{\partial r_i} + \frac{\partial B_i}{\partial r_i} + \frac{\partial B_i}{\partial R} - e_i T + T. \tag{4.37}$$

[10] Note from Eq. (4.35) that the supplier's choice of r_i depends on s_i, T but not on s_{-i} and thus $\frac{\mathrm{d}r_j}{\mathrm{d}s_i} = 0, \forall i \neq j$.

Using Eq. (4.35) in Eq. (4.37) and rearranging gives the optimal choice of state subsidies, $\{s_1, ..., s_n\}$, for a given federal FIT, T:

$$\forall i : s_i(T) = \frac{\partial B_i}{\partial r_i} + \frac{\partial B_i}{\partial R} - e_i T. \tag{4.38}$$

For given state subsidies, $\{s_1, ..., s_n\}$, the federal government faces the maximization problem

$$\max_{T(s_1,...,s_n)} \Pi^{FED} = \sum_{i=1}^{n} \left[-C_i(r_i) + B_i(r_i, R)\right]. \tag{4.39}$$

Differentiating with respect to T yields

$$\frac{\partial \Pi^{FED}}{\partial T} = \sum_{i=1}^{n} \left[-\frac{\partial C_i}{\partial r_i} \frac{\mathrm{d}r_i}{\mathrm{d}T} + \frac{\partial B_i}{\partial r_i} \frac{\mathrm{d}r_i}{\mathrm{d}T} + \sum_{j=1}^{n} \frac{\partial B_j}{\partial R} \frac{\partial R}{\partial r_i} \frac{\mathrm{d}r_i}{\mathrm{d}T} \right]. \tag{4.40}$$

Recall, that by assumption $\frac{\partial^2 C_i(r_i)}{\partial r_i^2}$ is constant and identical for all states. Differentiating both sides of Eq. (4.35) with respect to T and rearranging gives $\frac{\mathrm{d}r_i}{\mathrm{d}T} = \left[\frac{\partial^2 C_i(r_i)}{\partial r_i^2}\right]^{-1} = b^{-1}$. Thus, the assumed cost structure implies that $\forall i, j : \frac{\mathrm{d}r_i}{\mathrm{d}T} = \frac{\mathrm{d}r_j}{\mathrm{d}T}$.

Setting Eq (4.40) to zero, $\frac{\partial \Pi^{FED}}{\partial T} = 0$, dividing by $\frac{\mathrm{d}r_i}{\mathrm{d}T}$, recognizing $\frac{\partial R}{\partial r_i} = 1$ and rearranging yields the simplified first order condition

$$\sum_{i=1}^{n} \frac{\partial C_i}{\partial r_i} = \sum_{i=1}^{n} \left[\frac{\partial B_i}{\partial r_i} + \sum_{j=1}^{n} \frac{\partial B_j}{\partial R} \right] = \sum_{i=1}^{n} \frac{\partial B_i}{\partial r_i} + n \sum_{j=1}^{n} \frac{\partial B_j}{\partial R}. \tag{4.41}$$

Using Eq. (4.35) in Eq. (4.41) gives the optimal choice of the federal FIT, T, depending on the state subsidies $\{s_1, ..., s_n\}$:

$$\begin{aligned} \sum_{i=1}^{n} [s_i + T] &= \sum_{i=1}^{n} \frac{\partial B_i}{\partial r_i} + n \sum_{j=1}^{n} \frac{\partial B_j}{\partial R} \\ \iff n\,T + \sum_{i=1}^{n} s_i &= \sum_{i=1}^{n} \frac{\partial B_i}{\partial r_i} + n \sum_{j=1}^{n} \frac{\partial B_j}{\partial R} \end{aligned}$$

$$\iff T(\{s_1, ..., s_n\}) = \frac{1}{n}\sum_{i=1}^{n}\frac{\partial B_i}{\partial r_i} + \sum_{j=1}^{n}\frac{\partial B_j}{\partial R} - \frac{1}{n}\sum_{i=1}^{n} s_i \qquad (4.42)$$
$$= \frac{1}{n}\sum_{i=1}^{n}\left[\frac{\partial B_i}{\partial r_i} - s_i\right] + \sum_{j=1}^{n}\frac{\partial B_j}{\partial R}.$$

Solving the system of reaction functions, given by Eq. (4.38) and Eq. (4.42), for T and $\{s_1, ..., s_n\}$ yields the RE support in Nash equilibrium, which we denote by $\tilde{T}$ and $\{\tilde{s_1}, ..., \tilde{s_n}\}$.

$$\tilde{T} = \frac{1}{n}\sum_{j=1}^{n}(n-1)\frac{\partial B_j}{\partial R} + \frac{1}{n}\tilde{T}\sum_{i=1}^{n} e_i$$
$$\overset{(4.2)}{=} \frac{n-1}{n}\sum_{j=1}^{n}\frac{\partial B_j}{\partial R} + \frac{1}{n}\tilde{T}$$
$$\iff \tilde{T} = \sum_{j=1}^{n}\frac{\partial B_j}{\partial R}. \qquad (4.43)$$

Using Eq. (4.43) in Eq. (4.38) we obtain the equilibrium state subsidies

$$\forall i : \tilde{s}_i = \frac{\partial B_i}{\partial r_i} + \frac{\partial B_i}{\partial R} - e_i\sum_{j=1}^{n}\frac{\partial B_j}{\partial R}. \qquad (4.44)$$

The total support of RE in state i is then

$$\tilde{T} + \tilde{s}_i = \frac{\partial B_i}{\partial r_i} + \sum_{j=1}^{n}\frac{\partial B_j}{\partial R} + \frac{\partial B_i}{\partial R} - e_i\sum_{j=1}^{n}\frac{\partial B_j}{\partial R}. \qquad (4.45)$$

Eq. (4.45) differs from the first-best given in Eq. (4.8) only in the two additional two last terms. It follows from $\frac{\partial B_j}{\partial R} > 0$, that REs are over-supported (under-supported), if the term's sum is positive (negative), or, following some simple algebra, if a state's share of marginal benefits from national RE is higher (lower) than its relative burden share

$$\tilde{T} + \tilde{s}_i \gtreqless \Psi_i^* \iff \frac{\frac{\partial B_i}{\partial R}}{\sum_{j=1}^n \frac{\partial B_j}{\partial R}} \gtreqless e_i. \tag{4.46}$$

4.D Proof of Proposition 4.2

Consider that RE support in some states is non-optimal as the efficiency condition Eq. (4.17) is not satisfied due to $\Delta e_i := e_i - \frac{\frac{\partial B_i}{\partial R}}{\sum_{j=1}^n \frac{\partial B_j}{\partial R}} \neq 0$. Following Eqs. (4.14-4.16), total RE support can be written as

$$\begin{aligned}
\forall i:\ \tilde{T} + \tilde{s}_i &= \frac{\partial B_i}{\partial r_i} + \sum_{j=1}^n \frac{\partial B_j}{\partial R} - \left[\frac{\frac{\partial B_i}{\partial R}}{\sum_{j=1}^n \frac{\partial B_j}{\partial R}} + \Delta e_i\right] \sum_{j=1}^n \frac{\partial B_j}{\partial R} + \frac{\partial B_i}{\partial R} \\
&= \frac{\partial B_i}{\partial r_i} + \sum_{j=1}^n \frac{\partial B_j}{\partial R} - \Delta e_i \sum_{j=1}^n \frac{\partial B_j}{\partial R}.
\end{aligned} \tag{4.47}$$

From the optimality conditions of the RE capacity supplier, we know that $\frac{\partial C_i}{\partial r_i} = T + s_i$ (cf. Eq. 4.35). If the equilibrium of marginal costs and RE support (Eq. 4.47) changes due to $\Delta e_i \neq 0$, RE deployment r_i deviates from its first-best by an amount, which we call $\Delta r_i := r_i - r_i^*$. The shift of total RE support from FIT and subsidy from its optimal amount is $-\Delta e_i \sum_{j=1}^n \frac{\partial B_j}{\partial R}$ (cf. Eq. 4.47, Eq. 4.8), which directly corresponds to a shift Δr_i. This correspondence is visualized in Figure 4.1.

In the plane of RE support and capacity and for linear marginal functions, the difference of the slopes of the marginal cost and benefit functions (i.e., of the curvatures of the original functions, also referred to as *sensitivity of the marginal functions*), respectively multiplied with Δr_i on the horizontal axis, directly corresponds to the shift in total support on the vertical axis:

$$\forall i:\ \frac{\partial^2 C_i}{\partial r_i^2} \Delta r_i - \left[\frac{\partial^2 B_i}{\partial r_i^2} + \sum_{j=1}^n \frac{\partial^2 B_j}{\partial R \partial r_i}\right] \Delta r_i = -\Delta e_i \sum_{j=1}^n \frac{\partial B_j}{\partial R}. \tag{4.48}$$

Rearrange to get

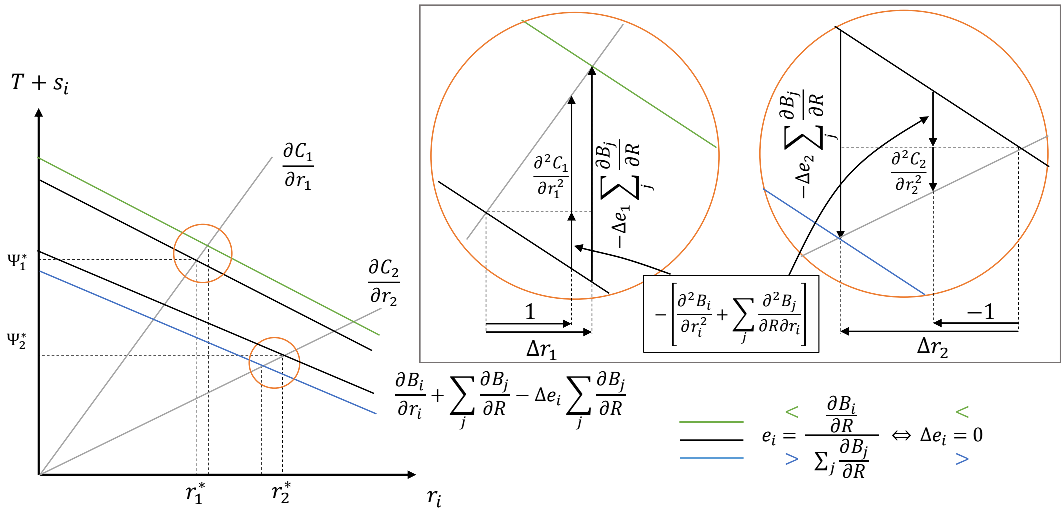

Figure 4.1: Equilibrium allocation of RE capacities and policies exemplified for two states when federal cost distribution is under-burdened to state 1 ($\Delta e_1 < 0$) and over-burdened to state 2 ($\Delta e_2 > 0$). There is over-deployment of RE in state 1 and under-deployment in state 2. The change in RE deployment Δr_i is determined from the slopes of the marginal RE support and cost functions. The orange circles detail the situation.

$$\forall i: \ \Delta r_i = -\Delta e_i \left[\frac{\partial^2 C_i}{\partial r_i^2} - \frac{\partial^2 B_i}{\partial r_i^2} - \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_i} \right]^{-1} \sum_{j=1}^{n} \frac{\partial B_j}{\partial R}. \tag{4.49}$$

Now, let $\mu = 1, ..., m$ be the states, which are under-burdened and $\nu = 1, ..., k$ the ones that are over-burdened (i.e., $\Delta e_\mu < 0, \Delta e_\nu > 0$). If follow directly that $\Delta r_\mu > 0, \Delta r_\nu < 0$. Summing Eq. (4.49) over μ and ν, respectively, adding up RE capacities in under- and over-burdened states, and recognizing that $\sum_{j=1}^{n} \frac{\partial B_j}{\partial R} > 0$ does not depend on i, we obtain

$$\begin{aligned} R \gtreqless R^* \iff \sum_{\mu=1}^{m} \Delta r_\mu + \sum_{\nu=1}^{k} \Delta r_\nu \gtreqless 0 \iff \\ -\sum_{\mu=1}^{m} \Delta e_\mu \left[\frac{\partial^2 C_\mu}{\partial r_\mu^2} - \frac{\partial^2 B_\mu}{\partial r_\mu^2} - \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_\mu} \right]^{-1} \gtreqless \\ \sum_{\nu=1}^{k} \Delta e_\nu \left[\frac{\partial^2 C_\nu}{\partial r_\nu^2} - \frac{\partial^2 B_\nu}{\partial r_\nu^2} - \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_\nu} \right]^{-1}. \end{aligned} \tag{4.50}$$

4.E Proof of Proposition 4.3

The decision problem for a *nationwide quota* and *state subsidies* is given by Eq. (4.18) – Eq. (4.20). Assuming that P, depicting the equilibrium price on the quota market, is unbound and determined competitively, it follows directly from suppliers' profit maximization and market clearing (cf. Helm 2003):

$$\forall i : \frac{\partial C_i}{\partial r_i} = s_i + P, \tag{4.51}$$

$$R := \sum_{i=1}^{n} r_i = Q. \tag{4.52}$$

We write $r_i(P, s_i)$ as the amount of capacity that satisfies Eq. (4.51).

For given state subsidies, $\{s_1, ..., s_n\}$, the federal government's optimisation problem reads

$$\max_{Q(s_1,...,s_n)} \Pi^{FED} = \sum_{i=1}^{n} \left[-C_i(r_i) + B_i(r_i, R) \right]. \tag{4.53}$$

Differentiating with respect to Q yields

$$\frac{\partial \Pi^{FED}}{\partial Q} = \sum_{i=1}^{n} \left[-\frac{\partial C_i}{\partial r_i} \frac{\mathrm{d} r_i}{\mathrm{d} Q} + \frac{\partial B_i}{\partial r_i} \frac{\mathrm{d} r_i}{\mathrm{d} Q} + \sum_{j=1}^{n} \frac{\partial B_j}{\partial R} \frac{\partial R}{\partial r_i} \frac{\mathrm{d} r_i}{\mathrm{d} Q} \right].$$

Setting to zero, $\frac{\partial \Pi^{FED}}{\partial Q} = 0$, dividing by $\frac{\mathrm{d} r_i}{\mathrm{d} Q}$, recognizing $\frac{\partial R}{\partial r_i} = 1$ and rearranging yields the simplified first order condition[11]

$$\sum_{i=1}^{n} \frac{\partial C_i}{\partial r_i} = \sum_{i=1}^{n} \left[\frac{\partial B_i}{\partial r_i} + \sum_{j=1}^{n} \frac{\partial B_j}{\partial R} \right] = \sum_{i=1}^{n} \frac{\partial B_i}{\partial r_i} + n \sum_{j=1}^{n} \frac{\partial B_j}{\partial R}, \tag{4.54}$$

which is identical to the condition for choosing an optimal FIT (Eq. 4.41).

Using Eq. (4.51) in Eq. (4.54) we obtain the condition for the federal government's optimal quota choice, for given state subsidies

[11]The assumption $\forall i : \frac{\partial^2 C_i(r_i)}{\partial r_i^2} = b$ implies $\forall i : \frac{\mathrm{d} r_i}{\mathrm{d} Q} = b^{-1} \frac{\mathrm{d} P}{\mathrm{d} Q}$ which is thus identical for all states.

$$
\begin{aligned}
&\sum_{i=1}^{n} [s_i + P] = \sum_{i=1}^{n} \frac{\partial B_i}{\partial r_i} + n \sum_{j=1}^{n} \frac{\partial B_j}{\partial R} \\
\Longleftrightarrow\ & n\, P + \sum_{i=1}^{n} s_i = \sum_{i=1}^{n} \frac{\partial B_i}{\partial r_i} + n \sum_{j=1}^{n} \frac{\partial B_j}{\partial R} \\
\Longleftrightarrow\ & P(s_1, ..., s_n) = \frac{1}{n} \sum_{i=1}^{n} \frac{\partial B_i}{\partial r_i} + \sum_{j=1}^{n} \frac{\partial B_j}{\partial R} - \frac{1}{n} \sum_{i=1}^{n} s_i. \qquad (4.55)
\end{aligned}
$$

Next, we turn to the states' reaction functions. Note, that a state takes the auctioned quota Q as given, but a state's RE capacities affect the equilibrium quota price $P(r_i(s_i))$. Using Eq. (4.51) and Eq. (4.52) in the states' objectives (Eq. 4.19) and differentiating with respect to s_i yields

$$
\forall i : \frac{\partial \Pi_i^{ST}}{\partial s_i} = - \frac{\partial C_i}{\partial r_i} \frac{\mathrm{d} r_i}{\mathrm{d} s_i} + \frac{\partial B_i}{\partial r_i} \frac{\mathrm{d} r_i}{\mathrm{d} s_i} - e_i Q \frac{\partial P}{\partial r_i} \frac{\mathrm{d} r_i}{\mathrm{d} s_i} + P \frac{\mathrm{d} r_i}{\mathrm{d} s_i} + r_i \frac{\partial P}{\partial r_i} \frac{\mathrm{d} r_i}{\mathrm{d} s_i}.
$$

Setting to zero, dividing by $\frac{\mathrm{d} r_i}{\mathrm{d} s_i}$ and rearranging yields the simplified first order condition to the states' maximization problem

$$
\forall i : \frac{\partial C_i}{\partial r_i} = \frac{\partial B_i}{\partial r_i} + [r_i - e_i Q] \frac{\partial P}{\partial r_i} + P. \qquad (4.56)
$$

The states' reaction functions are obtained by using Eq. (4.51) in Eq. (4.56)

$$
\begin{aligned}
&\forall i : s_i + P = \frac{\partial B_i}{\partial r_i} + [r_i - e_i Q] \frac{\partial P}{\partial r_i} + P \\
\Longleftrightarrow\ & \forall i : s_i(P) = \frac{\partial B_i}{\partial r_i} + [r_i - e_i Q] \frac{\partial P}{\partial r_i}. \qquad (4.57)
\end{aligned}
$$

