A guideline through complexity: assessing security of electricity supply

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Complexity in energy systems is increasing. In this context, I ask whether more complex models are superior per se to provide a sound basis for decision making processes. I start with comparing two modeling approaches to assess the security of electricity supply with different levels of complexity as a case study: deterministic capacity balances and probabilistic simulations. Then, I abstract the findings by introducing a mathematical framework to determine the optimal level of detail for a modeling approach. Using this framework, I demonstrate that the optimal model design is not reached by ever increasing model complexity, but by maximizing the net benefit of a model considering the interpreters of the results. Further, I provide a stepwise approach using guiding questions to achieve this optimum. I summarize my findings as complexity dilemma: the more sophisticated the prevailing research question, the greater the need to depict the details of the underlying system, leading to more complex modeling approaches, but the less stable (well-conditioned) and traceable the model outcome is, due to prevailing uncertainties regarding input data, and the more costly sensitivity analyses become.

Keywords

security of supply; energy system modeling; complexity; uncertainty

JEL classifications

C15, C18, C52, C63, Q40

Abbreviations

ARM	*Adequacy Reference Margin*	*LoLP*	*Loss of Load Probability*
BNetzA	German Federal Network Agency	MAF	Mid-term Adequacy Forecast
entso-e	European Network of Transmission System Operators for Electricity	NTC	Net Transmission Capacity
LoD	*Level of Detail*	*RAC*	*Reliable Available Capacity*
LoLE	*Loss of Load Expectation*	*RC*	*Remaining Capacity*
		TSO	Transmission system operator

Indices

i	Power plant block	t	Time

Formula symbols

β	Benefit	c	Cost

1 Introduction

The results of energy system analyses are often used to provide a sound basis for political discussions and to enable evidence-based decisions. According to Bale et al. (2015), current developments in energy systems increase the complexity of both energy systems and energy system models, resulting in the need to transfer insights from the field of complexity science to energy system modeling. Within the field of tension between complexity and accuracy, the appropriate level of modeling complexity needs to be chosen with care. There is the need not to exaggerate simplifications (Stirling, 2010), but also to be sparse with resources leading to the overall goal of parsimony in energy system modeling (DeCarolis et al., 2017). Further, studies from different fields of research have revealed that modeling with a higher degree of complexity does not necessarily lead to more accurate model results (see Orth et al., 2015; Li et al., 2015; Priesmann et al., 2019).

In this context, I ask whether more complex modeling approaches to analyze energy systems provide additional benefits for the interpreters of results *per se* or if they come with drawbacks that need to be born in mind when applying the models and interpreting the results. The motivation behind this is the experience that modelers in the field of energy system modeling tend to keep expanding the complexity of their models to depict more details of the modeled energy systems while decision makers from policy and industry tend to rely on the results of ever more complex models – often even without asking for potential limits.[1] I am challenging this view.

To provide tangible insights and to make my trains of thought traceable for the reader, I start by comparing two modeling approaches to assessing security of electricity supply at different levels of complexity as a case study: rather straightforward *deterministic capacity balances* and quite complex *probabilistic simulations*. By implementing, applying, and comparing both models, I

[1] A recent example for this is the call by European Commission (2016) to solely rely on probabilistic methods for the assessment of security of electricity supply on a European level.

create the necessary foundation for the next step: abstracting the findings from the field of security of supply assessments to more general statements regarding energy system modeling and introducing a mathematical framework to derive the optimal *Level of Detail (LoD)* for modeling approaches.

Overall, my research goal is to generalize findings from the field of security of supply assessments and to offer answers to the following guiding research questions:

(1) What are the benefits and drawbacks of more complex models to provide policy-relevant insights in the field of energy sciences?

(2) *How can an optimal level of detail for an energy system model be defined?*

Thus, my research addresses the call by Bale et al. (2015) to transfer insights from complexity science to the field of energy system analysis. As the optimal model design strongly depends on the prevailing research questions, I provide a stepwise approach to reach the optimal level of detail for individual applications.

Assessing the security of electricity supply in central Europe represents a particularly interesting case study as a starting point to assess the complexity of energy system models. One reason for this is that discussions on future levels of security of electricity supply in many central European countries such as Germany are currently gaining momentum due to a domestic nuclear phase-out by 2023 and planned reductions in capacity of coal-fired power plants over the next 18 years, combined with capacity reductions in neighboring countries (Nolting and Praktiknjo, 2020). Another reason is the complexity of the real-world system that can be concluded from its high degree of *variety* (the amount and kind of elements in a system), *connectivity* (amount and kind of relations between elements), and *dynamics* (unpredictability) according to complexity management literature (Klabunde, 2013, p. 6)[2].

[2] The roots of complexity management in economics lie in the so-called *St. Galler Managment Concept* by Schuh et al. (1998).