Note, that by assumption $\forall i : \frac{\partial^2 C_i(r_i)}{\partial r_i^2} = b$. Differentiating both sides of Eq. (4.30) with respect to P and rearranging gives $\forall i : \frac{\partial P}{\partial r_i} = b$. Thus, under a nationwide quota the marginal effect of RE capacities on the quota price is identical across all states. We denote the Nash equilibrium of the federal and state governments RE support as $\bar{P}, \bar{s_1}, ..., \bar{s_n}$. The equilibrium quota price is given by inserting Eq. (4.57) in Eq. (4.55):

$$\begin{aligned}
\bar{P} &= \frac{1}{n}\sum_{i=1}^{n}\frac{\partial B_i}{\partial r_i} + \sum_{j=1}^{n}\frac{\partial B_j}{\partial R} - \frac{1}{n}\sum_{i=1}^{n}\left[\frac{\partial B_i}{\partial r_i} + [r_i - e_i Q]\frac{\partial P}{\partial r_i}\right] \\
&= \sum_{j=1}^{n}\frac{\partial B_j}{\partial R} - \frac{1}{n}\sum_{i=1}^{n}[r_i - e_i Q]\frac{\partial P}{\partial r_i} \\
&= \sum_{j=1}^{n}\frac{\partial B_j}{\partial R} - \frac{1}{n}\frac{\partial P}{\partial r_i}\left[\sum_{i=1}^{n} r_i - Q\sum_{i=1}^{n} e_i\right] \\
&\overset{(4.52),(4.2)}{=} \sum_{j=1}^{n}\frac{\partial B_j}{\partial R} - \frac{1}{n}\frac{\partial P}{\partial r_i}[Q - Q] \\
\Longleftrightarrow \quad \bar{P} &= \sum_{j=1}^{n}\frac{\partial B_j}{\partial R}. \qquad (4.58)
\end{aligned}$$

Inserting the equilibrium quota price from Eq. (4.58) into the reaction function in Eq. (4.57), we obtain the state subsidies in Nash equilibrium:

$$\begin{aligned}
\forall i : \bar{s}_i &= \frac{\partial B_i}{\partial r_i} + [r_i - e_i Q]\frac{\partial}{\partial r_i}\sum_{j=1}^{n}\frac{\partial B_j}{\partial R} \\
&= \frac{\partial B_i}{\partial r_i} + \left[\frac{r_i}{Q} - e_i\right] Q\frac{\partial}{\partial r_i}\sum_{j=1}^{n}\frac{\partial B_j}{\partial R}. \qquad (4.59)
\end{aligned}$$

In equilibrium total RE support in a state is:

$$\bar{P} + \bar{s}_i \overset{(4.57),(4.58)}{=} \sum_{j=1}^{n}\frac{\partial B_j}{\partial R} + \frac{\partial B_i}{\partial r_i} + \left[\frac{r_i}{Q} - e_i\right] Q\sum_{j=1}^{n}\frac{\partial^2 B_j}{\partial R \partial r_i}. \qquad (4.60)$$

The total support, Eq. (4.60), differs from the first-best, Eq. (4.8), only in the additional last term. Writing this observation formally, we obtain under which conditions RE is over-supported, under-supported or optimal:[12]

$$\bar{P} + \bar{s}_i \gtreqless \Psi_i^*$$

[12]Note that Eqs. (4.51), (4.60) provide the solution for the chosen r_i's. However, an explicit formulation is impossible for our approach with general functions. Thus, it is more insightful to analyze the optimality via the support instead of the RE quantities.

$$\overset{(4.60),(4.8)}{\Longleftrightarrow} \sum_{j=1}^{n} \frac{\partial B_j}{\partial R} + \frac{\partial B_i}{\partial r_i} + \left[\frac{r_i}{Q} - e_i\right] Q \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_i} \gtreqless \frac{\partial B_i}{\partial r_i} + \sum_{j=1}^{n} \frac{\partial B_j}{\partial R}$$

$$\overset{Q>0}{\Longleftrightarrow} \left[\frac{r_i}{Q} - e_i\right] \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_i} \gtreqless 0. \tag{4.61}$$

Consequently, a nationwide quota is first-best in two cases: (i) the marginal benefits of national RE deployment are independent of the inter-state distribution of RE, i.e. $\sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_i} = 0$, or (ii) in each state the RE deployment is proportional to the relative burden share, i.e. $r_i = e_i Q$.

For a strictly negative sum of cross derivatives, $\sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_i} < 0$, it follows from Eq. (4.61) that

$$\bar{P} + \bar{s}_i \gtreqless \Psi_i^* \iff \frac{r_i}{Q} \lesseqgtr e_i. \tag{4.62}$$

4.F Proof of Proposition 4.4

We can obtain the efficiency condition for national deployment following the same steps as for the support with FIT and subsidy (Eq. 4.47–4.50). First, we write the total amount of RE support where Δe_i depicts the derivation from the efficiency condition in Eq. (4.62):

$$\forall i:\ \bar{P} + \bar{s}_i = \frac{\partial B_i}{\partial r_i} + \sum_{j=1}^{n} \frac{\partial B_j}{\partial R} - \Delta e_i R \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_i}. \tag{4.63}$$

Assuming, again, linear marginal costs and benefits, and considering the shift in total support as a function of the slopes of the marginal cost and benefit curves multiplied respectively with Δr_i we obtain

$$\forall i:\ \frac{\partial^2 C_i}{\partial r_i^2} \Delta r_i - \left[\frac{\partial^2 B_i}{\partial r_i^2} + \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_i}\right] \Delta r_i = -\Delta e_i R \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial r_i \partial R} \tag{4.64}$$

$$\forall i:\ \Delta r_i = -\Delta e_i \left[\frac{\partial^2 C_i}{\partial r_i^2} - \frac{\partial^2 B_i}{\partial r_i^2} - \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_i}\right]^{-1} R \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial r_i \partial R}. \tag{4.65}$$

Let again $\mu = 1, ..., m$ be the states, which are under-burdened and $\nu = 1, ..., k$ the ones that are over-burdened. Summing over μ and ν, respectively, and adding up the deployment changes we find

$$\begin{aligned}
R \gtreqless R^* \iff & \sum_{\nu=1}^{k} \Delta r_\nu + \sum_{\mu=1}^{m} \Delta r_\mu \gtreqless 0 \iff \\
& -\sum_{\mu=1}^{m} \Delta e_\mu \left[\frac{\partial^2 C_\mu}{\partial r_\mu^2} - \frac{\partial^2 B_\mu}{\partial r_\mu^2} - \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_\mu} \right]^{-1} \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_i} \gtrless \\
& \sum_{\nu=1}^{k} \Delta e_\nu \left[\frac{\partial^2 C_\nu}{\partial r_\nu^2} - \frac{\partial^2 B_\nu}{\partial r_\nu^2} - \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_\nu} \right]^{-1} \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_i}.
\end{aligned} \tag{4.66}$$

4.G Proof of Proposition 4.5

Comparing a state's equilibrium subsidy under nationwide auction (Eq. 4.59) and FIT (Eq. 4.44) yields

$$\begin{aligned}
& \bar{s}_i \gtreqless \tilde{s}_i \\
\overset{(4.59),(4.44)}{\iff} & \frac{\partial B_i}{\partial r_i} + [r_i - e_i R] \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_i} \gtrless \frac{\partial B_i}{\partial r_i} + \frac{\partial B_i}{\partial R} - e_i \sum_{j=1}^{n} \frac{\partial B_j}{\partial R} \\
\iff & r_i \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_i} - e_i R \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_i} \gtrless \frac{\partial B_i}{\partial R} - e_i \sum_{j=1}^{n} \frac{\partial B_j}{\partial R} \\
\iff & r_i \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_i} - \frac{\partial B_i}{\partial R} \gtrless -e_i \left[\sum_{j=1}^{n} \frac{\partial B_j}{\partial R} - R \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_i} \right].
\end{aligned} \tag{4.67}$$

For strictly negative cross derivatives, $\sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_i} < 0$, the term in parenthesis is strictly positive, so that Eq. (4.67) simplifies to

$$\iff \frac{\frac{\partial B_i}{\partial R} - r_i \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_i}}{\sum_{j=1}^{n} \frac{\partial B_j}{\partial R} - R \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_i}} \lesseqgtr e_i. \tag{4.68}$$

Equivalently, Eq. (4.68) can be written for a marginal quota price change from an increase in state i's RE capacities, $\frac{\partial P}{\partial r_i} = \sum_{j=1}^{n} \frac{\partial^2 B_j}{\partial R \partial r_i}$, (by inserting Eq. 4.58 in

Eq. 4.68)

$$\bar{s}_i \gtreqless \tilde{s}_i \iff \frac{\frac{\partial B_i}{\partial R} - r_i \frac{\partial P}{\partial r_i}}{\sum_{j=1}^{n} \frac{\partial B_j}{\partial R} - R \frac{\partial P}{\partial r_i}} \lesseqgtr e_i$$
$$\iff \frac{\frac{\partial B_i}{\partial R} - r_i \frac{\partial P}{\partial r_i}}{\sum_{j=1}^{n} \left[\frac{\partial B_j}{\partial R} - r_j \frac{\partial P}{\partial r_i}\right]} \lesseqgtr e_i, \tag{4.69}$$

where $r_i \frac{\partial P}{\partial r_i}$ is the change in federal support received in state i due to a marginal change in the state's RE capacities and, analog, $R \frac{\partial P}{\partial r_i}$ is the change in federal support received for the total nationwide RE capacities.

5

Modeling coordination between renewables and grid: Policies to mitigate distribution grid constraints using residential PV-battery systems

Abstract
Distributed photovoltaic (PV) generation is one of the pillars of energy transitions around the world, but its deployment in the distribution grid requires costly reinforcements and expansions. Prosumage – consisting of a household-level PV unit coupled with a battery storage system – has been proposed as an effective means to facilitate the integration of renewable energy sources and reduce distribution grid stress. However, tapping its full potential requires regulatory interventions; otherwise, system costs could rise despite increasing flexibility. We analyze the effectiveness of different policy schemes to mitigate the need for distribution capacity expansion by incentivizing beneficial storage operation. Our novel top-down modeling approach allows analyzing effects on market prices, storage dispatch, induced distribution grid requirements, system costs, and distributional implications. Based on German power system data, numerical results indicate that distribution grid requirements can be reduced through simple feed-in policies. A uniform limit on maximum grid feed-in can leave distribution system operators better off, even if they fully compensate prosumage households for foregone revenue. Policies imposing more differentiated limits at the regional level result in only marginal efficiency improvements. Complete self-sufficiency (autarky) is socially undesirable, as it confines important balancing potential and can increase system costs despite adding storage.
Keywords: Residential storage, renewable integration, distribution system operator, prosumage, policy, multi-level games, MPEC
Reference: Neetzow, P., Mendelevitch, R., & Siddiqui, S. (2018). Modeling coordination between renewables and grid: Policies to mitigate distribution grid constraints using residential PV-battery systems. *Energy Policy, 132*, 1017–1033.
A preliminary version of this paper (Neetzow et al., 2018a, *DIW Discussion Papers 1766*) provides an extended overview of the model solution strategies, which is also part of this chapter and given in Appendix 5.E.
Preliminary versions of the paper were also presented and discussed at Young Energy Economists and Engineers Seminar 2017 in Nuremberg, IAEE European Conference 2017 in Vienna, the SET-Nav Modeling Workshop 2018 at DIW Berlin and IAEE International Conference 2018 in Groningen.

5.1 Introduction

Distributed solar photovoltaic (PV) generation is one of the pillars of the energy transition in Germany, Europe, and around the world. Its deployment at the distribution grid level poses new challenges to distribution system operators (DSOs), who are charged with the provision and operation of medium and low-voltage grids (Pudjianto et al., 2013). As regulated regional monopolies, DSOs are required to guarantee high quality and high reliability of services at all times. Thus, distribution grids are sized to handle even very rare peak events (Resch et al., 2017). Previously, dimensioning of distribution grids was driven by residential loads, where the probability of simultaneous peaks is low. By contrast, on a sunny day, all PV units in a region may generate close to their peak output simultaneously. Hence, the dimensioning of distribution grid infrastructure is now driven to an increasing degree by PV feed-in (Spiliotis et al., 2016). For Germany, studies have estimated additional investment requirements in the distribution grid of 23–49 billion EUR for the period 2015-2032 due to deployment of renewable energy sources (RES) (German Federal Ministry for Economic Affairs and Energy, 2014).

At the same time, decreasing battery storage costs (Schmidt et al., 2017) have led to the increased deployment of coupled PV battery systems (Kairies et al., 2016, Navigant Research, 2016). In Germany, such coupled systems will in many cases be more profitable than stand-alone PV installations from 2020 onwards (Dietrich & Weber, 2018). Extending the concept of electricity-producing and -consuming households (prosumers), we use the term *prosumage* to refer to residential households with coupled PV units and battery storage (see Schill et al., 2017b, Green & Staffell, 2017). Storage connected to the household's PV unit could absorb excess PV generation that cannot be handled by the grid. However, the mere availability of additional storage in the system is no panacea. In fact, system-beneficial distributed storage operation requires appropriate market and policy designs (Ruester et al., 2014, Green & Staffell, 2017).

In this paper we focus on the policy design by addressing the following research questions: What is the effectiveness of different policy schemes to mitigate the need for distribution capacity expansion by incentivizing beneficial storage operation? How cost-efficient are such policies and what are their distributional implications? Analyzing these requires advanced modeling setups, such that strategic interactions between players can be considered. We employ a novel top-down modeling approach that allows us to quantify the effects of regulatory interventions on prosumage dispatch decisions and associated DSO capacity requirements as well as resulting feedback effects on market prices and system costs. To that end, we set up a two-level model that incorporates strategic decisions of DSOs as well as interactions with prosumage, generators, and the transmission level.

We establish a link between bottom-up assessments, which focus on the individual installation level (see, e.g., López Prol & Steininger, 2017, Solano et al., 2018), and system-level analyses, which do not include any representation of the prosumage (Hinz et al., 2018) or the transmission grid level (Kubli, 2018). In our setup, regionally dispersed prosumage is aggregated such that we obtain a representative prosumage within one DSO region. The representative prosumage household participates in an energy-only market with nodal pricing at the level of the high-voltage transmission system. We focus on the prosumage-induced distribution grid requirements, which we model as a dedicated link between prosumage and the transmission network.

In line with the predominant practice in most European countries, for most of our scenarios, we assume the shallow grid charge scheme for the recovery of the initial grid connection cost of prosumage (Hinz et al., 2018). Therefore, costs that arise from DSO link congestion are not passed on to prosumage households, and nodal prices fail to reflect costs induced on the distribution grid level. We take the DSOs' perspectives and allow them to incentivize prosumage to reduce network congestion. This is distinct from other approaches in the literature, which focus on prosumage and examine merits and implications of self-consumption (Green & Staffell, 2017, Yu, 2018, Solano et al., 2018). We calibrate the model to power system data for Germany for the year 2015 and add proportional storage capacities to each small-scale PV unit. Yet, the general model structure might also be recalibrated to other regions. We assess the effect of different policy scenarios on nodal prices, the required capacity of the DSO link, as well as on overall system costs and distributional implications between different players in the electricity system. As a benchmark, we use a first-best system configuration (*Smart* scenario), which minimizes system costs. We compare it to the status quo with and without storage, as well as to two feed-in policy scenarios and an autarky case, which assumes self-sufficiency as the goal of prosumage. We provide recommendations on simple policy interventions that support system-friendly prosumage dispatch and that prevent lock-in effects.

The remainder of the paper is structured as follows: The next section situates our work within the related literature. Section 5.3 provides the model description. Consecutively, we introduce the six modeled scenarios in Section 5.4 as well as our calibration to German power system data in Section 5.5. Section 5.6 presents the solution strategy used to obtain the numerical results, which are provided and discussed in Section 5.7. Section 5.8 concludes and elaborates on policy implications.

5.2 Background and related literature

Our contribution connects two interrelated bodies of literature. On the one hand, it is embedded in the broader literature on options for mitigating the need for distribution grid expansion due to increasing deployment of RES, which we discuss in Section 5.2.1. On the other hand, it is part of the more specific debate on the merits of residential storage and prosumage, and the system-level implications of its increasing diffusion, which we detail in Section 5.2.2. In bridging these two bodies of literature, we contribute to the analysis of policy design for distribution grids, which we discuss in the context of the related literature in Section 5.2.3. Our sophisticated model design bridges the transmission system and the distribution system levels and requires advanced modeling techniques that have only recently been employed in the literature. We detail our contribution to this literature in Section 5.2.4.

5.2.1 Options for mitigating distribution grid expansion

An extensive body of literature focuses on the challenges that increasing shares of RES create for distribution networks, and measures that have been proposed to mitigate them (see e.g., Agricola et al., 2012, Klobasa & Mast, 2014, German Federal Ministry for Economic Affairs and Energy, 2014). Resener et al. (2018) provide an extensive review of models for investment and operational planning that aim at optimizing distribution grid capacities given increasing RES feed-in. Instead of long-term capacity expansion, for instance, short-term operations can be altered such that the available grid capacities are sufficient (Spiliotis et al., 2016, Eyer, 2009).

Georgilakis & Hatziargyriou (2015) give an overview on methods and models for distribution grid planning that incorporate distributed RES generation. Of particular interest are studies that focus on the provision of operational flexibility. Knezovic et al. (2015) review different options for utilizing flexibility from electric vehicles and discuss their potential to reduce distribution grid capacity requirements. However, the paper discusses general implications for policy design in qualitative terms only and does not provide model-based computations to support its claims. More closely related to our work, Spiliotis et al. (2016) focus on the potential of household demand response to defer grid expansion in the case of two specific distribution networks configurations. von Appen & Braun (2018) analyse strategic investment decisions of 70 households and one DSO. They evaluate different charging schemes for grid costs and the option to curtail PV generation. Both studies disregard effects on the electricity system level. Resch et al. (2017) present an extensive review of potential revenue streams for battery systems in Germany and discuss their ability to provide flexibility under different operation strategies. However, they focus on large-scale battery systems and disregard the feedback between operation strategy, market prices, and system costs.

5.2.2 Flexibility provision from coupled PV and battery systems

Storage is known for its potential to mitigate network congestion (Virasjoki et al., 2016, Denholm & Sioshansi, 2009, Agricola et al., 2012) also in the distribution grid (Schill et al., 2017b, Ruester et al., 2014). However, increasing available storage capacities may also increase required grid capacities (Haller et al., 2012a, Neetzow et al., 2018b, Resch et al., 2017). Essential for the interplay between storage and grid is the mode of operation of the storage. Prosumage storage can be charged heuristically during peak PV feed-in or as soon as the PV generation exceeds own demand (Schill et al., 2017b, Moshövel et al., 2015). Another option is price-driven operation, where the dispatch decision is triggered by real-time or projected market prices. In turn, the mode depends on market characteristics such as price formation, grid tariffs, and subsidies (Ruester et al., 2014) as well as on behavioral factors such as the goal of self-sufficiency or profit maximization (Graebig et al., 2014).

Furthermore, research has been conducted on the effects of integrated small-scale storage and PV generation, i.e., prosumage. Melgar Dominguez et al. (2018) use an integrated cost minimization approach to optimize PV and storage deployment as well as operation, considering DSO-owned storage in a distribution test network. While general system effects of prosumage are discussed and modeled by Schill et al. (2017b), their quantitative analysis omits impacts on the network. More specifically, Moshövel et al. (2015) show the potential to reduce network stress induced by a single prosumage household by cutting off PV peak generation with a beneficial battery-charging strategy. They do not, however, account for feedback effects of the proposed strategies to the overall system. Green & Staffell (2017) focus on the effect of maximizing prosumage self-consumption on distribution grid requirements and find that it increases capacity requirements. Whereas their work is limited to this extreme case, in the present study we assess a set of different policy options. Also focusing on self-consumption, Yu (2018) finds that prosumage puts business models of incumbent players in the French electricity system under stress.

5.2.3 Policy design for distribution grids

Along with the literature addressing the technological and economic challenges that come with the restructuring of energy systems towards RES, there is a growing body of literature examining the regulatory interventions and market design changes necessary to make the future system work cost-efficiently (see, e.g., Ruester et al., 2014, Pérez-Arriaga et al., 2017). One strand of this literature is concerned with the efficiency of future electricity systems. MacGill & Smith (2017) provide recommendations for future policy design based on insights from past experience with prosumers' impacts on established electricity market business models in Australia. Also taking Australia as an example, Pollitt (2018) argues that the solution to challenges posed by distributed generation and storage should be a combination of charges for network use and available capacity, as well as marketing of new services. The author highlights the need for modeling to assist in tailoring regulatory intervention. Faerber et al. (2018) detail, based on expert interviews, how distribution network charging schemes should be adapted in the transformation towards smart grids. Focusing on various pricing options to recover network fixed cost, they argue that solutions to the problem might be borrowed from the transmission level.

Smart grids could allow for cost-efficient distribution grid pricing. Brandstätt et al. (2017) suggests a solution to the issue of non-discriminatory data availability, which is one of the central prerequisites for reaping their full potential.

Highly granular locational marginal prices (LMP) could indicate the impact of a grid user's decisions on the need for expanding the network (Sotkiewicz & Vignolo, 2006) and cost-efficiently recover investment in network capacity, at least in theory (Bohn et al., 1984, Pérez-Arriaga et al., 2017). However, such a system is not likely to emerge for regulatory, economic, or behavioral reasons (Green & Staffell, 2017). Pérez-Arriaga et al. (2017) argues that LMPs would not be an appropriate mechanism to recover distribution network costs. It would require perfect information on the household level, which raises issues of data privacy. Moreover, their implementation might induce high price differentials even within regions, which may be socially undesirable.

Another strand of literature is concerned with the distributive implications of distribution grid charging schemes. Kubli (2018) assesses the costs induced by further diffusion of prosumage in Switzerland, and analyze how different consumer groups are affected by the recovery of these costs. Similarly, Jargstorf et al. (2015) examines the effectiveness of tariffs to internalize grid costs for prosumage. However, both articles use a system dynamics approach without detailed modeling of the techno-economical interactions on the electricity market. Hinz et al. (2018) apply a detailed electricity market model of Germany to study the effect of alternative cost recovery mechanisms for distribution grids. They check for distributive justice between different regions and assess the implications of charging generators as opposed to charging consumers. While these studies focus on radical changes in the regulatory design for distribution grid, we suggest incremental policy changes that do not deviate from the shallow grid charge scheme. These could prove to be more easily implementable steps towards adapting electricity systems.

5.2.4 Modeling approach

Analyzing strategic interactions and technical constraints on the interplay between the transmission network, the distribution grid level, prosumage, and generators requires a sophisticated modeling design. Kubli (2018) uses a system dynamics approach but accounts neither for feedback from prosumage dispatch on distribution grid requirements nor for market price effects on prosumage dispatch. Other existing detailed electricity market models either do not incorporate prosumage (Hinz et al., 2018) or lack representation of the transmission grid (Schill et al., 2017b).

Our approach follows a hierarchical decision sequence, allowing the DSOs to strategically set policy parameters while anticipating associated market outcomes and dispatch decisions of prosumage and generators. To derive numerical results, this setup is implemented as a two-level game structure, which is necessary to analyze strategic interactions in energy markets and being used to an increasing extent. Cardell et al. (1997) analyze generator market power in the context of transmission constraints. Transmission is disregarded by Bushnell (2003), who differentiates between hydro and thermal generation technologies for strategic interaction, as well as by Schill & Kemfert (2011) and Sioshansi (2014), who examine the interplay between generators and storage. While all the above studies assume that the players act in a simultaneous move game, Wang et al. (2017) analyze a hierarchical setup with a strategic storage operator anticipating her own influence on the market.

All these studies consider strategic operational behavior alone. Strategic transmission investment to mitigate generator market power is additionally taken into account by Jenabi et al. (2013), Huppmann & Egerer (2015), Zerrahn & Huppmann (2017) in multi-level games. While Huppmann & Egerer (2015) consider hierarchical decisions in transmission extension (within-country and between-countries), neither of the studies that consider strategic investment considers distribution grids or storage.

In summary, to our knowledge, there is no approach in the literature to date that comprehensively analyzes interactions between multiple distribution system operators and prosumage within a transmission network and also examines the effectiveness of different regulatory schemes while taking into account the hierarchical market design. Yet, such a comprehensive setup is required to study an appropriate market design that ensures a system-beneficial prosumage operation. We aim to fill this research gap with the paper at hand. Our results are highly relevant to recent debates on the integration of prosumage into energy markets and the importance of regulatory design in shaping this process.

5.3 Model description

We present the first approach to incorporate network stress on the distribution grid level into a large-scale electricity DC-load flow model. Our setup consists of a multi-nodal TSO network, which connects demand centers and large-scale generation (conventional and renewable). The representative prosumage consists of prosumage demand, small-scale PV, and storage (Figure 5.1A) and is connected to the TSO network via dedicated DSO links. The links can be interpreted as the dedicated cumulative DSO capacity necessary to allow prosumage integration into the system. Regional DSOs ensure sufficient DSO link capacity to accommodate all prosumage inflows and outflows. They may incentivize prosumage to reduce its DSO link use via a compensation. We deliberately leave out all other parts of the distribution grid, for instance, those connecting non-prosumage demand (e.g. from non-prosumage households, industry, etc.) or RES to the TSO network (Figure 5.1B). The capacities for generation, prosumage, and the TSO network are exogenously given from a calibration and assumed fixed.

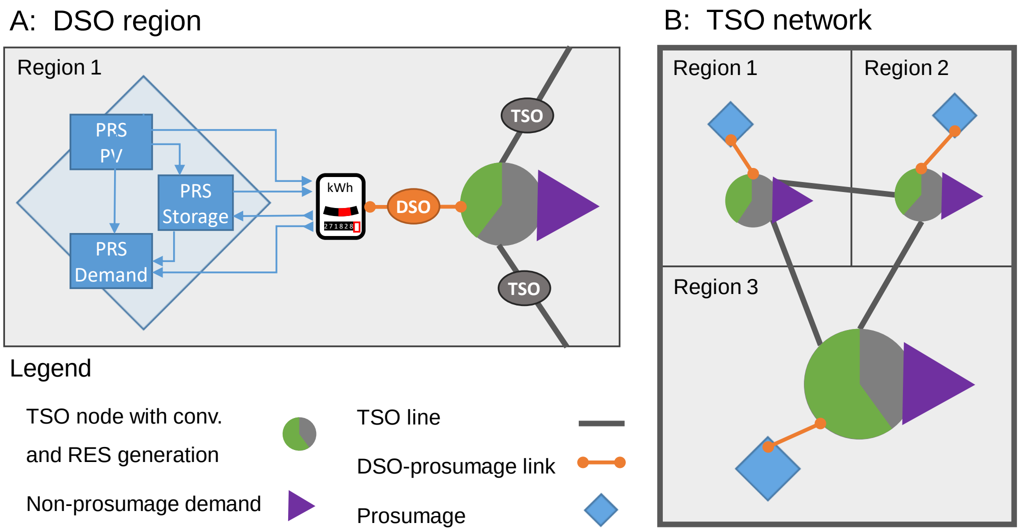

Figure 5.1: ***A:*** Detailed representation of one DSO region. In every DSO region there exists representative non-prosumage demand, conventional and RES generation as well as prosumage. The representative prosumage household consists of prosumage demand, small-scale PV and storage and connects to the TSO network via a DSO link. ***B:*** Illustrative transmission network topology with one associated DSO region at each of the multiple (here: three) TSO nodes.

5.3.1 Sets, parameters, variables

A nomenclature for sets, parameters and variables is given in Appendix 5.A. We use lowercase letters for variables (endogenous to the model) and uppercase letters for parameters (exogenous to the model). Nodes of the TSO network are denoted by $n, m \in \mathcal{N} = \{1, ..., N\}$. Lines connecting the TSO nodes are denoted by $l \in \mathcal{L} = \{1, ..., L\}$. Time slices are denoted by $t \in \mathcal{T} = \{1, ..., T\}$.

5.3.2 The prosumage household's problem

There is one representative non-strategic **prosumage household** connected to each of the TSO nodes n. The prosumage household's objective function is given in Eq. (5.1) and is the sum of the cost of purchasing electricity on the market to supply own demand $m2d_{n,t}$ or to be stored in the storage $m2s_{n,t}$, minus the revenue from selling PV generation $pv2m_{n,t}$ and electricity from storage to the market $s2m_{n,t}$. Each of these transactions is valued with market price $p^{TSO}_{n,t}$, which corresponds to the nodal price at the adjacent transmission network node. We assume that prosumage households are price-takers. Note that these prices reflect possible TSO network constraints, but disregard congestion on the DSO level. This constitutes a market failure as prosumage does not properly internalize costs on the DSO level associated with its dispatch. Demand that cannot be satisfied (lost load) $lol^{PRS}_{n,t}$ incurs costs of the value of lost load $VOLL$. In addition, the representative prosumage household might receive compensation for an imposed policy that would restrict the prosumage operation. For our particular setup, this is depicted by the term $(1 - \alpha_n) \cdot \overline{G}^{PRS}_n \cdot \lambda^{\alpha}_{n,t}$. We devote Section 5.4 to explaining the policy-induced compensations in more detail.

$$\begin{aligned}\min_{var^{PRS}} obj^{PRS}_n = \sum_t p^{TSO}_{n,t} \cdot (m2d_{n,t} + m2s_{n,t} - s2m_{n,t} - pv2m_{n,t}) \\ + lol^{PRS}_{n,t} \cdot VOLL - (1 - \alpha_n) \cdot \overline{G}^{PRS}_n \cdot \lambda^{\alpha}_{n,t} \qquad (5.1)\end{aligned}$$

The representative prosumage household is subject to several constraints (given in Appendix 5.B: Eqs. 5.6 - 5.13). The household's own demand can be satisfied by three sources: its own supply from PV generation, from storage, or from the market. Under some circumstances, these might not be sufficient to satisfy demand, resulting in lost load (Eq. 5.6). For each point in time, PV feed-in can be balanced in four ways: self-consumption, sales to the market, storage, or as a measure of last resort, curtailment (Eq. 5.7). Eq. (5.8) gives the temporal balance for the storage, where the current energy level equals the previous level reduced by outflows and increased by inflows. The latter are reduced by the round-trip efficiency. The storage level cannot exceed the energy storage capacity (Eq. 5.9). Moreover, storage in(out)-flow cannot exceed its power capacity (Eqs. 5.10 and 5.11). Eq. (5.12) sets the boundary conditions for storage, where final storage levels have to be equal to initial storage levels. The final Eq. (5.13) depicts the operating constraints that arise from the institutional design. The prosumage feed-in to the market cannot be higher than a fraction α_n of its own PV generation capacity (also see Figure 5.2). We devote Section 5.4 to analyzing the respective policy options in more detail.

5.3.3 The generator's problem

Besides the prosumage household, there is one representative (non-strategic) operator of **conventional generation** at each TSO node. The operator maximizes its revenue by dispatching conventional generation $g_{n,t}$ to provide electricity. We assume a quadratic generation cost function $g_{n,t}^2/2 \cdot C_{n,t}^{GEN}$ characterized by the cost parameter $C_{n,t}^{GEN}$.[1] The generated electricity is sold at market price $p_{n,t}^{TSO}$ (Eq. 5.2). Furthermore, the generator is constrained by the available generation capacity (Eq. 5.14).

$$\min_{var^{GEN}} obj_n^{GEN} = g_{n,t}^2/2 \cdot C_{n,t}^{GEN} - g_{n,t} \cdot p_{n,t}^{TSO} \tag{5.2}$$

5.3.4 The DSO's problem

The **DSO** is in charge of the link that connects the prosumage household to the TSO node, which has a capacity $\overline{f}_n^{DSO}$.[2] The objective of the **DSOs** is to minimize capacity costs of the DSO link as well as compensation costs paid to incentivize the prosumage household to reduce its network use. To account for the length of the capacity planning horizon, marginal capacity investment costs MC^{DSO} are multiplied by the number of hours considered, i.e., the cardinality of t ($|\mathcal{T}|$) (Eq. 5.3).

$$\min_{var^{DSO}} obj_n^{DSO} = \overline{f}_n^{DSO} \cdot MC^{DSO} \cdot |\mathcal{T}| + \sum_t (1-\alpha_n) \cdot \overline{G}_n^{PRS} \cdot \lambda_{n,t}^{\alpha} \tag{5.3}$$

[1] The parameter $C_{n,t}^{GEN}$ thus describes a linear marginal cost function of the form $MC_{n,t}^{GEN}(g_{n,t}) = C_{n,t}^{GEN} \cdot g_{n,t}$.

[2] In reality, the DSO is responsible for supplying grid connectivity for all types of consumers, not only prosumage households, but also regular households, industrial operations, as well as utility-scale renewable generation. In this paper, we focus on the interaction among prosumage households, DSO, and TSO. Therefore, we aggregate residual demand $D_{n,t} - G_{n,t}^{RES}$ (excluding prosumage) to the TSO node level.

This is subject to two balance constraints: one for the inflow, i.e., from the TSO node to the prosumage household (Eq. 5.15), and one for outflows, i.e., from the prosumage household to the TSO node (Eq. 5.16). Eq. (5.15) ensures that DSO link capacity is large enough for the inflow. Eq. (5.16) is connected to the policy design and obtains its effectiveness in connection with Eq. (5.13). It guarantees a minimum share of α_n of the maximum PV generation capacity for prosumage as admissible outflow (also see Figure 5.2).

5.3.5 Balancing by the TSO

Finally, the **TSO** ensures cost-efficient balancing of the flows in the TSO network, which follow the usual linearized DC-load flow approach of Kirchhoff's Laws (see, e.g., Schweppe et al., 1988). The nodal balance is given in Eq. (2.4). Here, the residual non-prosumage demand is given by non-prosumage demand minus potential generation from RES. As in the prosumage household's problem, we allow for curtailment and lost load in case there is an excess or a shortage of power. Line flows and imports are calculated using network transfer and susceptance matrices as well as the nodal phase angle difference to a swing node (Eq. 5.18, Eq. 5.19 and 5.22). TSO line capacity has to accommodate positive and negative TSO network flows (Eqs. 5.20 and 5.21).

5.3.6 Model structure

The interactions between DSO and prosumage necessitate a two-level model structure. On the lower decision level, conventional power generators and prosumage are price-takers and Stackelberg followers in an equilibrium energy-only market. Acting as Stackelberg leaders on the upper decision level, i.e., anticipating the lower level reactions, regional DSOs balance incentive payments and required link capacity. Thereby, they may change the equilibrium of the lower level, i.e., the dispatch decisions of generators and prosumage households. Mathematically, this setup constitutes a Mathematical Program under Equilibrium Constraints (MPEC) for each of the DSOs.

The TSO network connects the DSOs and ensures balancing. Thus, the DSOs' decisions (optimal strategies) are not mutually independent either: The chosen policy of one DSO will influence the choices of others, as a more restrictive capacity in one region and resulting higher nodal prices might incentivize an increase in prosumage feed-in in other regions. This, in turn, would increase the compensation required to make local prosumage households indifferent. Enforcing an equilibrium between the DSOs would require solving an Equilibrium Program under Equilibrium Constraints (EPEC) (Ruiz et al., 2012). Solution methods for EPECs are currently limited to small-scale applications (Gabriel et al., 2012). We leave the exact solution of this problem to future research, as the purpose of the paper at hand is to provide empirically relevant results for large-scale systems. In this paper, we approximate the EPEC's solution by decoupling the respective DSO problems and instead solve a set of separate two-level MPECs (see Section 5.6).

5.4 Scenarios

In this section, we introduce six scenarios to evaluate different policy mechanisms: *Smart*, *No storage*, *No policy*, *Autarky*, *KfW policy* and *DSO-wise policy.* Table 5.1 provides an overview. While *Smart*, *No storage* and *No policy* can be implemented as single-level optimization problems, *Autarky*, *KfW policy* and *DSO-wise policy* incorporate strategic interactions between players in a Stackelberg leader-follower setting, and thus require a more sophisticated solution approach.

Table 5.1: Overview of scenarios by storage availability, game structure, maximum feed-in as well consideration of DSO link costs. While in *No storage* and *Smart*, prosumage feed-in is optimized from a total system cost perspective, it is unrestricted in *No policy*, set to a generic limit in *KfW policy*, and is set to a DSO-specific limit in *DSO-wise policy.* No prosumage feed-in is allowed for the *Autarky* scenario.