For the case study, I define future scenarios for the analysis of security of electricity supply in Germany, while accounting for import capacities from neighboring countries: In the *base scenario*, the security of supply situation in Germany in 2023 is examined, taking into account the decision to phase-out nuclear energy. In the *reduction scenario*, additional reductions in coal-fired power plant capacities of 8 GW are included, reflecting current reduction plans over the course of decarbonization. The comparison of these two scenarios and the investigation of the impact of uncertain input data allows a comprehensive and tangible evaluation of the methods and provides the necessary basis to abstract to more general conclusions regarding the efficient complexity of modeling approaches. The remainder of this paper is structured as follows. In section 2, I provide a literature review on relevant definitions of complexity and the current state of the art regarding the assessment of security of supply. In section 3, I briefly introduce the methods of conducting deterministic capacity balances and probabilistic simulations. In section 4, I summarize central assumptions and input data for the comparison. The results of both methods are demonstrated in section 5. Then, I discuss the influence of uncertain input data in section 6. In section 7, the findings of the model comparison are summarized and an abstract mathematical model to define the optimal level of detail as well as a guideline to achieve this level are introduced. Section 8 concludes the paper and provides policy recommendations.

2 Literature background

The literature section is organized in two sub-sections: First, I provide a short overview of relevant literature regarding complexity in energy system modeling. Second, I summarize recent studies focusing on the assessment of security of electricity supply.

2.1 Complexity in energy system modeling

The goal of this section is to shed light on the current state of the art regarding research on complexity and to carve-out possibilities for its transition to the field of energy sciences. Therefore, I will introduce relevant terms from system theory, then identify energy systems as special kind of systems, and finally summarize recent literature on complexity[3] in energy system models.

Literature on general system theory (see e.g. Bertalanffy, 1950; Straussfogel and Von Schilling, 2009) defines systems as complexes of interacting elements and demonstrates that a system cannot be described by its elements alone. Today, this property is referred to as *emergence*. In his Nobel lecture, Laughlin (1999) states that by looking at individual elements of systems, the behavior of the overall system is in many cases not recognizable and thus the physical reductionist idea is "wrong a great deal of time, and perhaps always" (Laughlin, 1999).

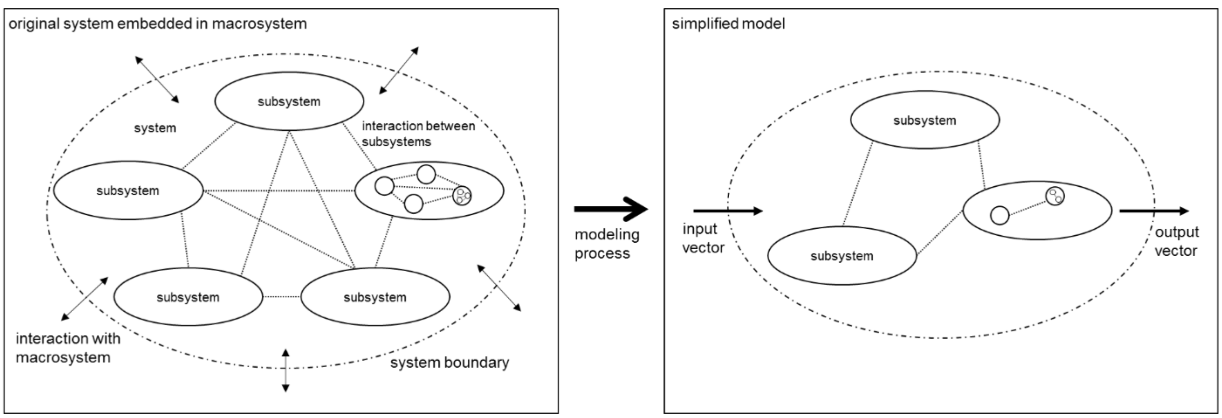

Figure 1: Illustration of modeling process as abstraction from the underlying system

In the view of system theory, energy systems represent one particular category of systems. As experiments on energy systems themselves are often not possible or only possible at very high cost, energy system models are tools that are frequently used to analyze the systems' behavior.[4] As has been argued by Bale et al. (2015), energy system models need to meet the requirements of scientific methods to provide insights in the system under investigation: they need to be *purposeful*, *repeatable*, *unbiased*, and make a *novel contribution*. Overall, energy system models

[3] Complexity needs not to be mistaken by the term complicated. While the latter mainly refers to the size of a model (e.g., measured by the number of variables and equations), complexity is a much more comprehensive concept.

[4] For an overview on different types of energy system models and a possible categorization, see e.g. Winkelmueller (2006), Ma and Nakamori (2009), Lund et al., (2017), Subramanian et al. (2018), and Ridha et al., (2020).

are an attempt to serve a purpose (i.e. answer a specific research question) by representing the most relevant parts of the analyzed systems and introducing necessary simplifications. Hence, the model tries to depict the emergent behavior of the energy system under investigation (i.e., output variables) and its dependence from external circumstances (i.e., input variables). Figure 1 illustrates this relationship.