Scenario	**Storage**	**Max. prosumage feed-in**	**Compensation[a]**	**Costs of DSO link**	**Game structure**
Smart	✓	optimized	implicit	fully internalized	min cost
No storage		optimized	implicit	fully internalized	min cost
No policy	✓	unrestricted	n/a	disregarded	min cost
Autarky	✓	no feed-in	n/a	partly avoided	Stackelberg
KfW policy	✓	generic limit	explicit	partly internalized	Stackelberg
DSO-wise policy	✓	DSO-specific limit	explicit	partly internalized	Stackelberg

[a] Compensation for prosumage dispatch restrictions by DSO

The ***Smart*** scenario provides a benchmark in which total system costs are minimized. To this end, *Smart* envisions a power system setup, where storage systems are available in prosumage households and a first-best pricing mechanism is implemented. In our setup, this is equivalent to a capacity tariff, which prosumage households have to pay for using the DSO grid. Consequently, the interaction of prosumage household demand, generation and storage dispatch, as well as DSO grid expansions are fully taken into account. The ***No storage*** scenario assumes the same system cost minimizing perspective of the TSO as in the *Smart* scenario, but, in contrast to all other scenarios, there is no prosumage storage capacity available in the system. In the ***No policy*** scenario, DSO capacity and respective costs are excluded from the TSO's consideration. This scenario represents a situation in which dispatch decisions on the prosumage level are driven by the market prices, i.e. derived from locational marginal costs at the TSO nodes. Thus, prosumage households do not account for their effect on DSO capacity requirements.

In contrast to the first three, the remaining scenarios incorporate the two-level Stackelberg game structure. Interaction is reflected in the compensation terms of their objective functions as well as Eq. (5.13), which imposes an operational constraint on prosumage, reducing the admissible feed-in to the market (Figure 5.2). The adequate choice of the policy variable α_n can reduce the market failure induced by the prosumage household disregarding DSO capacity costs. If α_n is large there are no or few restrictions on grid feed-in from prosumage, while for $\alpha_n = 0$ no feed-in is allowed.

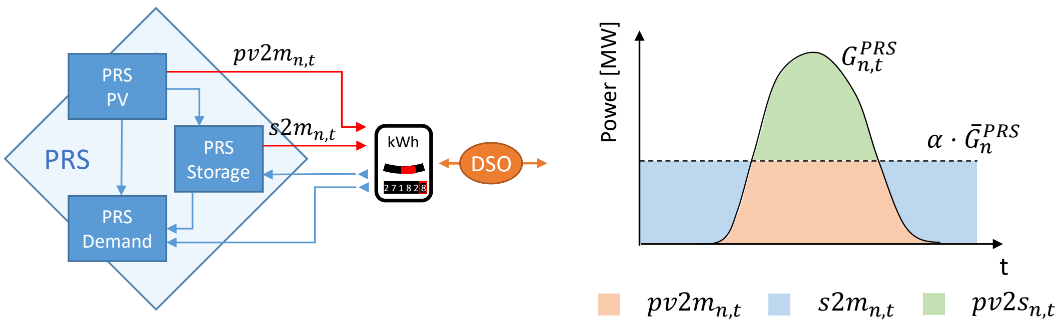

Figure 5.2: Possible prosumage feed-in after introduction of the policy variable α_n. Maximum grid feed-in from prosumage into the DSO link $(pv2m_{n,t} + s2m_{n,t})$ is reduced to a fraction α_n of prosumage PV capacity. Excess PV generation must be consumed, stored or curtailed.

In the ***Autarky*** scenario, prosumage is determined to maximize self-sufficiency, i.e., the share of own PV generation in its demand (see Luthander et al., 2015), and to reduce market interactions. This can be represented by $\forall n: \ \alpha_n = 0$.

As a consequence, prosumage will never feed into the DSO link and will instead use storage to satisfy its own demand from its own generation. Yet, if demand cannot be met by either PV generation or storage, prosumage can still purchase electricity from the market using the DSO link. Even though the *Autarky* scenario imposes operational costs on prosumage, we abstain from compensation payments as we assume that the autarky decision is made by the prosumage household for non-monetary reasons (Graebig et al., 2014).

In the ***KfW policy*** scenario, the policy is exogenously set for all DSOs such that $\forall n: \quad \alpha_n = 0.5$. The name is chosen in analogy to a storage promotion program that is in place in Germany and supported by the state-backed investment bank KfW.[3] As a consequence, prosumage feed-in is limited to half the available prosumage PV capacity. This, in turn, reduces the required distribution grid capacity and therefore grid investment costs. Yet, the restriction of the prosumage household's dispatch decisions might reduce revenues. The shadow price $\lambda^{\alpha}_{n,t}$ of Eq. (5.13) provides a unit of measurement for the foregone marginal revenue due to the imposed restriction. To compensate the prosumage household for this loss, we include the compensation payment $\sum_t (1-\alpha_n) \cdot \overline{G}^{PRS}_n \cdot \lambda^{\alpha}_{n,t}$ from the DSO to the prosumage household. As the desired grid feed-in from the prosumage household is unknown to the DSO, it compensates up to the maximum potential feed-in inhibited by the policy $(1-\alpha_n) \cdot \overline{G}^{PRS}_n$, making the prosumage household at least indifferent compared to a scenario without a policy.

In the ***DSO-wise policy*** scenario, we assume that α_n can be chosen freely by the nth DSO, i.e., every DSO restricts the dispatch of its associated prosumage. Again, we assume that the respective DSO has to compensate the prosumage household. The compensation scheme is the same as under the *KfW policy*. Yet, the DSO-specific choice allows each DSO to balance costs for capacity investment and prosumage compensation. The compensation increases the more restrictive the policy gets: on the one hand directly from a decreasing α_n, and on the other hand indirectly from the increase of shadow price $\lambda^{\alpha}_{n,t}$, which is a function of the market price $p^{TSO}_{n,t}$.

[3] In the German storage support scheme, favorable credit terms for household storage units are granted if the maximum share of PV feed-in is limited to 50 % of PV generation capacity through storage operation (KFW, 2016).

5.5 Model calibration

We calibrate the model with state-wise (*Bundesland*) aggregated data on the German electricity system (i.e., $n \in \mathcal{N} = \{$BB, BE, BW, BY, HB, HE, HH, MV, NI, NRW, RP, SH, SL, SN, ST, TH$\}$),[4] for the year 2015. Hence, we assume that the distribution grid of each respective state is operated by one DSO.[5] Wherever possible, we use the electricity data provided in Kunz et al. (2017). The relevant available data on conventional plants, renewable energy capacities,[6] time series for wind feed-in, demand, as well as properties of the transmission grid are all aggregated to a state level. Furthermore, for each state, we estimate a linear approximation to its unit level merit order curve using a least-squares fit. The derived marginal generation costs are corrected for the availability of generation capacities and therefore are time-dependent. The value of lost load $VOLL$ is assumed to be 200EUR/MWh.[7] We allocate all PV-systems $\leq$ 10 kWh which amount for 5.8 GW (Open Power System Data, 2018)[8] to prosumage. For the purpose of our analysis, we assume that each of these PV systems is accompanied by proportional storage capacities (in total 2.9 GW, 11.6 GWh) with a round trip efficiency of 0.9. To test the soundness of our findings, we additionally conduct a sensitivity analysis on the storage power capacities (for 1.45 GW and 5.8 GW).

State-level, capacity-normalized time series for PV feed-in are taken from Koch et al. (2016).[9] We approximate the share of household consumption in load by BDEW household standard load profiles (Bundesverband der Energie- und Wasserwirtschaft e.V., 2015) and total German household consumption in 2015 (Umweltbundesamt, 2017). Finally, prosumage demand is approximated by the state-wise number of PV-systems $\leq$ 10 kWh (Open Power System Data, 2018)

[4]German Federal States: Brandenburg (BB), Berlin (BE), Baden-Wurttemberg (BW), Bavaria (BY), Hesse (HE), Bremen (HB), Hamburg (HH), Mecklenburg-West Pomerania (MV), Lower Saxony (NI), North Rhine-Westphalia (NRW), Rhineland-Palatinate (RP), Schleswig-Holstein (SH), Saarland (SL), Saxony (SN), Saxony-Anhalt (ST), Thuringia (TH)

[5]Even though there are about 890 different DSOs in Germany (BNetzA, 2018), we reduce complexity while maintaining DSO diversity by using this assumption.

[6]We consider the renewable technologies run-off-river, biomass, geothermal, hydro, and waste as non-dispatchable units with partly seasonal availabilities.

[7]Even though $VOLL$ might appear low compared to, e.g., London Economics (2013), it exceeds the maximum unit generation costs. Thus, an increase of $VOLL$ would have no effect on the occurrence of lost load due to inelastic demand. Furthermore, for the recent model calibration, we find no lost loads.

[8]We derive the share of PV-systems $\leq$ 10 kWh from (Open Power System Data, 2018) but use the data on total capacity from Kunz et al. (2017).

[9]The study uses the weather year 2011 and the predicted distribution of PV-systems in 2020.

and by assuming the average yearly demand of a single prosumage household to be 5 MWh, which is in line with Beck et al. (2016), Bertsch et al. (2017). DSO unit investment costs are assumed to be 2 EUR per MW and hour.[10] However, we also provide sensitivities for 1 and 4 EUR per MW and hour. An overview of parameters is given in Appendix 5.C.[11]

We compute a whole year with an hourly temporal resolution. However, for computational reasons, we do not compute all hours of the year at once but solve all days separately. To make all days $\tau \in \{1, ..., 365\}$ independent of one another, we fix the energy levels of all storage capacities at the end of every day to their initial energy levels (see Eq. 5.12) and assume $E_n^{PRS} = \overline{E}_n^{PRS}/2$.

5.6 Solution strategy

In the following, we explain the individual model reformulations and steps that are necessary to solve the mathematical problems defined by the different scenarios. More detailed descriptions including comprehensive equations are given in Neetzow et al. (2018a) and Appendix 5.E.

We solve the scenarios *Smart*, *No storage* and *No policy* as non linear (quadratic) system cost minimization problems (NLP) for each day. To implement the *No storage* scenario, we parametrize $\overline{E}_n^{PRS} = \overline{P}_n^{PRS} = 0$, such that no storage capacity is available. Finally, the *No policy* scenario neglects DSO capacity constraints and associated costs in its objective. Here, we compute the required DSO capacity ex post from the maximum flow that occurs on the DSO link.

The remaining scenarios require multi-level solution techniques. We abstain from solving the inter-DSO coordination problem by fixing all imports into a DSO region $im_{n,t}^{TSO}$ to values obtained in the *Smart* scenario and by adjusting the generation parameters $\overline{G}_{n,t}^{GEN}$ and $C_{n,t}^{GEN}$, such that regional generation can be increased at market price. The remaining mathematical problem is an individual MPEC for each DSO region. We solve the MPECs as mixed-integer linear prob-

[10] This figure is based on calculations from Klobasa & Mast (2014). The study reports 1.4 bn EUR of additional annual investment requirements for distribution grid expansions in order to integrate a capacity of 92.1 GW in PV and wind generation for the period up to 2020. In the future, they assume these requirements will increase further by about 50 % up to 2030. Distributing costs over examined hours gives us a value of ≈ 2 EUR per MW of installed RES capacity (or potential RES feed-in) and hour.

[11] The model and a comprehensive dataset can be found under https://doi.org/10.18452/20118.

lems (MILP) using disjunctive constraints (Fortuny-Amat & McCarl, 1981) and through a discretization of the feasible realizations of α_n.

We implement the problems in GAMS and use the commercial solvers CONOPT for NLP and CPLEX for MILP. Computation time is about 30 h for the scenario simulations of one year (System: quad-core CPU 2.8 GHz, 16 GB RAM).

5.7 Results and discussion

The following section presents modeling results and discusses possible implications. First, we focus on one particular day and one region to detail the general mechanisms that drive the effects of the different policy options on prosumage storage dispatch. We find that the DSO capacity requirement is especially high during the morning hours when PV generation starts to ramp up while price-driven storage is discharging. Subsequently, we compare the efficiency of the policies examined for different DSO networks. Even though the outcomes of the policy mechanisms are largely consistent overall, quantitative results on capacity reduction potential and necessary compensation differ substantially. Looking at daily required DSO link capacity aggregated across regions, we find that storage exerts ambiguous effects that depend crucially on the policy choice. While "smart" operation of storage reduces capacity needs, these are increased if no policies are implemented. Feed-in policies are also effective in reducing capacity requirements but reach their limit at the point where loads dominate the grid needs. Another important cost driver consists in operational restrictions, which increase system costs for *No storage* and *Autarky* in particular. Finally, we evaluate effects on the electricity system level and distributional implications for different players. Compared to no policy, simple feed-in policies are able to close about half the gap towards a minimum-cost system. While non-prosumage demand and RES generally benefit from storage availability, this result does not hold for the demand under *Autarky*.

5.7.1 Policy mechanisms at the individual DSO level

To analyze the mechanisms behind the policies, we first focus on the effects on one particular day and region. We chose the weekday with the highest PV generation – Monday, May 25 – and focus here on the results for Bavaria, which has about 13 GW of PV capacity deployed. Figure 5.3 shows the realized nodal prices, storage dispatch, and flows in the DSO link for each of the scenarios.

Prices for all scenarios show the typical “duck curve” pattern (California ISO, 2016) with higher prices in the morning and evening demand peaks and depressed prices during the day due to PV feed-in. The *No storage* scenario exhibits the most pronounced peaks and valleys. When storage is introduced into such a system, it allows for inter-temporal shifting and thereby reduces price extremes (peaks and valleys are less pronounced in all other scenarios). Prices as well as storage operation are similar for the scenarios *Smart*, *No policy*, *KfW policy* and *DSO-wise policy*, and differences mainly arise during few hours when the DSO capacities are highly stressed. Interestingly, this is not necessarily the case during times of very high PV generation, as the associated low prices can provide sufficient incentives for market-driven prosumage storage to be charged, and thus mitigate high feed-ins. Instead, differences occur during the morning hours at about 8-9 AM. Here, PV generation already exceeds a third of the daily peak but prices are still relatively high. Therefore, in a scenario in which grid stress is disregarded (*No policy*), storage is further discharged, leading to additional distribution grid stress. Remarkably, in this scenario, peak grid feed-in is even higher than in the *No Storage* scenario. Those scenarios that take the DSO capacities into account (*Smart, DSO-wise policy, KfW policy*) show lower storage discharge for these hours. This, in turn, reduces the feed-in and grid requirements and indicates the effectiveness of the policies.

The *Autarky* scenario exhibits similar prices to the *No storage* scenario, except for the mid-day hours, where the price valley is less pronounced due to the prohibition of market feed-in from prosumage. In particular, excess prosumage PV generation that cannot be stored must be curtailed. As a consequence, the storage utilization is much lower than in the other storage scenarios and not driven by price differentials like in the other scenarios. Lastly, it is the only scenario without any market interaction. In addition to the prohibition of feed-in, also no purchase from the market is needed for the day considered, such that prosumage is fully self-sufficient and does not need any DSO capacity. However, this picture changes for days with lower PV generation.

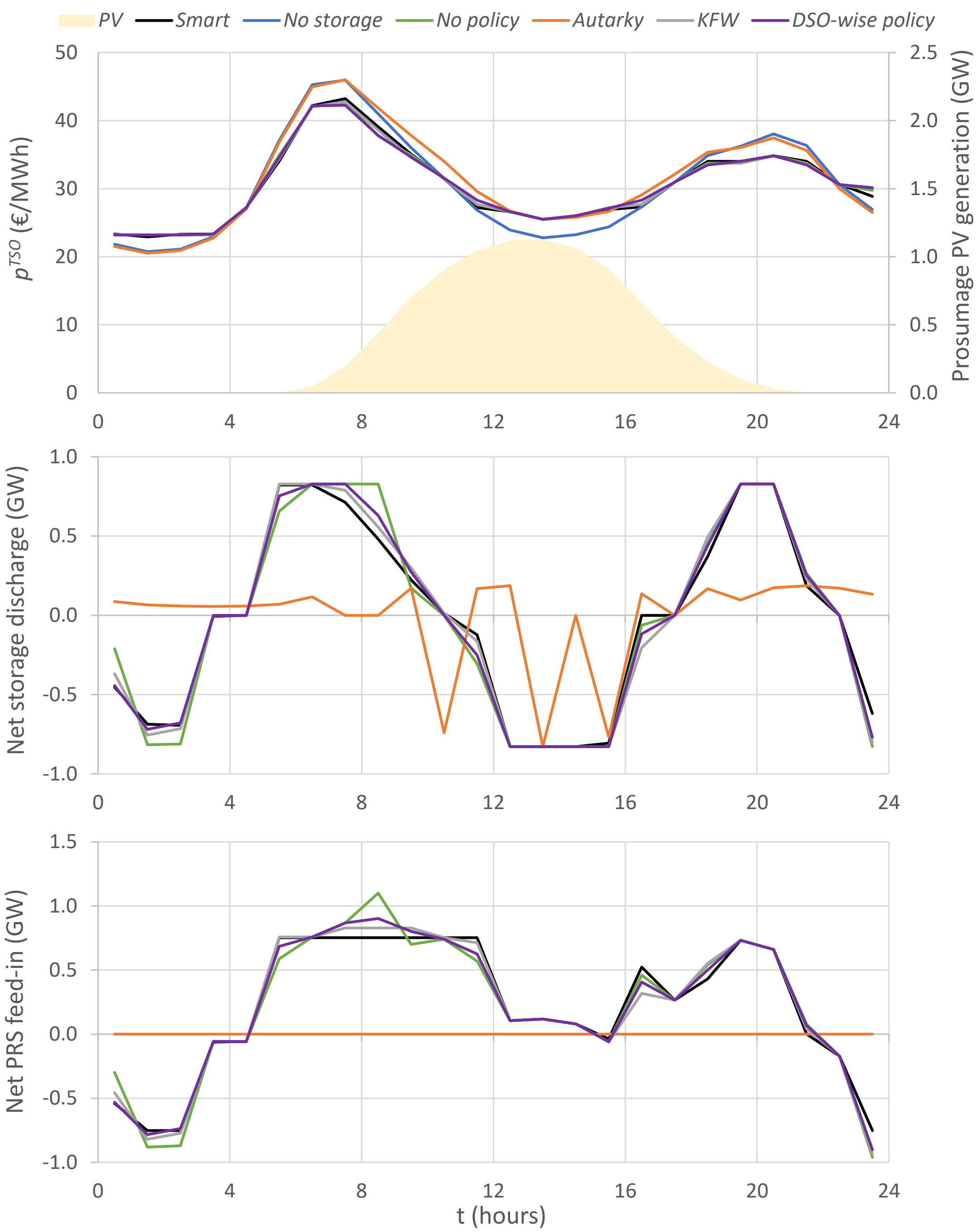

Figure 5.3: Price curves, prosumage PV generation, storage net discharge, and flow on the DSO link for May 25 in Bavaria. With exception of the *Autarky* scenario, storage charges at low price hours. The discharge during periods of high prices is influenced by the choice of scenario and crucially affects the DSO capacity needs.