When abstracting from the original system to energy system models, a trade-off between the *complexity* of the modeling approach and the *accuracy of results* arises. This trade-off has, e.g., been analyzed by Bale et al. (2012) leading to the conclusion that complexity also influences the communicability of results to a non-scientific audience (e.g., policy-makers). Additionally, some recent studies analyzed the trade-off between accuracy and complexity of energy system models with a particular focus on optimization models (DeCarolis et al., 2017; Priesmann et al., 2019). These studies did not find a general superiority of more complex models. This is in line with findings from other fields of research that have demonstrated overfitting in cases where input data is of poor quality (Li et al., 2015; Orth et al., 2015). Another direction of research focuses on finding optimal solutions within the trade-off between computation time (as proxy for model complexity) and accuracy of results (Pollok and Bender, 2014).

Hence, there is some literature on complexity in energy system models. However, a concise methodological comparison in the field of assessing security of electricity supply as well as an abstract mathematical model and a systemic guideline to define and reach the optimal *Level of Detail (LoD)* have not been published to the best of my knowledge. Hence, the prevailing work constitutes a novel contribution.

2.2 Assessments of security of electricity supply

Having introduced basic principles of complexity in energy system modeling, I will now focus on literature regarding the assessment of security of electricity supply, as this lays the basis for the model comparison to be made as a first step before abstracting to a more general level. In principle, two approaches can be distinguished: On the one hand are rather straightforward *deterministic capacity balances* between secured feed-in power and electricity load during the hour of peak load. On the other hand, complex *probabilistic simulations* in hourly resolution are used to determine key figures of supply security under consideration of stochastic influences on (1) the availability of fossil power plant blocks, (2) the fluctuating feed-in of renewables, and (3) electricity load. Both approaches have been applied in various studies by consulting companies, research institutions and transmission system operators (TSOs) in different contexts. Table 1 provides an overview of existing studies, methods used and core results achieved. Figure 2 summarizes the essential characteristics and common implementations of the two model classes. Here, it can be seen that deterministic capacity balances represent rather straightforward, top-down models to derive non-probabilistic key figures such as capacity margins. They are usually conducted for one hour per year (i.e. the hour with the highest electricity load) and consider only one (often worst-case) weather situation. On the other hand, probabilistic simulation models represent rather complex, bottom-up models that are used to calculate stochastic key figures such as expected loss of load durations per year. They are commonly performed in hourly resolution and reflect different weather situations (so-called historic weather years[5]).

From the sheer number of studies, the range of different and often opposing key-findings and the heterogeneity of the authors and principals, it can be concluded that there is a considerable need for a structured evaluation of the methods used. It thus represents an interesting case study and starting point for the investigation of complexity in modeling. Hence, my work contributes to the existing gap of a comprehensive complexity comparison for existing approaches.

[5] A weather year represents the meteorological conditions in an area and is used to calculate weather dependent electricity load and feed-in profiles. See e.g. Behm et al. (2020).

Table 1: Summary of literature review on recent studies in the field of assessing the security of electricity supply

Reference	Methodology	Geographical scope	Time horizon	Key findings
Matthes et al., 2012	Deterministic capacity balance	Germany and neighboring countries	2020, 2030	Focused capacity markets are necessary to ensure security of supply
Frontier economics and Formaet Services, 2014	Probabilistic simulation	Germany and neighboring countries	2013-2035	Energy Only Markets can guarantee security of supply in central Europe
entso-e, 2015	Deterministic capacity balance	European Union	2016, 2020, 2025	High share of RES increases pressure on security of supply
Heddrich and Lenck, 2015	Deterministic simulation (Power2Sim model)	European Union	2023	It is not necessary to maintain power plant capacities as a reserve
Consentec and r2b energy consulting (2015)	Probabilistic simulation	Germany and neighboring countries	2015, 2025	Security of electricity supply is at high levels in future scenarios for 2025
Hobohm et al., 2015	Probabilistic simulation	Central Europe (PLEF region) and neighboring countries	2009-2014 (ex-post), 2030 (ex-ante)	International dependency of security of supply increases
Gils et al., 2016	Probabilistic simulation	Germany and neighboring countries	2020, 2023, 2025	Supply shortages in Northern Germany from 2023 at the latest, in Southern Germany from 2025 at the latest
entso-e, 2017	Probabilistic simulation (Monte-Carlo)	European Union	2020, 2025	International dependency of supply security, supply shortages are expected in Germany in 2025
Agora, 2017	Deterministic capacity balance	Germany	2020, 2023	Security of supply in Germany is not affected if the 20 oldest lignite-fired power plants are shut down
TSOs in the Pentalateral Energy Forum, 2018	Probabilistic simulation	Central Europe (PLEF region)	Winter 2018/19 and winter 2023/24	In winter 2023/24 the security of supply in Germany, Luxembourg and the Netherlands is at risk
German TSOs, 2018	Deterministic simulation	European Union	2018/19 and 2020/21	There is a need for grid reserve beyond 2020
entso-e, 2018	Probabilistic simulation (Monte-Carlo)	European Union	2020, 2025	Supply interruptions are to be expected in central Europe in capacity reduction scenarios
Hufendiek et al., 2018	Probabilistic simulation	Germany (divided into North and South) and neighboring countries	2025	Electricity supply in Germany in 2025 is secured, but Southern Germany will depend on imports
BUND, 2018	Deterministic capacity balance	Germany and European Reserves	2017, 2020, 2023	Significantly accelerated coal phase-out in Germany is possible without endangering the security of supply
Guerrero-Mestre et al., 2018	Probabilistic simulation (Monte-Carlo)	European Union	2025	No supply shortages are expected in most European countries; only Finland, Greece and Ireland will face problems