5.7.2 Comparing results for different DSO networks

Next, we compare results between different states, which resemble separate DSO networks. The optimal trade-off between flexibility provided by the prosumage storage and required DSO capacity is driven by the local share of prosumage in residential demand, local generation patterns, weather conditions, and transmission grid characteristics. Figure 5.4 shows the maximum allowable feed-in shares (α) for the *Smart*, *No policy*, *KfW policy*, and *DSO-wise policy* scenarios and induced compensation payments for the latter two. For the majority of states, the required feed-in capacity is lowest in the *Smart* scenario, followed by *KfW policy*, *DSO-wise policy*, and the *No policy* scenario. Hence, the qualitative pattern that was described above for Bavaria generally holds.[12] Quantitatively, however, there are great differences among the states and thus among the different DSOs. Particularly in states with high demand, high PV generation, and high prosumage shares (BW, BY), DSOs need to provide relatively high compensation to reduce prosumage feed-in. In other large states that have lower PV deployment and prosumage shares (NI, NRW), the compensation is also smaller. Also, the policy's effectiveness for different DSOs varies. While in Thuringia (TH), the feed-in reduction potential is substantial, in Lower Saxony (NI) it turns out to be very low, especially for the *DSO-wise policy* scenario.

[12]Except for the small state Bremen, in which load rather than feed-in is the determining factor.

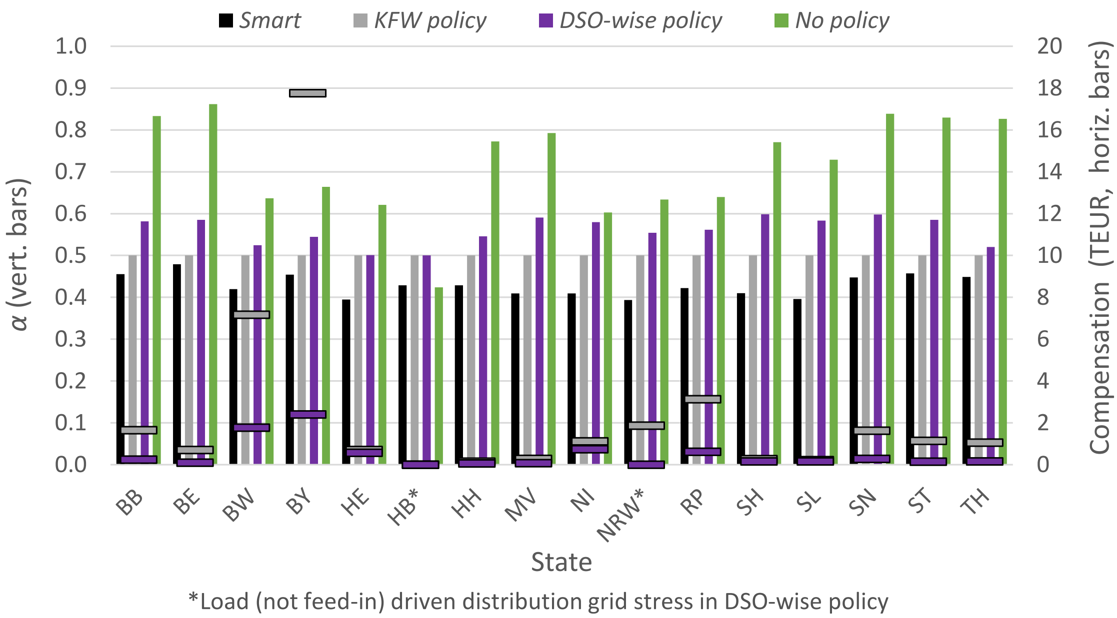

Figure 5.4: State-wise DSO capacity as share of PV peak generation (α_n) and compensation payment for May 25. In the *DSO-wise policy*, α_n is greater than for *KfW policy in most cases*. If distribution stress is solely driven by loads, both policies are ineffective and there is no compensation.

5.7.3 Aggregate results on DSO capacities

With a good understanding of the underlying mechanisms, we can now focus on the policies' state-aggregate effects on DSO capacity requirements. Figure 5.5 depicts the sum of daily necessary DSO capacities for all regions throughout the entire year, while Figure 5.6 gives the share of required DSO capacity which is feed-in-driven.[13] In the benchmark scenario without storage (*No storage*), we find the highest grid requirement in summer, driven by high PV grid feed-in. In fact, in about half of the time, DSO capacity is exclusively driven by feed-in in this scenario. Introducing storage into the system substantially decreases required DSO capacities in the scenario *Smart*. However, the picture changes in the case of purely self-optimizing prosumage (*No policy*). Here, capacity requirements do increase, not only compared to *Smart* but also in reference to the *No storage* scenario and a substantial share of DSO capacity requirements comes as a consequence of feed-ins. Consequently, additional storage capacities can have ambiguous effects on DSO capacities that depend on their mode of operation.

[13]Note that for the entire year, even larger capacities than the daily maximums might be needed if the state-wise maximums do not coincide.

Figure 5.5: Daily necessary DSO capacity. While in the base case scenarios DSO capacity requirements are PV driven and highest during the summer months, all policy scenarios have lower capacity needs during summer compared to winter. Maximum *Smart* capacity = 2.6 GW.

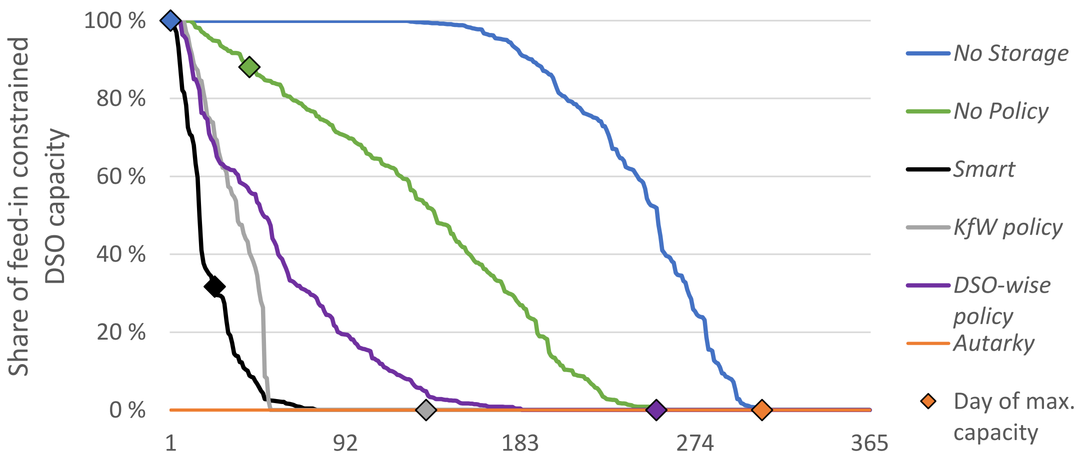

Figure 5.6: Daily share of feed-in-constrained DSO capacity sorted by size. Day of max (diamond) represents the day of the maximum required DSO capacity.

Looking at the scenarios *KfW policy* and *DSO-wise policy*, we find that they are effective in mitigating capacity requirement peaks compared to *No policy* during the summer months (April–September) with high PV generation. As these account for the highest capacity requirements, the policies manage to reduce the needed capacity. Comparing the two scenarios, the fact that the *DSO-wise policy* scenario has a higher level of feed-in-induced capacity requirements suggests that the *KfW policy* policy is overly restrictive. For both scenarios, the remaining grid requirement peak now occurs during the winter months (October–March) and is mainly driven by prosumage load (i.e., flows from the market to the prosumage household) (Figure 5.6), which the policies cannot affect. As a consequence, also a yearly optimization – as opposed to the day-by-day consideration – could not reduce the needed DSO capacity in the *DSO-wise policy* or *KfW policy* scenario. An exception arises if storage capacities are low (see Figures 5.10 and 5.12). Here, peak grid use in the *KfW* scenario still occurs during summer feed-in and can effectively be mitigated by the *DSO-wise policy.*

In the *Autarky* scenario, DSO capacity requirements are fully driven by load as there exists no feed-in (see Figure 5.6). During summer, the DSO capacity requirement is reduced substantially, amounting to more than 100 days without any need for DSO capacity. Nevertheless, the scenario is not very effective in reducing load-driven capacity needs during days with very low PV generation as long as seasonal storage is not available. Eventually, almost as much DSO capacity has to be deployed as with the other policies or in the *No storage* scenario.

5.7.4 System costs and distributional effects

To analyze the system-level effects of the different policy options, we look at the change in yearly system costs and players' objectives compared to the *Smart* scenario (Figure 5.7). To do this, we convert the obtained daily capacities (Figure 5.5) to yearly values. In the scenarios *No storage*, *No policy*, *Autarky* and *KfW*, the DSOs must provide the peak utilized capacity throughout the entire year, while the peak capacities in *Smart* and *DSO-wise policy* could still be reduced, e.g., by increasing compensation to save yearly investments. To account for these differences, we compute the yearly costs and objectives for *No storage*, *No policy*, *Autarky* and *KfW* using the peak capacity and for *Smart* using the mean daily capacity.[14] For the *DSO-wise policy*, summer feed-in peaks might

[14] This method may slightly over- or underestimate the actual capacity needs in *Smart*.

be reduced by stricter policies, but winter loads cannot. We thus use the peak capacity from 21.9.–21.3. throughout the whole year.

From the analysis above, we know that maximum DSO capacity requirements associated with the market interactions of prosumage are about the same for the scenarios *No storage, KfW policy, DSO-wise policy*, and *Autarky*. Therefore, necessary capacity investment costs compared to the *Smart* scenario are similar for these four scenarios as well. However, they differ in the dispatch of generation and storage units, and consequently also in associated operation costs. We find that system costs in the scenarios *DSO-wise policy* and *KfW policy* increase by 0.5 percentage points compared to *Smart*. With a 0.9 percentage points increase, the rise in costs is substantially higher in the *No policy* scenario. For these three scenarios, the increase comes solely from inefficiently high distribution grid capacities, while operational costs decrease. This phenomenon arises due to the greater operational freedom of prosumage storage (higher distribution grid capacity allows more market interaction), which leads to a reduction in generation costs due to the consideration of the TSO nodal prices. In the Smart scenario, this freedom is restricted as a means to achieve the lower, cost-efficient distribution grid capacities.

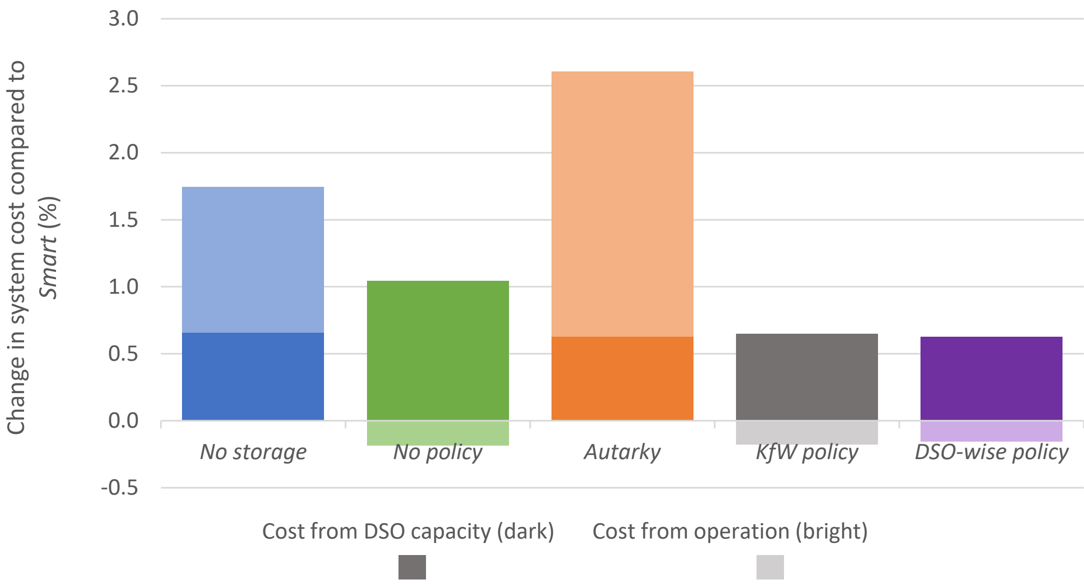

Figure 5.7: Change in prosumage-induced DSO capacity costs as well as operational costs, which add up to total system costs, compared to the *Smart* scenario. While DSO capacity costs are particularly high in the *No policy* scenario, operational costs are even lower than in *Smart* in the scenarios *No policy*, *KfW policy*, and *DSO-wise policy* but are substantially higher for *No storage* and *Autarky*.

Clearly, the mechanisms change substantially for *No storage* and the *Autarky* scenario with its severe restrictions on market interaction. For both of them, operational costs increase substantially. In the *No storage* scenario, that increase is driven by the fact that expensive peak generation during high demand hours cannot be substituted by cheaper off-peak generation using storage. In the *Autarky* scenario, storage operation is also heavily restricted. Besides that, excess prosumage PV generation is no longer available to the market, which leads to curtailment and adds to increasing operational costs.

Testing the sensitivity of these results (see Appendix 5.D.2) on changing storage power capacities and distribution grid capacity unit costs, we find that a ceteris paribus increase (decrease) of both parameters, respectively, implies a more (less) pronounced change in total system cost compared to *Smart*. For instance, with double storage capacities system costs under *DSO-wise policy* and *KfW policy* increase by 1.1 %, under *No policy* by 1.5 % compared to *Smart*. For double DSO costs, we find an increase of 1.2 % for *DSO-wise policy* and *KfW policy* and of 1.7 % for *No policy* compared to *Smart*. Thus, while the qualitative cost-saving effects of the policies are robust, their quantitative effectiveness does not proportionally increase with higher storage capacities or DSO unit capacity costs.

Finally, we assess the beneficiaries and losers of different scenarios. We have seen before that DSO costs from investment are rather similar for the scenarios *No storage*, *Autarky*, *KfW policy* and *DSO-wise policy* and about 115 % higher than in the *Smart* scenario. Taking the costs of compensating prosumage into account as well adds another 8 % to the *KfW policy* scenario, and 4 % under the *DSO-wise policy* (Figure 5.8, left). Particularly, due to the compensation, prosumage-households are slightly better off under the *KfW policy*. However, the improvements from the increased operational freedom in the *No policy*, *KfW policy*, and *DSO-wise policy* scenarios compared to the *Smart* scenario are small at < 10%. In contrast, prosumage households lose substantially if aiming for *Autarky* due to lost PV revenues and inefficient storage operation.

Let us now also take a look at non-prosumage demand and renewable generators. We define their objectives as

$$obj_n^D = \sum_t (D_{n,t} - lol_{n,t}^{TSO}) \cdot p_{n,t}^{TSO} + lol_{n,t}^{TSO} \cdot VOLL \tag{5.4}$$

$$obj_n^{RES} = -\sum_t (G_{n,t}^{RES} - curt_{n,t}^{TSO}) \cdot p_{n,t}^{TSO}, \tag{5.5}$$

Renewable generation and non-prosumage demand both lose in the *No storage* scenario by 0.5 % and 0.3 % respectively relative to *Smart* (Figure 5.8, right). This shows that storage facilitates renewable capacity deployment (see, e.g., Denholm & Hand, 2011), while conventional generators lose (Sioshansi, 2010).[15] Renewable generators also gain substantially in the *Autarky* scenario because the prosumage PV curtailment increases prices, particularly when there is also a substantial amount of generation from non-prosumage PV. From the demand perspective, however, these higher prices induce higher costs. Finally, the two players are relatively indifferent between the scenarios *Smart*, *No policy*, *KfW policy* and *DSO-wise policy*, with their objectives deviating by below 0.1 %.

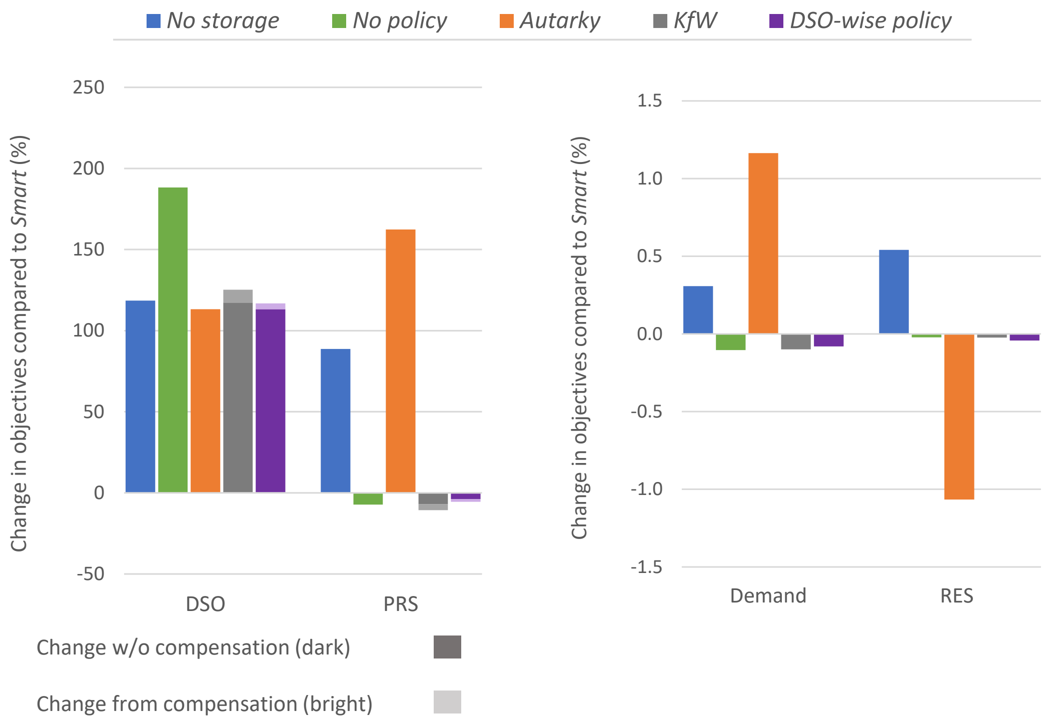

Figure 5.8: Distributional effects of different scenarios. From our objective definitions (see Eqs. 5.1, 5.3, 5.4, 5.5), positive values indicate a deterioration (less revenues and/or higher costs), while negative values imply improvement for the respective player. Due to compensation (brighter segment of individual bars), prosumage household reap the highest benefits in the *KfW policy* scenario. They lose most in the *Autarky* scenario.