Deterministic capacity balance

- **Top-down approach**, i.e. the modeling is based on a high emergence level of the system behavior.
- **Low model complexity**, i.e. effort and costs for implementation and computing time are negligible.
- Calculated **key figures of supply security:**
  - ***Reliable Available Capacity (RAC)***: Proportion of the installed capacity that is available to cover load at peak load.
  - ***Remaining Capacity (RC)***: Difference between RAC and peak electricity load. This surplus is available to cover unexpected loads and to compensate for power plant outages that have not been accounted for.
  - ***Adequacy Reference Margin (ARM)***: Percentage of installed capacity that must always be available to ensure security of electricity supply.
- **Common approach**:
  - Focus on **peak load hour**, which is defined in many studies as the 19^{th} hour of the third Wednesday in January.
  - Consideration of one **(worst-case) weather year**.

Probabilistic simulation

- **Bottom-up approach**, i.e. the modeling starts with sub-elements of the overall system.
- **High model complexity**, i.e. significant effort and cost for implementation as well as long computing times despite frequent use of high-performance computers
.
- Calculated **key figures of supply security:**
  - ***Loss of Load Probability (LoLP)***: Probability of load shortfall during the examined hour.
  - ***Loss of Load Expectation (LoLE)***: Load shortfall duration in hours to be expected during the scenario year under consideration.
  - ***Expected Energy not Served (EEnS)***: Amount of energy demand in MWh that is expected not to be covered during a given year.
- **Common approach**:
  - Consideration of **8,760 hours per scenario year**.
  - Analysis of **different weather years**.

Figure 2: Summarizing comparison of modeling approaches. For references, please see Table 1.

3 Methods

Having identified existing research gaps, I now introduce the two different methods to assess security of electricity supply that I use as a starting point for comparing complexity. Here, I provide only short introductions to the methods as the focus of this study is to investigate the complexity of the modeling approaches and to derive optimal levels of complexity rather than introducing two methods for assessing security of electricity supply. For a more comprehensive model description, see Nolting and Praktiknjo (2020). While my study is mostly based on insights form the assessment of security of supply, I will generalize these findings in section 7 and introduce an abstract mathematical framework to approach optimal levels of complexity.

3.1 Deterministic capacity balance

To conduct a deterministic capacity balance, the available domestic electricity supply and the import potential during peak load hour are summed up and compared to the electricity load during this hour. The key indicator, the *Remaining Capacity* (*RC*), can then directly be determined as difference between demand and supply side. A positive sign indicates that excess power is available, whereas a negative sign indicates a supply shortage during peak load hour.

Although called deterministic capacity balances, this method relies on input from probabilistic assessments: an indirectly considered significance level results from the determination of the share of installed capacity per generator type that can be assumed to be available during peak load hour (so-called *capacity credit*). For the calculation of the capacity credits, a significance level $\alpha = 95\%$ is commonly used. The capacity credit per generator type at this significance level is again derived from probabilistic analyses, such as *Monte Carlo* simulations of power plant availability. Portfolio effects must be taken into account, as the joint failure of many small generation units is less likely than the non-availability of one large unit. Using $\alpha = 95\%$, I derive the capacity credits as shown in Table 2.

Table 2: Capacity credit per generator type, i.e. the share of installed capacity that is available during peak load hour at a significance level of $\alpha = 95\%$

Nuclear	**Natural gas**	**Distributed generation**	**Hard coal**	**Lignite**	**Oil**	**Waste**	**Other fossil fuels**
0.95	0.91	0.80	0.91	0.92	0.95	0.86	0.93

Run-of-the-river	**Hydro pump storage**	**Wind**	**Photovoltaics**	**Biomass**	**Battery storage**
0.30	0.80	0.07	0.00	0.65	0.50

As can be seen in Table 2, the share of photovoltaics that are available to cover peak load emerges to be 0%. This is due to the fact that the peak load hour in most central European countries occurs after 5 p.m. in the months of November, December, or January. Therefore, no yield from solar generation units is expected. The available contribution of wind turbines during this time is 7% of the installed capacity.

To account for import potentials, national capacity balances are conducted for all central-European countries with direct electrical connections at the time of German peak load. This procedure leads to national balances shown in Figure 3. When calculating the import potential in Germany, the bilateral interconnection capacities (Net Transfer Capacities, NTCs) were taken into account (entso-e, 2018).

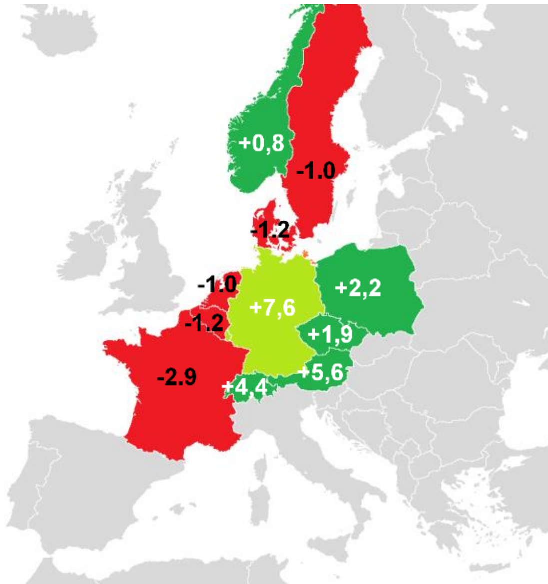

Figure 3: National capacity balances in GW as well as secured import capacity for Germany during peak load hour taking into account bilateral Net Transfer Capacities (NTCs)

3.2 Probabilistic simulation model

For the probabilistic assessment of security of electricity supply, (1) the distribution function of the availability of power plant capacities and (2) the residual load (i.e. the difference between electricity load and feed-in of renewable energies) are determined in hourly resolution. From the intersection of the curve of the distribution function with the residual load, the probability of covering the electricity load can be determined for each hour of the year. This relationship is illustrated in Figure 4. In the example shown, the probability of covering the load is 80%. The *Loss of Load Probability* (*LoLP*) is defined as the counter probability to this and emerges as 20%, here.

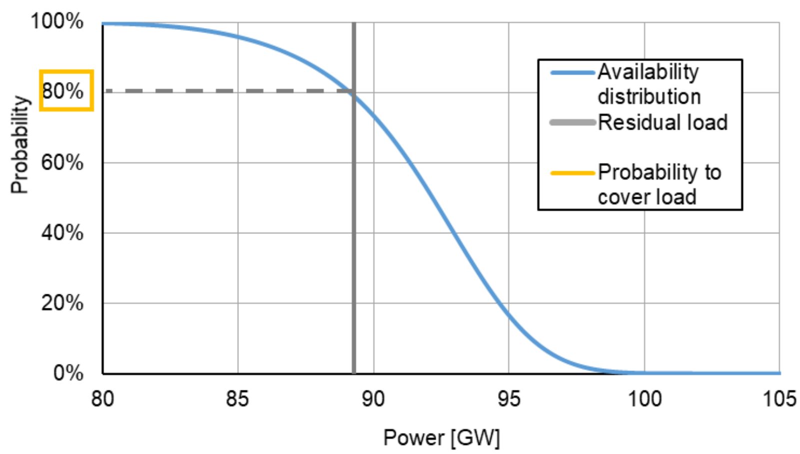

Figure 4: Determining the probability to cover load.

To determine the distribution function marked blue in Figure 4, the probability of non-availability of a single power plant block following a *Bernoulli Distribution* is derived based on its probability of planned non-availability and the probability of unplanned non-availability during the course of a year. Then, the overall distribution at system level needs to be determined by aggregating the single units' outage probabilities. I apply the mathematical concept of *recursive convolution* for this operation (Billinton et al., 1996; Brückl, 2006). Other approaches such as *Monte Carlo* simulations aim at the same goal of representing the system's emergent behavior based on the non-availability probabilities on single power plant units. As the *recursive convolution* allows for an exact representation of the system's availability distribution, this approach is used here. By using high-performance computers and parallelizing the program code, an average runtime of ~2.5 hours for the scenario year considering all 30 weather years could be achieved. Further investigations have shown that an additional reduction of runtimes can be achieved by using tailor-made metamodels and approximations (Nolting et al., 2020). In order to avoid a distortion of the comparison due to the approximation error associated with this, the results of the exact calculations are presented below. Overall, hourly fluctuations occur on both the load and the feed-in side, which must be taken into account in the simulation model and thus require an hourly resolution: (1) fluctuations of the electrical load due to calendar effects, (2) fluctuations in the feed-in of renewable energies, (3) variation of the non-availability probability of freely dispatchable power plant units. This relationship is illustrated in Figure 5.