[15]Exceptions to this rule may arise, e.g., if storage is owned by oligopolistic generators (Schill & Kemfert, 2011).

5.7.5 Limitations

Our model setup and calibration rely on some critical assumptions that need to be borne in mind when interpreting the results. For the parametrization of DSO investment costs, we assume unit capacity costs and therefore disregard the economies of scale that are inherent to this infrastructure investment. Taking these into account would reduce system cost differentials between scenarios with high and low distribution grid requirements, while our qualitative results would still hold. Even though we use Germany to calibrate our model, we deviate from some institutional conditions of the national electricity market, such as the single bidding zone. To derive more nuanced estimates on the effects of market structures, the model can be further adapted to the regulatory settings of the region. Furthermore, it can be recalibrated to analyze other target regions. However, we are confident that our qualitative findings are widely robust for different market structures as well as other regions.

In our representation of storage, we assume that operational conditions do not change over time and do not account for capacity degradation. Reducing the depth of discharge or charging rates can increase battery life (Choi & Lim, 2002) but would also have impacts on the electricity system level. Moreover, we assume that the choice of battery size is independent of the regulatory design, which is aimed at battery dispatch. We leave the assessment of incentives for private storage investment to future research, as this would further complicate the already complex game structure of our setup.

Contrary to small-scale DSO system and prosumage analyses on the individual home or community level, our approach uses a coarse DSO representation but allows us to draw conclusions for a large system. We are aware that our model does not capture all technical aspects of distribution grid management, such as voltage regulation, power factor correction, or the reduction of energy losses (Resener et al., 2018). Moreover, we disregard DSO capacity needed for non-prosumage demand or other small-scale generation. We also abstract from the range of voltage levels handled by DSOs (from the household level at 230 V to the high-voltage level at 110 kV for Germany) for regional distribution and interconnection. In a trade-off between complexity and tractability, we aggregate the individual components of the distribution grid, comprised, e.g., of distribution lines, transformers, and capacitors. Moreover, our approach simplifies the resulting coordination problem arising among the different DSOs when setting the individual feed-in restriction.

With the methods described in Section 5.6, we enforce an equilibrium between the DSOs, but there might well exist other equilibria that we do not explore here.

5.8 Conclusions and policy implications

The increasing number of residential PV systems paired with storage (prosumage) has great potential to benefit the electricity grid as well as the energy system as a whole. Prosumage households provide private capital for both renewable energy and storage deployment and thus play an important role in the modernization of power systems. Furthermore, household ownership may improve the general acceptance towards RES (Musall & Kuik, 2011). As residential battery storage systems become increasingly available and financially viable (Muenzel et al., 2015), the structures of production and storage ownership are inverted, and the technical system characteristics change as well. There is no longer a clear hierarchy, with large conventional generators at high voltage levels and successive transmission and distribution to the consumers. Instead, decentralized generation – especially from renewable sources – is fed in along all voltage and grid levels of the system. In this paper, we have analyzed how such storage options can contribute to the integration of RES into a future power system by mitigating distribution grid use and thus facilitating diffusion without the need for grid expansions. Realizing the potential of storage is accompanied by both technical and institutional challenges. To analyze these, we have deployed a comprehensive multi-level capacity planning and dispatch model that mimics the interplay between conventional demand and prosumage, conventional generation and renewables, as well as the DSO and the TSO grid levels. The model accounts for institutional settings and decision-making power of the different players.

Our analysis shows that if storage is deployed without appropriate policies, significant potential system benefits are left untapped. In particular, much of the positive price-moderating effect of storage is eaten up by additional distribution grid requirements. We advise policymakers to provide legal conditions that incentivize prosumage households to operate storage in a system-beneficial manner, e.g., by restricting grid feed-in from PV generation. Simple policies like the restriction of maximum grid feed-in based on the nominal PV generation capacity (our *KfW policy* scenario) are effective in mitigating DSO stress from high prosumage feed-ins. Feed-in policies are, however, ineffective in regulating load-driven DSO stress, e.g., due to high prosumage demand and storage charging from the market at times with low PV generation. As a consequence, even more elaborate feed-in policies cannot further reduce DSO capacity needs substantially. In particular, this holds for high storage capacities (cf. Appendix 5.D.1). Consequently, complementary load policies are needed, that are able to restrict power purchases from the prosumage household, particularly for charging the storage. This is also reflected by the decreased policy effectiveness for larger storage capacities. In general, we like to caution decisionmakers when making decisions about storage, as it contributes to both, load as well as feed-in, and may potentially aggravate both kinds of DSO stresses if no respective operational restrictions or incentives are in place.

Neglecting distribution grid costs (*No policy* scenario) induces a system cost increase of about 0.9 % compared to a system-optimizing perspective (*Smart* scenario). Doubling storage capacities increases this figure to 1.5 %. Under both storage options, the increase can be reduced by about half a percentage point if simple feed-in policies (*KfW policy*, *DSO-wise policy*) are implemented. Even though these effects are rather small in absolute terms, it is important to note that the changes are all driven by prosumage households, who only contribute about 1 % of total generation and demand.[16] A higher share of prosumage households will likely induce a respective increase in costs. Significant differences between policy interventions are apparent when looking at the distributional effects on prosumage households and DSOs. While prosumage autarky is more beneficial to the DSO than an unregulated scenario, the prosumage household is worse off. In contrast, policies with incentive payments improve the DSO situation compared to the unregulated scenario and the prosumage situation compared to the *Autarky* scenario.

In a nutshell, decision makers should be cautious about the following aspects: 1) Prosumage has a great potential to shape the future power system and facilitate its transition towards sustainability. 2) Nevertheless, prosumage may also have adverse effects, such as an associated increase in distribution grid requirements. 3) To tap the full potential of advantages from prosumage, appropriate policies are needed. Feed-in policies can be utilized to partly mitigate grid needs but must be complemented by load policies to realize the full potential. 4) Careful policy design is vital: otherwise, system costs might even increase with storage.

[16] In our parametrization, it is annual prosumage demand: 4.9 TWh, prosumage PV generation: 6 TWh, total system demand (incl. PRS): 515 TWh.

These findings open up multiple promising avenues for future research: First, this analysis could be extended to include one or multiple load policies. It is likely that even a simple load policy would allow further reductions in DSO capacity needs by addressing cases in which they are driven by peak load in the current scenarios. For instance, one may restrict the amount of combined prosumage demand and storage charging from the grid in a similar fashion as the maximum feed-in is restricted. It is straightforward that the same cap for load and feed-in DSO grid use should be implemented to use the capacity efficiently. Again, any operational restriction should be appropriately compensated. Focusing more on loads also opens the option to look at the influence of electric vehicle diffusion, which will likely play a major role in future DSO capacity planning.

Moreover, the model can be used to assess the effects of different storage ownership structures (independent vs. prosumage vs. DSO vs. TSO), which may change the incentives for its dispatch and thus imply effects on system operation costs, grid capacity requirements, and distribution of rents. Another promising avenue for further research is the coordination required between different DSOs (a policy set by one DSO may have impacts on prices and thus influence required incentive payments by other DSOs) and the path-dependency that would be implied by any uncoordinated decision making. Furthermore, the incentives arising from the distribution of network charges could be further investigated. This would allow for an investigation of the trade-off between private storage capacity investment and different possible revenue streams and avoided costs on the prosumage side. In this context, also additional revenue streams for prosumage households such as balancing markets or other system services could be assessed.

Appendices

5.A Nomenclature

Table 5.2: Sets and parameters used in the model.

Name	**Description**
Sets	
$n, m \in \mathcal{N} = \{1, ..., N\}$	TSO nodes
$l \in \mathcal{L} = \{1, ..., L\}$	TSO lines
$\tau \in \mathcal{D} = \{1, ..., 365\}$	Days of the year
$t \in \mathcal{T} = \{1, ..., 8760\}$	Hours of the year
Parameters	
$D_{n,t}^{PRS}$	Demand from prosumage [GW]
$G_{n,t}^{PRS}$	PV generation from prosumage [GW]
$\overline{G}_{n}^{PRS}$	Prosumage PV capacity [GW]
$\overline{E}_{n}^{PRS}$	Energy capacity of storage [GWh]
$\overline{P}_{n}^{PRS}$	Storage power capacity [GW]
E_{n}^{PRS}	Inital storage level [GWh]
η	Round-trip storage efficiency [-]
$C_{n,t}^{GEN}$	Generation cost parameter [(EUR/MWh)/GW]
$\overline{G}_{n,t}^{GEN}$	Seasonally available generation capacity [GW]
MC^{DSO}	DSO unit capacity cost per hour of grid use [TEUR/(GW·h)]
$D_{n,t}$	Non-prosumage demand [GW]
$G_{n,t}^{RES}$	Non-prosumage generation potential from RES [GW]
$VOLL$	Value of lost load [EUR/MWh]
$H_{l,n}$	Network transfer matrix [1/Ω]
$B_{n,m}$	Network susceptance matrix [1/Ω]
$\overline{F}_{l}^{TSO}$	Capacities of TSO lines [GW]

Table 5.3: Primal variables (var) and dual variables (du) of the model.

Superset	Name	Description
Variables		
var^{PRS}	$pv2d_{n,t}$	Flow from prosumage PV to prosumage demand [GW]
	$s2d_{n,t}$	Flow from prosumage storage to prosumage demand [GW]
	$m2d_{n,t}$	Flow from market to prosumage demand (purchase) [GW]
	$m2s_{n,t}$	Flow from market to prosumage storage (purchase) [GW]
	$s2m_{n,t}$	Flow from prosumage storage to market (sale) [GW]
	$pv2s_{n,t}$	Flow from prosumage PV to prosumage storage [GW]
	$pv2m_{n,t}$	Flow from prosumage PV to market (sale) [GW]
	$e^{PRS}_{n,t}$	Energy level of storage [GWh]
	$lol^{PRS}_{n,t}$	Lost load at prosumage
	$curt^{PRS}_{n,t}$	Curtailment at prosumage
var^{GEN}	$g_{n,t}$	Conventional generation [GW]
var^{DSO}	$\overline{f}^{DSO}_n$	DSO capacity connected to node n [GW]
	α_n	Policy variable [-]
var^{TSO}	$f^{TSO}_{l,t}$	Flow at TSO line [GW]
	$im^{TSO}_{n,t}$	Inflow from TSO network [GW]
	$lol^{TSO}_{n,t}$	Lost load at TSO node [GW]
	$curt^{TSO}_{n,t}$	Curtailment at TSO node [GW]
	$\theta_{n,t}$	Phase angle [deg]
Duals		
du^{PRS}	$\lambda^{PV}_{n,t}$	Shadow price on PV generated electricity [EUR/MWh]
	$\lambda^{D}_{n,t}$	Shadow price on electricity consumed by prosumage [EUR/MWh]
	$\lambda^{STOR}_{n,t}$	Shadow price on electricity in the storage [EUR/MWh]
	$\lambda^{CHARGE}_{n,t}$	Shadow price on storage charge [EUR/MW]
	$\lambda^{DISCH}_{n,t}$	Shadow price on storage discharge [EUR/MW]
	$\lambda^{\overline{E}}_{n,t}$	Shadow price on storage capacity [EUR/MWh]
	λ^{E}_{n}	Shadow price for refilling the storage [EUR/MWh]
	$\lambda^{\alpha}_{n,t}$	Shadow price on policy constraint [EUR/MW]
du^{GEN}	$\lambda^{\overline{G}}_{n,t}$	Shadow price on generation capacity [EUR/MW]
du^{TSO}	$p^{TSO}_{n,t}$	Wholesale electricity price at the TSO node [EUR/MWh]

5.B Players' constraints

5.B.1 Prosumage

$$0 = pv2d_{n,t} + s2d_{n,t} + m2d_{n,t} + lol^{PRS}_{n,t} - D^{PRS}_{n,t} \qquad (\lambda^{D}_{n,t}) \tag{5.6}$$

$$0 = -pv2d_{n,t} - pv2s_{n,t} - pv2m_{n,t} - curt^{PRS}_{n,t} + G^{PRS}_{n,t} \qquad (\lambda^{PV}_{n,t}) \tag{5.7}$$

$$0 = \begin{cases} -s2d_{n,t} + \eta \cdot m2s_{n,t} - s2m_{n,t} + \eta \cdot pv2s_{n,t} - e^{PRS}_{n,t} + E^{PRS}_{n}, & \text{if } t = 1 \\ -s2d_{n,t} + \eta \cdot m2s_{n,t} - s2m_{n,t} + \eta \cdot pv2s_{n,t} - e^{PRS}_{n,t} + e^{PRS}_{n,t-1}, & \text{otherwise} \end{cases}$$
$$(\lambda^{STOR}_{n,t}) \tag{5.8}$$

$$0 \leq e^{PRS}_{n,t} - \overline{E}^{PRS}_{n} \qquad (\lambda^{\overline{E}}_{n,t}) \tag{5.9}$$

$$0 \leq m2s_{n,t} + pv2s_{n,t} - \overline{P}^{PRS}_{n} \qquad (\lambda^{CHARGE}_{n,t}) \tag{5.10}$$

$$0 \leq s2d_{n,t} + s2m_{n,t} - \overline{P}^{PRS}_{n} \qquad (\lambda^{DISCH}_{n,t}) \tag{5.11}$$

$$0 = e^{PRS}_{n,T} - E^{PRS}_{n} \qquad (\lambda^{E}_{n}) \tag{5.12}$$

$$0 \leq \alpha_n \cdot \overline{G}^{PRS}_{n} - s2m_{n,t} - pv2m_{n,t} \qquad (\lambda^{\alpha}_{n,t}) \tag{5.13}$$

5.B.2 Generator

$$0 \leq g_{n,t} - \overline{G}^{GEN}_{n,t} \qquad (\lambda^{\overline{G}}_{n,t}) \tag{5.14}$$

5.B.3 DSO

$$0 \leq \overline{f}^{DSO}_{n} - m2d_{n,t} - m2s_{n,t} \tag{5.15}$$

$$0 \leq \overline{f}^{DSO}_{n} - \alpha_n \cdot \overline{G}^{PRS}_{n} \tag{5.16}$$

5.B.4 TSO

$$0 = -im^{TSO}_{n,t} + m2d_{n,t} + m2s_{n,t} - s2m_{n,t} - pv2m_{n,t} - g_{n,t} + D_{n,t} - G^{RES}_{n,t} + curt^{TSO}_{n,t} - lol^{TSO}_{n,t} \quad (p^{TSO}_{n,t}) \tag{5.17}$$

$$0 = -im^{TSO}_{n,t} + B_{n,m} \cdot \theta_{n,t} \tag{5.18}$$

$$0 = -f^{TSO}_{l,t} + H_{l,n} \cdot \theta_{n,t} \tag{5.19}$$

$$0 \leq -f^{TSO}_{l,t} + \overline{F}_{l} \tag{5.20}$$

$$0 \leq f_{l,t}^{TSO} + \overline{F}_l \tag{5.21}$$

$$0 = \theta_{\hat{n},t} \tag{5.22}$$

5.C Data

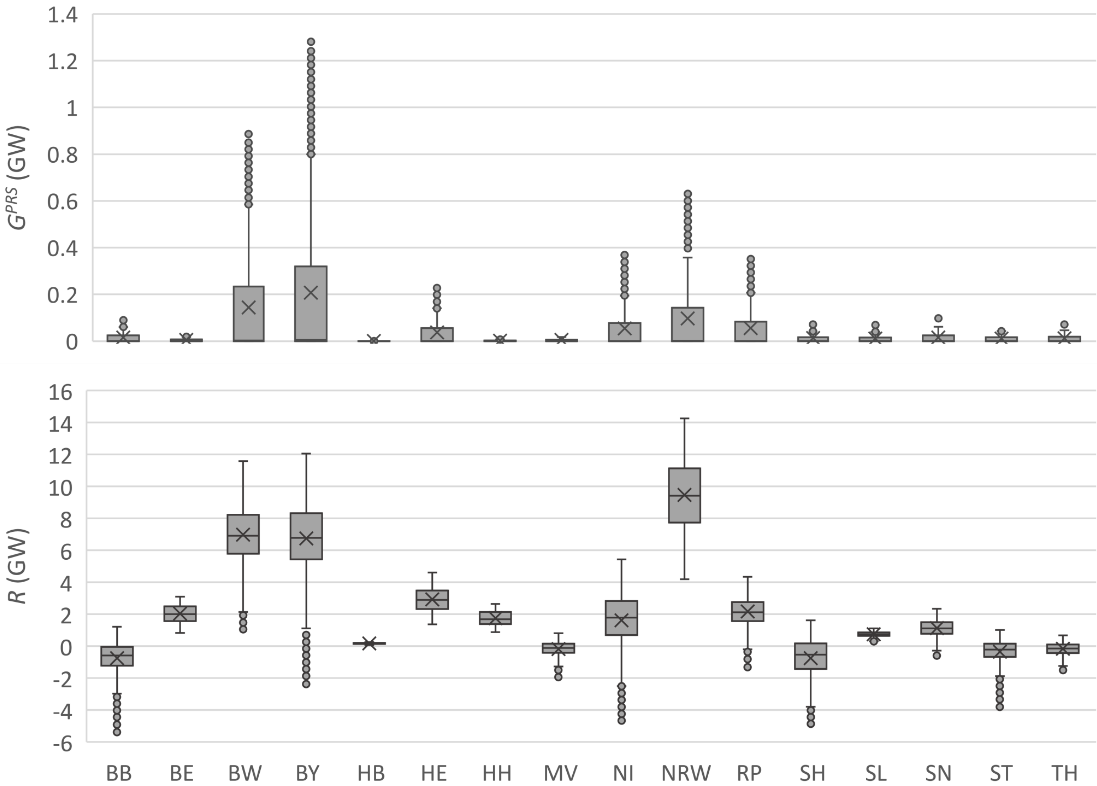

Figure 5.9: Overview on data by state. **Top:** prosumage household PV generation. **Bottom:** residual demand (excluding prosumage). Level and distribution of residual demand varies significantly between states. Prosumage households are concentrated on only few states. Data source: own computations on the basis of Open Power System Data (2018), Kunz et al. (2017), Koch et al. (2016).

Table 5.4: Generation cost parameters as well as conventional and prosumage capacities by state. Data source: own computations on the basis of Open Power System Data (2018), Kunz et al. (2017).