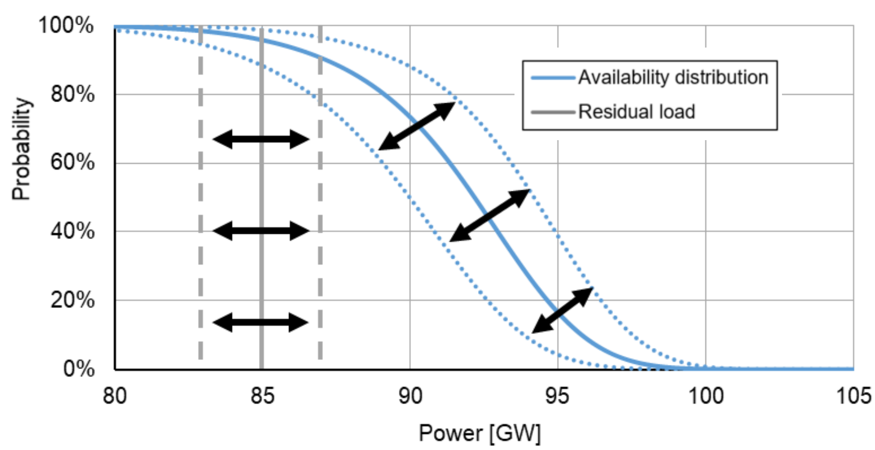

Figure 5: Time dependency of availability distribution and residual load.

4 Central assumptions and model input data

To allow for a fair comparison of the methods to assess security of electricity supply, I make use of a common data basis and define a relevant *case study*. As mentioned in the introduction, I carry out a scenario analysis for the year 2023 as the basis of the complexity comparison. For this, I define two scenarios: The *base scenario*, which includes all reductions already planned in the fossil fuel power plant park and the nuclear phase-out in Germany by the end of 2022; and the *reduction scenario*, which, based on the proposals of the Commission on Growth, Structural Change and Employment (2019) and the Coal Exit Act currently in the legislative process (German Government, 2020), takes into account an additional reduction of coal-fired power plant capacities of 8 GW. To keep the results traceable, only publicly available data sets from established institutions that can be considered unbiased are used for both models. The following four sources serve as the main data basis: the Network Development Plan by German transmission system operators (BNetzA, 2017), the Mid-term Adequacy Forecasts (MAF) for 2016 and 2017 published by the European Network of Transmission System Operators for Electricity (entso-e, 2017, 2016), and the German Federal Network Agency's block-mapped list of power plants (BNetzA, 2018a).

4.1 Domestic capacities per power plant type

For the currently installed capacities per power plant type, the block-mapped list of power plants by Federal Network Agency (BNetzA, 2018a) was used. Future planned extensions and deconstructions were taken into account in accordance with BNetzA (2018b). In addition, an expansion path for combined heat and power units according to BNetzA (2017) was included. The expansion path for renewable energies in Germany is based on the data used in the MAF 2018 (entso-e, 2018). The power plant park used in the modelled scenario year 2023 for Germany is shown in Figure 6.

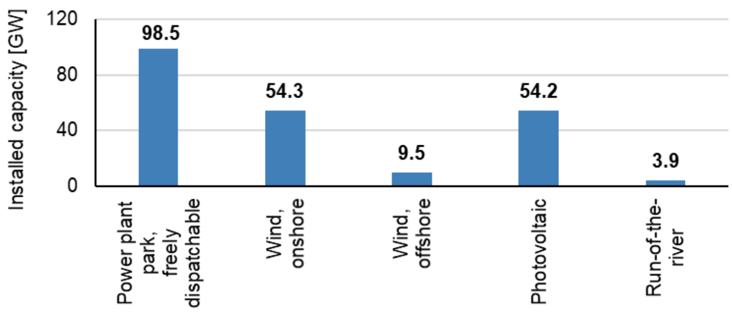

Figure 6: Installed capacity in Germany in year 2023, base scenario

4.2 Electricity load

To simulate the temperature dependence of electricity loads, country-specific polynomial regression functions were derived using the approach used by entso-e (2017). These functions reflect the relationship between electricity load and the outdoor temperature. Using this relationship, load curves for temperature data of 30 weather years (1986-2015) were generated.

4.3 Feed-in time series from renewable energies

To model the feed-in of fluctuating renewable energies, two data sets developed by the Joint Research Centre of the European Commission are used (González Aparicio et al., 2017, 2016). These data sets comprise standardized hourly feed-in hydrographs for wind (offshore and onshore) and photovoltaic for 30 weather years (1986-2015). In addition, data from the European Union's Earth Observation Program (Copernicus, 2018) were used for the daily feed-in of run-of-river power plants. Based on these time series and the assumed installed renewable energy capacities for the scenario year (see Figure 6 and Figure 7), the feed-in hydrographs were derived for all weather years.