	$C_{n,t}^{GEN}$ [(EUR/MW)/GW]			$\overline{G}_{n,t}^{GEN}$ [GW]			$\overline{G}_{n}^{PRS}$	$\overline{P}_{n}^{PRS}$	$\overline{E}_{n}^{PRS}$
	Mean	Min	Max	Mean	Min	Max	[MW]	[MW]	[MWh]
BB	20.6	18.5	24.4	3.1	2.6	3.4	135.2	67.6	270.4
BE	50.9	47.6	54.6	2.1	1.9	2.2	46.6	23.3	93.1
BW	10.5	9.7	12.1	6.7	5.7	7.2	1129.2	564.6	2258.4
BY	7.9	7.2	9.4	9.8	8.2	10.7	1657.3	828.7	3314.6
HB	335.7	314.5	356.9	0.1	0.1	0.1	1.7	0.9	3.4
HE	35.1	32.9	37.3	2.1	2	2.3	323.2	161.6	646.5
HH	33.6	31.5	35.7	1.5	1.4	1.6	21.7	10.8	43.4
MV	87.2	81.7	92.7	0.7	0.6	0.7	44.1	22.1	88.3
NI	8.8	8.1	9.9	8.3	7.4	9	514.9	257.5	1029.9
NRW	2.8	2.6	3.1	23.5	21	25.5	861.8	430.9	1723.6
RP	19.5	18.2	20.7	3.4	3.2	3.6	473.3	236.6	946.5
SH	40.9	37.1	49.1	2.3	1.9	2.5	121.9	61	243.8
SL	28.4	26.7	30.1	1.9	1.8	2	96.3	48.2	192.6
SN	6.4	5.6	7.7	5.2	4.3	5.8	133.1	66.5	266.2
ST	52.8	48	60.4	1.6	1.4	1.7	94.4	47.2	188.9
TH	199.5	187.2	211.7	0.4	0.4	0.4	98.5	49.2	197
Total				72.7	63.9	78.7	5753	2876	11506

5.D Sensitivity results

5.D.1 Daily necessary DSO capacity

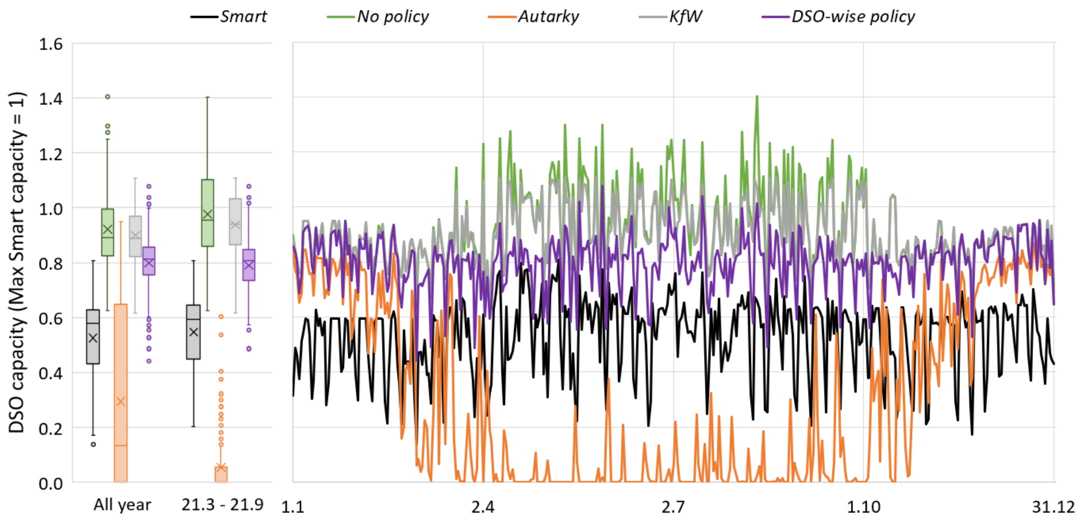

Figure 5.10: Daily necessary DSO capacity with half storage power capacity ($\sum_n \overline{P}_n^{PRS} = 1.45$GW). The reference DSO capacity (Max *Smart* capacity=2.6 GW) is taken from the results with regular storage capacity.

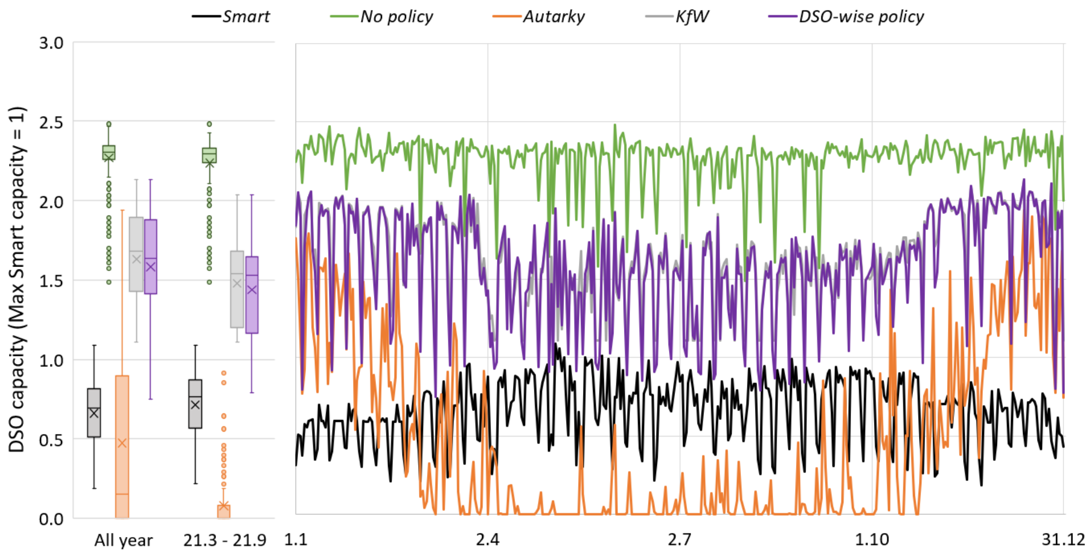

Figure 5.11: Daily necessary DSO capacity with double storage power capacity ($\sum_n \overline{P}_n^{PRS} = 5.8$GW). The reference DSO capacity (Max *Smart* capacity=2.6 GW) is taken from the results with regular storage capacity.

5.D.2 Change in system cost

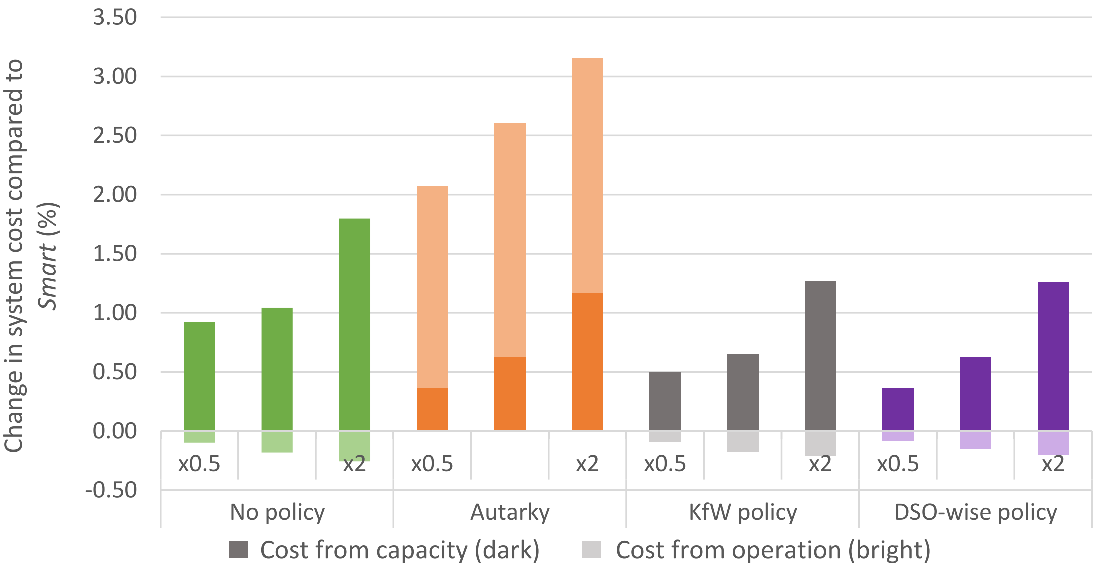

Figure 5.12: Sensitivity results on the effect of altering **storage power capacities** (half, double) on change in prosumage-induced DSO capacity costs as well as operational costs compared to the *Smart* scenario.

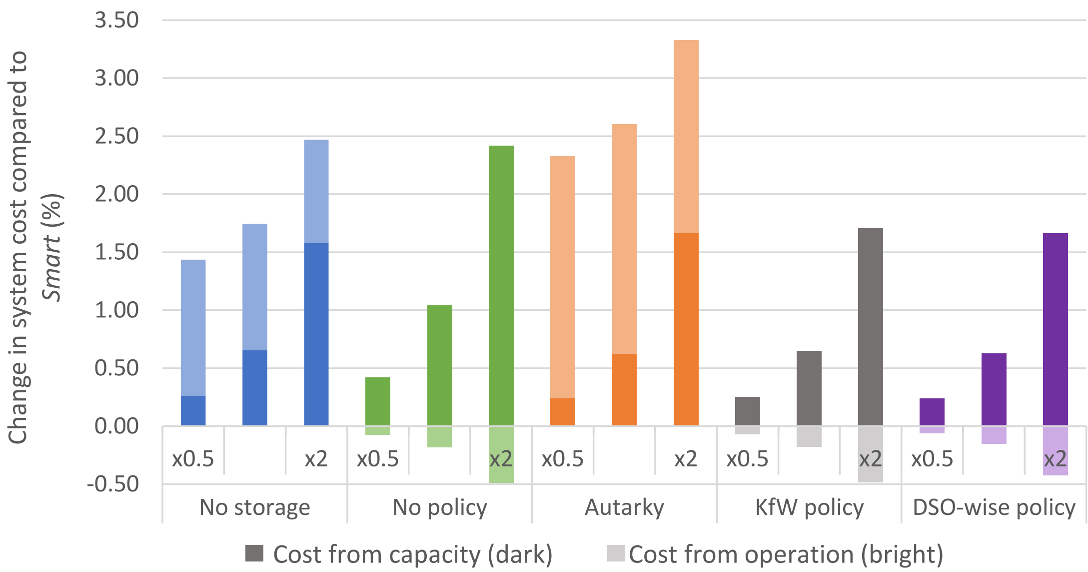

Figure 5.13: Sensitivity results on the effect of altering **DSO capacity costs** (half, double) on change in prosumage-induced DSO capacity costs as well as operational costs compared to the *Smart* scenario.

5.E Solution strategy for multi-level scenarios

The following section[17] provides detailed descriptions on our approach to solving the three multi-level scenarios (*Autarky, KFW policy, DSO-wise policy*) and thus complements Section 5.6. First, we describe how the inter-DSO coordination problem is reduced to separate problems of the respective DSOs and the adjacent prosumage household and generator at each TSO node (Section 5.E.1). Then we show how these problems can be linearized to yield globally optimal results for the discretized solution space (Section 5.E.2).

5.E.1 Derive separated MPECs from EPEC

As discussed in Section 5.3, the problem of finding an equilibrium not only within a DSO region but also between the DSOs requires us to solve an Equilibrium Problem under Equilibrium Constraints (EPEC). To reduce complexity, we enforce the between-DSO equilibrium by fixing imports and exports between DSO networks, thus separating the DSO problems. The remaining Stackelberg game between one DSO and the respective adjacent prosumage and conventional generation can then be characterized by a Mathematical Program under Equilibrium Constraints (MPEC). We set up the state-wise MPEC by adding the prosumage and conventional generation first-order optimality conditions, representing the lower level of the Stackelberg game, to the respective DSO problem.

To allow DSOs a realistic assessment of the effect of their policy intervention on market prices ($p_{n,t}^{TSO}$), we add the respective TSO nodal balance to their problem. However, we fix imports to values obtained in the *Smart* scenario, which we denote by $IM_{n,t}^{TSO}$. Moreover, we adjust the parameters of the respective conventional generator to mimic the reaction of the entire conventional generation fleet, rather than only accounting for adjacent conventional generation. We do this by (i) first, introducing an adjusted generation cost parameter $\hat{C}_{n,t}^{GEN}$ ($\forall n,t:\ \hat{C}_{n,t}^{GEN} = p_{n,t}^{TSO}/g_{n,t} \mid g_{n,t} > 0$). Here, $p_{n,t}^{TSO}$ and $g_{n,t}$ are taken from results of the *Smart* scenario.[18] (ii) Second, we increase the state-wise available generation capacity

[17] This section is not part of the published version of the paper but is available in a prior working paper version: Neetzow et al. (2018a).

[18] Note that $p_{n,t}^{TSO} = \lambda_{n,t}^{\overline{G}} + C_{n,t}^{GEN} \cdot g_{n,t}$. If generation in a region is at its capacity limit there is a positive price mark-up $\lambda_{n,t}^{\overline{G}} \geq 0$, which reflects the price differential to other regions. Otherwise, if $\lambda_{n,t}^{\overline{G}} = 0$, then $\hat{C}_{n,t}^{GEN} = C_{n,t}^{GEN}$.

by 10 %, i.e., $\forall n: \hat{\overline{G}}^{GEN}_{n,t} = 1.1 \cdot \overline{G}^{GEN}_{n,t}$. These additional local capacities mimic the option to increase imports from the TSO grid.

This setup now allows the DSO to approximate the effects of its decisions on TSO nodal prices and thus on dispatch of prosumage and conventional generation without the need for further coordination between the DSOs. In turn, market prices are the key determinant of potential compensation payments. As a consequence, the solution that we obtain does not fully satisfy the optimality of the between-DSO coordination game. But our parameter adjustment provides a good approximation while substantially reducing complexity and allowing us to obtain numerical results.

In the following, we detail the individual components of the resulting MPEC. For convenience, we use slack variables denoted by s for the lower level first-order optimality conditions to write inequalities as equalities.

$$\min_{\substack{var^{PRS}, du^{PRS} \\ var^{GEN}, du^{GEN} \\ var^{DSO}, s}} obj^{DSO}_n = \overline{f}^{DSO}_n \cdot MC^{DSO} \cdot |\mathcal{T}| + \sum_t (1-\alpha_n) \cdot \overline{G}^{PRS}_n \cdot \lambda^{\alpha}_{n,t} \tag{5.23}$$

s.t.

Eqs. (5.15), (5.16)

$$0 = -IM^{TSO}_{n,t} + m2d_{n,t} + m2s_{n,t} - s2m_{n,t} - pv2m_{n,t} - g_{n,t} + R_{n,t} + curt^{TSO}_{n,t} - lol^{TSO}_{n,t} \quad (p^{TSO}_{n,t}) \tag{5.24}$$

$$0 = pv2d_{n,t} + s2d_{n,t} + m2d_{n,t} + lol^{PRS}_{n,t} - D^{PRS}_{n,t} \qquad (\lambda^{D}_{n,t}) \tag{5.25}$$

$$0 = -pv2d_{n,t} - pv2s_{n,t} - pv2m_{n,t} - curt^{PRS}_{n,t} + G^{PRS}_{n,t} \qquad (\lambda^{PV}_{n,t}) \tag{5.26}$$

$$0 = \begin{cases} -s2d_{n,t} + \eta \cdot m2s_{n,t} - s2m_{n,t} + \eta \cdot pv2s_{n,t} - e^{PRS}_{n,t} + E^{PRS}_n, & \text{if } t = 1 \\ -s2d_{n,t} + \eta \cdot m2s_{n,t} - s2m_{n,t} + \eta \cdot pv2s_{n,t} - e^{PRS}_{n,t} + e^{PRS}_{n,t-1}, & \text{otherwise} \end{cases} \quad (\lambda^{STOR}_{n,t}) \tag{5.27}$$

$$0 = e^{PRS}_{n,t} - \overline{E}^{PRS}_n - s^{\overline{E}}_{n,t} \qquad (\lambda^{\overline{E}}_{n,t}) \tag{5.28}$$

$$0 = m2s_{n,t} + pv2s_{n,t} - \overline{P}^{PRS}_n - s^{CHARGE}_{n,t} \qquad (\lambda^{CHARGE}_{n,t}) \tag{5.29}$$

$$0 = s2d_{n,t} + s2m_{n,t} - \overline{P}^{PRS}_n - s^{DISCH}_{n,t} \qquad (\lambda^{DISCH}_{n,t}) \tag{5.30}$$

$$0 = e^{PRS}_{nt,T} - E^{PRS}_n \qquad (\lambda^{E}_n) \tag{5.31}$$

$$0 = \alpha_n \cdot \overline{G}^{PRS}_n - s2m_{n,t} - pv2m_{n,t} - s^{\alpha}_{n,t} \qquad (\lambda^{\alpha}_{n,t}) \tag{5.32}$$

$$0 = g_{n,t} - \hat{\overline{G}}^{GEN}_{n,t} - s^{\overline{G}}_{n,t} \qquad (\lambda^{\overline{G}}_{n,t}) \tag{5.33}$$

$$0 = \lambda^{PV}_{n,t} - \lambda^{D}_{n,t} - s^{pv2d}_{n,t} \qquad \perp pv2d_{nt,t} \geq 0 \tag{5.34}$$

$$0 = -\lambda^{D}_{n,t} + \lambda^{STOR}_{n,t} + \lambda^{DISCH}_{n,t} - s^{s2d}_{n,t} \qquad \perp s2d_{n,t} \geq 0 \tag{5.35}$$

$$0 = p^{TSO}_{n,t} - \lambda^{D}_{n,t} - s^{m2d}_{n,t} \qquad \perp m2d_{n,t} \geq 0 \tag{5.36}$$

$$0 = p^{TSO}_{n,t} - \eta\lambda^{STOR}_{n,t} + \lambda^{CHARGE}_{n,t} - s^{m2s}_{n,t} \qquad \perp m2s_{n,t} \geq 0 \tag{5.37}$$

$$0 = -p^{TSO}_{n,t} + \lambda^{STOR}_{n,t} + \lambda^{DISCH}_{n,t} + \lambda^{\alpha}_{n,t} - s^{s2m}_{n,t} \qquad \perp s2m_{n,t} \geq 0 \tag{5.38}$$

$$0 = \lambda^{PV}_{n,t} - \eta\lambda^{STOR}_{n,t} + \lambda^{CHARGE}_{n,t} - s^{pv2s}_{n,t} \qquad \perp pv2s_{n,t} \geq 0 \tag{5.39}$$

$$0 = -p^{TSO}_{n,t} + \lambda^{PV}_{n,t} + \lambda^{\alpha}_{n,t} - s^{pv2m}_{n,t} \qquad \perp pv2m_{n,t} \geq 0 \tag{5.40}$$

$$0 = \begin{cases} \lambda^{STOR}_{n,t} - \lambda^{E}_{n} + \lambda^{\overline{E}}_{n,t} - s^{e}_{n,t}, & \text{if } t = T \\ \lambda^{STOR}_{n,t} - \lambda^{STOR}_{n,t+1} + \lambda^{\overline{E}}_{n,t} - s^{e}_{n,t}, & \text{otherwise} \end{cases} \qquad \perp e_{n,t} \geq 0 \tag{5.41}$$

$$0 = -\lambda^{D}_{n,t} + VOLL - s^{lol}_{n,t} \qquad \perp lol_{n,t} \geq 0 \tag{5.42}$$

$$0 = \lambda^{PV}_{n,t} - s^{curt}_{n,t} \qquad \perp curt_{n,t} \geq 0 \tag{5.43}$$

$$0 = -p^{TSO}_{n,t} + \hat{C}^{GEN}_{n} g^{GEN}_{n,t} + \lambda^{\overline{G}}_{n,t} - s^{g}_{n,t} \qquad \perp g^{GEN}_{n,t} \geq 0. \tag{5.44}$$

Here Eq. (5.23) is the objective function of an individual DSO, while Eq. (5.15), (5.16) are the DSO constraints. The TSO nodal balance with fixed imports from the previous *Smart* computation is given in Eqs. (5.24), (5.25)–(5.32) are the prosumage constraints with slack variables, Eq. (5.33) is the adjusted generation constraint, Eqs. (5.34)–(5.43) are the prosumage FOCs, and Eq. (5.44) is the generation FOC.