4.4 Import potentials

For the installed renewable energy capacities in central-European countries, the same data source as for Germany was used (entso-e, 2018) to ensure consistency. For the installed capacities of controllable power plants, the data set of MAF 2017 (entso-e, 2017) was initially used. Due to major changes in the data basis in the later MAF 2018 report (entso-e, 2018), the effects of these adjustments are discussed separately in section 6. Installed capacities in central-European countries are shown in Figure 7.

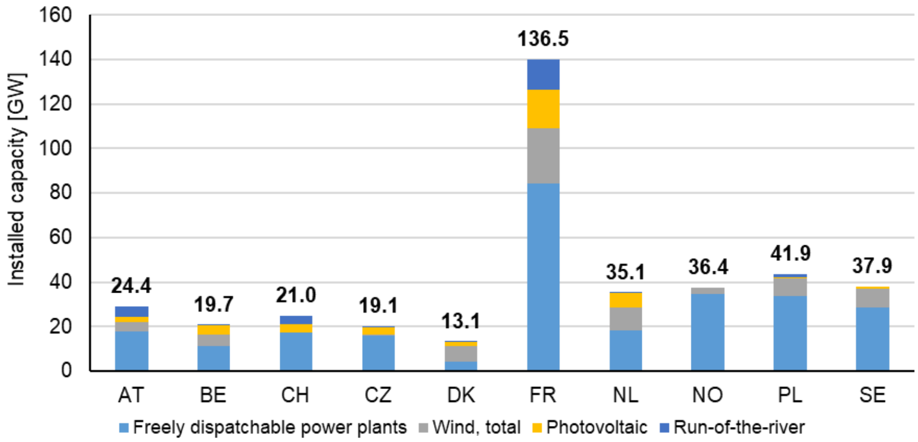

Figure 7: Installed capacity in central-European countries in 2023.

5 Results

Having briefly introduced both approaches to assess security of supply and having shown the most relevant input data for the case study, the results using both methods are shown in the following.

5.1 Deterministic capacity balance

Using the input data described in section 4 and applying the method as introduced in section 3.1, I derive the capacity balance as illustrated in Figure 8 for the *base scenario.* It can be seen that in the *base scenario*, taking all relevant influencing factors into account, there is a supply surplus of 6.4 GW at a significance level of $\alpha = 95\%$. It is also evident that the secured import capacity of 7.6 GW during the peak load hour is needed to meet the demand for power, as the national power supply of 89.2 GW would not be sufficient to cover the demand of 90.5 GW.

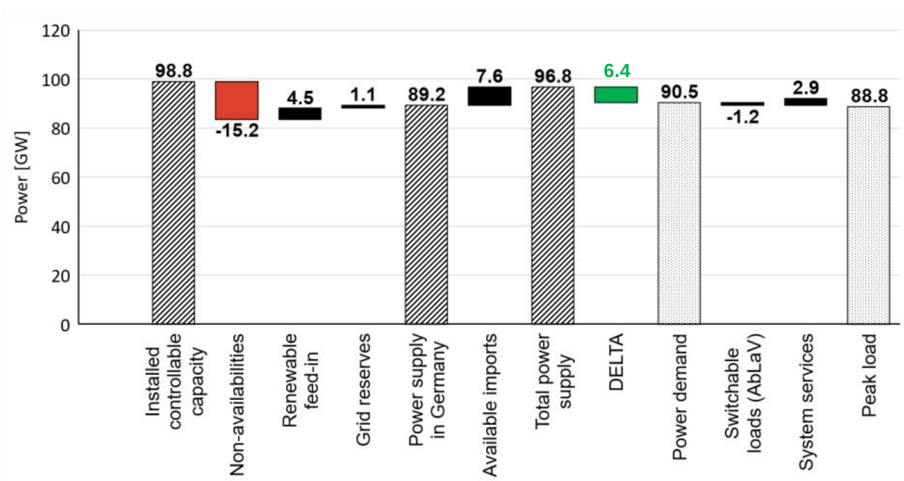

Figure 8: Deterministic capacity balance for Germany in 2023, base scenario

In the *reduction scenario*, taking into account an additional shutdown of 8 GW of coal-fired power plant capacity, I determine the capacity balance as shown in Figure 9. I find that in the case of a reduction, there is no longer a surplus of services at a significance level of $\alpha = 95\%$. This implies that the probability of a capacity shortage during the peak load hour exceeds 5%. Here, changes in the model results can directly be traced back to their origin in the input data.