The problem is non-linear in its objective Eq. (5.23) and due to complementarity slackness. To solve this problem, we reformulate the MPEC as a mixed-integer linear problem (MILP, see Section 5.E.2). The MILP yields globally optimal results for the given choice of discrete variables.

5.E.2 Setting up and solving the MPEC as mixed-integer linear problem (MILP)

To set up the MILP, we linearize Eq. (5.23) by allowing the solver to choose one of eleven discrete choices for $\forall n : \alpha_n \in \{0, 0.1, 0.2, ..., 1\}$. To realize this, we introduce $\overline{\alpha}_i$ and $bi^{\alpha}_{n,i}$, where i is an auxiliary set, $\overline{\alpha}_i \in \{0, 0.1, 0.2, ..., 1\}$ and $bi^{\alpha}_{n,i} \in \{0, 1\}$ is a binary vector such that $\forall n : \sum_i bi^{\alpha}_{n,i} = 1$. We change the non-linear Eq. (5.23) to the linear formulation

$$\min_{\substack{var^{PRS},du^{PRS}\\ var^{GEN},du^{GEN}\\ var^{DSO}}} obj_n^{DSO} = \overline{f}_n^{DSO} \cdot MC^{DSO} \cdot |\mathcal{T}| + \sum_i comp_{n,i}^{DSO} \tag{5.45}$$

where $comp_{n,i}^{DSO}$ is a vector that contains the amount of the optimal compensation for the optimal choice of i and zeros for all other $i's$. It is defined from the following set of equations.

$$\sum_t (1-\overline{\alpha}_i) \cdot \overline{G}_n^{PRS} \cdot \lambda_{n,t}^{\alpha} - comp_{n,i}^{DSO} - \widetilde{comp}_{n,i}^{DSO} \leq 0 \tag{5.46}$$

$$comp_{n,i}^{DSO} - M_{n,i}^{\alpha} \cdot bi_{n,i}^{\alpha} \leq 0 \tag{5.47}$$

$$\widetilde{comp}_{n,i}^{DSO} - M_{n,i}^{\alpha} \cdot (1 - bi_{n,i}^{\alpha}) \leq 0 \tag{5.48}$$

$$\sum_i bi_{n,i}^{\alpha} = 1 \tag{5.49}$$

$$\alpha_n = \sum_i \overline{\alpha}_i \cdot bi_{n,i}^{\alpha} \tag{5.50}$$

In this formulation $\widetilde{comp}_{n,i}^{DSO}$ contains the amounts of compensations for all but the optimal choice of i (for the optimal i, $\widetilde{comp}_{n,i}^{DSO}$ becomes zero). $M_{n,i}^{\alpha}$ resembles an appropriately large constant, which is larger than the maximum hourly compensation in every state. The last equation Eq. (5.50) makes the formulation compatible with the previous equations by defining α_n. This formulation allows us to replace the objective's non-linearity with a linear integer problem.

Next, we linearize the complementary conditions that arise from the FOCs of prosumage and generation. This is done by using a disjunctive constraint formulation (Fortuny-Amat & McCarl, 1981), which we apply to the complementarity conditions of equations Eq. (5.28) – (5.30), (5.32), (5.33) – (5.44). Instead of enforcing complementarity with the constraints themselves, we use the respective slack variables to formulate the disjunctive constraints. This replaces the bilinear complementarity conditions with linear integer constraints.

The disjunctive constraints for our problems can be written as:

$$s_{n,t}^{\overline{E}} - M_{n,t}^{\overline{E}} \cdot bi_{n,t}^{\overline{E}} \leq 0 \tag{5.51}$$

$$\lambda_{n,t}^{\overline{E}} - M_{n,t}^{\overline{E}} \cdot (1 - bi_{n,t}^{\overline{E}}) \leq 0 \tag{5.52}$$

$$s_{n,t}^{CHARGE} - M_{n,t}^{CHARGE} \cdot bi_{n,t}^{CHARGE} \leq 0 \tag{5.53}$$

$$\lambda_{n,t}^{CHARGE} - M_{n,t}^{CHARGE} \cdot (1 - bi_{n,t}^{CHARGE}) \leq 0 \tag{5.54}$$

$$s_{n,t}^{DISCH} - M_{n,t}^{DISCH} \cdot bi_{n,t}^{DISCH} \leq 0 \tag{5.55}$$

$$\lambda_{n,t}^{DISCH} - M_{n,t}^{DISCH} \cdot (1 - bi_{n,t}^{DISCH}) \leq 0 \tag{5.56}$$

$$s_{n,t}^{\alpha} - M_{n,t}^{\alpha} \cdot bi_{n,t}^{\alpha} \leq 0 \tag{5.57}$$

$$\lambda_{n,t}^{\alpha} - M_{n,t}^{\alpha} \cdot (1 - bi_{n,t}^{\alpha}) \leq 0 \tag{5.58}$$

$$s_{n,t}^{\overline{G}} - M_{n,t}^{\overline{G}} \cdot bi_{n,t}^{\overline{G}} \leq 0 \tag{5.59}$$

$$\lambda_{n,t}^{\overline{G}} - M_{n,t}^{\overline{G}} \cdot (1 - bi_{n,t}^{\overline{G}}) \leq 0 \tag{5.60}$$

$$s_{n,t}^{pv2d} - M_{n,t}^{pv2d} \cdot bi_{n,t}^{pv2d} \leq 0 \tag{5.61}$$

$$pv2d_{n,t} - M_{n,t}^{pv2d} \cdot (1 - bi_{n,t}^{pv2d}) \leq 0 \tag{5.62}$$

$$s_{n,t}^{s2d} - M_{n,t}^{s2d} \cdot bi_{n,t}^{s2d} \leq 0 \tag{5.63}$$

$$s2d_{n,t} - M_{n,t}^{s2d} \cdot (1 - bi_{n,t}^{s2d}) \leq 0 \tag{5.64}$$

$$s_{n,t}^{m2d} - M_{n,t}^{m2d} \cdot bi_{n,t}^{m2d} \leq 0 \tag{5.65}$$

$$m2d_{n,t} - M_{n,t}^{m2d} \cdot (1 - bi_{n,t}^{m2d}) \leq 0 \tag{5.66}$$

$$s_{n,t}^{m2s} - M_{n,t}^{m2s} \cdot bi_{n,t}^{m2s} \leq 0 \tag{5.67}$$

$$m2s_{n,t} - M_{n,t}^{m2s} \cdot (1 - bi_{n,t}^{m2s}) \leq 0 \tag{5.68}$$

$$s_{n,t}^{s2m} - M_{n,t}^{s2m} \cdot bi_{n,t}^{s2m} \leq 0 \tag{5.69}$$

$$s2m_{n,t} - M_{n,t}^{s2m} \cdot (1 - bi_{n,t}^{s2m}) \leq 0 \tag{5.70}$$

$$s_{n,t}^{pv2s} - M_{n,t}^{pv2s} \cdot bi_{n,t}^{pv2s} \leq 0 \tag{5.71}$$

$$pv2s_{n,t} - M_{n,t}^{pv2s} \cdot (1 - bi_{n,t}^{pv2s}) \leq 0 \tag{5.72}$$

$$s_{n,t}^{pv2m} - M_{n,t}^{pv2m} \cdot bi_{n,t}^{pv2m} \leq 0 \tag{5.73}$$

$$pv2m_{n,t} - M_{n,t}^{pv2m} \cdot (1 - bi_{n,t}^{pv2m}) \leq 0 \tag{5.74}$$

$$s_{n,t}^{e} - M_{n,t}^{e} \cdot bi_{n,t}^{e} \leq 0 \tag{5.75}$$

$$e_{n,t} - M_{n,t}^{e} \cdot (1 - bi_{n,t}^{e}) \leq 0 \tag{5.76}$$

$$s_{n,t}^{lol} - M_{n,t}^{lol} \cdot bi_{n,t}^{lol} \leq 0 \tag{5.77}$$

$$lol_{n,t} - M_{n,t}^{lol} \cdot (1 - bi_{n,t}^{lol}) \leq 0 \tag{5.78}$$

$$s_{n,t}^{curt} - M_{n,t}^{curt} \cdot bi_{n,t}^{curt} \leq 0 \tag{5.79}$$

$$curt_{n,t} - M_{n,t}^{curt} \cdot (1 - bi_{n,t}^{curt}) \leq 0 \tag{5.80}$$

$$s_{n,t}^{g} - M_{n,t}^{g} \cdot bi_{n,t}^{g} \leq 0 \tag{5.81}$$

$$g_{n,t} - M_{n,t}^{g} \cdot (1 - bi_{n,t}^{g}) \leq 0 \tag{5.82}$$

For all pairs of disjunctive constraints, M resembles an appropriately large constant[19] and $bi \in \{0,1\}$ a binary variable. For $bi = 0$, it is straightforward that $s = 0$ and $\lambda \geq 0$. Hence, this indicates a binding constraint. On the other hand, for $bi = 1$, it follows that $s \geq 0$ and $\lambda = 0$, which thus indicates a non-binding constraint.

These disjunctive constraints finalize the MILP formulation of our MPEC, which is implemented as

$$\begin{aligned}
&\text{Eq. (5.45)} \\
&\text{s.t. Eq. (5.15), (5.16), (5.24)} - \text{(5.44) without complementarities,} \\
&\quad\;\; \text{Eqs. (5.46)} - \text{(5.82)}
\end{aligned}$$

To facilitate solving this problem, we initialize the MILP with the solution of the *Smart* scenario. In doing so, we also incorporate the marginals of the equations Eqs. (5.6)–(5.13), (5.14), (5.17) to initialize the explicit dual variables.

[19] See, e.g., Gabriel & Leuthold (2010) for a discussion on how to choose appropriate constants.

If we glance at the most important revolutions in history, we see at once that the greatest number of these originated in the periodical revolutions on the human mind.

Alexander von Humboldt

6 Conclusion

The manifold challenges in transitioning power systems require comprehensive research efforts. This thesis progresses knowledge on various aspects of these challenges relevant for the efficient transformation to and integration of RE. First, in Chapter 2, I analyze how RE deployment depends on the rigid endowment of flexible and inflexible conventional power plants. Even though inflexible capacities hamper early RE deployment, it is accelerated as soon as RE starts to substitute inflexible plants. The consecutive Chapter 3 acknowledges the importance of other flexibility options. In particular, storage and transmission are crucial to deal with the generation variability and different locational potentials of RE. I evaluate how those options relate and find that they can complement and substitute each other. The kind of interdependence depends on a number of conditions like storage location, characteristics of transmission congestion and the alignment of marginal costs in adjacent regions.

Those two chapters show that efficiently integrating high shares of RE is non-trivial. The flexibility required can be provided by different technologies which can lead to unexpected interaction effects. On the one hand, this opens up avenues for future research: For a comprehensive analysis, long-term capacity dynamics will have to be combined with spatial considerations and short-term generation decisions. On the other hand, it is important that decision-makers and regulators take into account the implications of flexibility for the power system transition. Efficient planning has to consider all available options and acknowledge how they interdepend.

Chapter 4 shows that also providing favorable institutional conditions for RE capacity deployment can be a challenging task. When there is more than one government level involved, lower-level preferences may hinder cost-efficient support for RE. Furthermore, the choice of a state government to support RE and thus also the effective RE deployment in that state depends directly on the support instrument implemented on the federal level. Switching the federal policy, e.g. from a price to a quantity-based RE support, leads to a RE over-support in states with priorly too low support and vice versa. This has particularly interesting implications if these insights are integrated with further aspects of the transition to RE. For instance, the federal government may take into account restrictions in inter-state power transmission which might be ignored by the states governments. These restrictions can be intensified or reduced by higher or lower RE deployment in particular states. The instrument choice may thus provide a possibility for the federal government to manage further aspects of the transition. If the insights on RE support also apply to storage, it is straight forward to integrate the results from Chapters 3 and 4. By choosing the federal instrument that incentivizes storage deployment in particular states, the transmission requirement could be reduced.

The most comprehensive analysis of this thesis is provided in Chapter 5. By focusing on the interactions of prosumage and grids, it integrates RE and conventional generation, storage, different transmission network levels and policies. Due to the high complexity, the derived model is solved by using numerical simulations. This chapter confirms the main finding of Chapter 3 for a much more sophisticated setup by showing that the availability of storage may increase transmission requirements. Furthermore, it shows that simple regulations can mitigate network stress by incentivizing a system-beneficial storage operation from prosumage households. This underlines what was already indicated in the previous chapters: Technical solutions are crucial but must be complemented by appropriate institutional conditions. Otherwise, they might have adverse effects and do not unfold their full potential for the power system transition.

The theoretical analyses as well as the numerical simulation employed in this thesis comprise advantages but also caveats. While I analyze specific model limitations in every main chapter, here I discuss some broader implications of using these methods. Theoretical modeling yields very general results that, given the respective assumptions, entail a mathematical truth. The main challenge is to design models in a way that useable and meaningful results can be obtained. While very realistic and complex models often yield no solutions or are not generalizable, extremely simplified approaches are likely not meaningful as they do not sufficiently represent reality (cf. Boulding, 1956). In my theoretical approaches of Chapters 2 – 4, I have therefore focused on specific questions and constructed the models to consider the most relevant aspects in order to answer them. All these chapters provide relevant and useable results on economic mechanisms inherent to power systems. Nevertheless, they also rely on simplifying assumptions and naturally exclude many system aspects. While I am confident that my general results hold for many situations in more complex environments, the reader should be cautious when directly transferring theoretical insights into real-world settings.

The implications differ for the numerical simulation in Chapter 5. Here, the implemented complexity is much higher than in the theoretical models. In general, this allows a more accurate representation of reality, for instance, considering the interactions of multiple technologies and evaluating more nuanced policy options. However, to derive a solution, the model needs to be calibrated which may compromise the validity of results beyond the original scope. Furthermore, the high complexity may impair the view on mechanisms that drive the results. To address this latter issue, I do not only focus on aggregate results on costs and capacities but also analyze more granular data that entails insights on the underlying mechanisms. Nevertheless, the reader should be careful to transfer general insights to other regions with different power system characteristics.

Given the advantages and disadvantages of different methodological approaches, testing hypotheses with various methods increases robustness. For instance, I confirmed some theoretical findings on the interdependence of storage and transmission also by numerical simulation in a more complex setup. Furthermore, it can be helpful to calibrate theoretical models with data to judge whether their findings are empirically relevant as done in Chapters 3 and 4. In doing so, I show that certain combinations of conditions that theoretically yield an unexpected outcome, do actually occur empirically. Thus, it is likely that the theoretical outcomes will also exist under real-world conditions. Lastly, data use can be helpful to derive policy implications and for maintaining the link between theory and reality.

Some of the obtained results can be generalized beyond power systems. The distinction between flexible and inflexible provision of a good, which I make in Chapter 2 is not unique to electricity. It might also occur in transport, telecommunications and food production (cf. Eisenack & Mier, 2018). If then also the endowment with production assets is rigid, i.e., it cannot be optimally adjusted due to high asset specificity and disruptive innovations, my findings might be applicable. Furthermore, insights from Chapter 3 may be transferred to more general storage and transportation problems. A crucial condition is that the respective commodities or goods are subject to periodical price changes along the lines of peak and off-peak electricity provision. Finally, the results on RE support from multiple government levels (Chapter 4) generally hold for impure public goods.

This thesis has substantially advanced the knowledge on power system economics, yet many research questions remain unanswered. From a broader perspective, a highly important and promising avenue for future studies are the interactions between policies and power system flexibility options for the integration of RE. Chapter 5 has indicated the relevance of fitting institutions for the efficient interplay of flexibility options and policies. So far those interactions are often not sufficiently addressed in the scientific literature. Besides that, power system research should put more emphasis on second-best options. In particular, in quickly changing systems like the electricity sector, there are high uncertainties and it is unlikely that transitions happen along cost-minimal paths. Furthermore, many other aspects like strategic behavior or political economy issues likely prevent the implementation of first-best options. Especially if the optimal option is infeasible, research has to provide reasonable alternative strategies and their evaluations.

Only a few years remain to decarbonize power systems in order to achieve the Paris climate goals. Attaining them will require great efforts from engineering, economics and politics and there will be opposition from the beneficiaries of the old system. Fortunately, the recent developments in RE and storage technologies provide hope that the cause is not yet lost. An integrated assessment of the technological options together with the institutional arrangements may set a sound basis for future development. However, unsolved questions and challenges must not be an excuse to delaying the transition. Immediate ambitious action is needed, which should be guided by research that is successively updated to the most recent and most pressing problems. I hope that humanity will succeed in turning the tide to prevent the rapidly approaching climate catastrophe and that this thesis might be of use for these efforts.

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