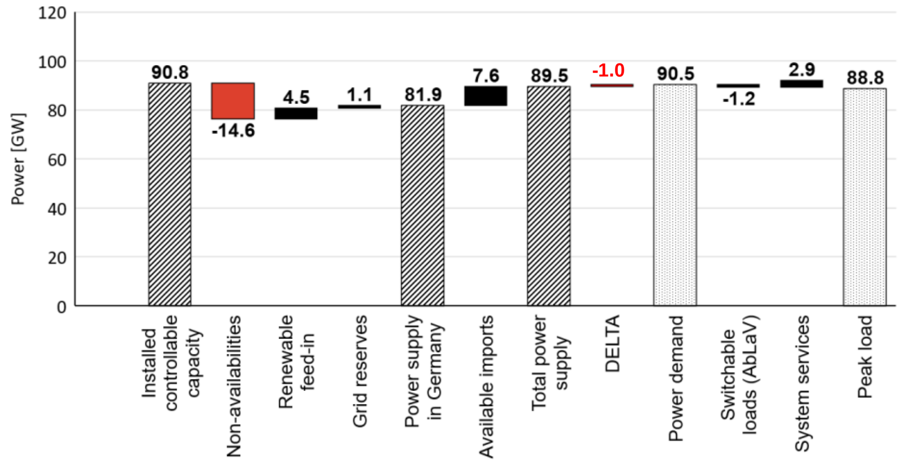

Figure 9: Deterministic capacity balance for Germany in 2023, reduction scenario

5.2 Probabilistic simulation model

Having shown the results of the deterministic capacity balance, I now present the outcomes of the probabilistic simulation model when applied to the case study under investigation. Table 3 shows relevant statistical parameters of the *Loss of Load Expectation* (*LoLE*) representing the main model output. Boxplots were chosen to visualize the resulting distributions in Figure 10, as they provide a condensed representation of the *LoLE* distribution over the weather years.

The results for the *base scenario* for the year 2023 do not imply any shortages to be expected. This result is in line with the core statement of the deterministic capacity balance shown in Figure 8 that there is surplus supply during peak load hour. For the *reduction scenario,* a mean *LoLE* of 0.3 h and a maximum *LoLE* of 2.6 h for a worst-case weather year also agrees with the negative sign of the capacity balance shown in Figure 9. In addition, the results of the simulation model demonstrate that on average, supply shortages are rather unlikely, although they may occur more frequently under unfavorable weather conditions. However, the model results are not traceable to the same extent as for deterministic capacity balances.

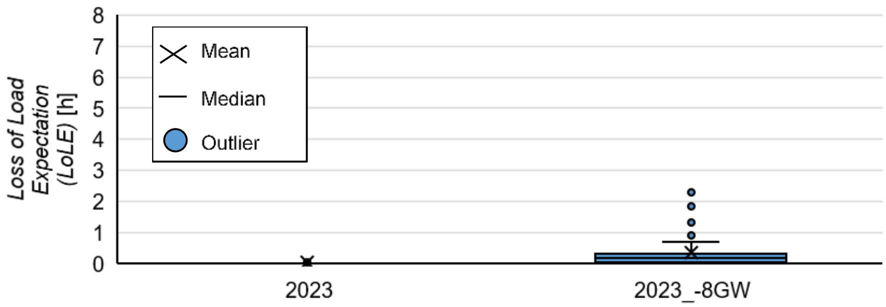

Figure 10: Presentation of the results of the probabilistic simulation model in boxplots, base scenario (left) and reduction scenario (right) for all 30 weather years under investigation

Table 3: Loss of Load Expectation (LoLE) in h, determined by probabilistic simulations

	Base scenario	**Reduction scenario**
Maximum	0.1	2.6
Third quantile (Q3, 75%)	0.0	0.3
Mean	0.0	0.3
Median (Q2, 50%)	0.0	0.1
First quantile (Q1, 25%)	0.0	0.0
Minimum	0.0	0.0

6 Discussion on uncertain input data

To extend the scope of the concrete model comparison I now investigate the influence of uncertain input data on the models' results. The results shown in section 5 are based on import capacities, which were calculated for the year 2023 on the basis of the installed capacities in Germany's neighboring countries as published by entso-e in the Mid-term Adequacy Forecasts (MAF) in 2017. Figure 11 illustrates the changes in the data basis in the MAF of 2018 published thereafter in relation to the data set according to MAF 2017.

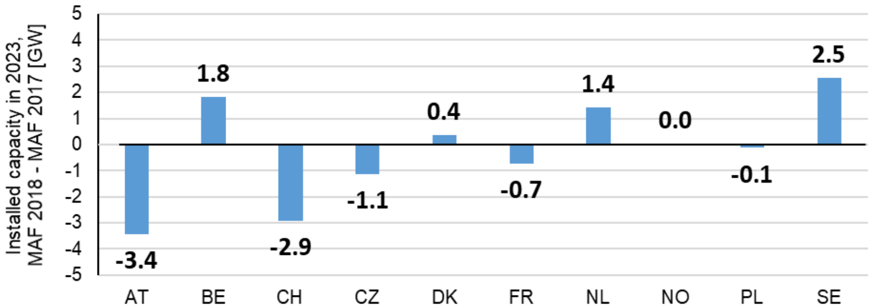

Figure 11: Changes in installed capacity in scenario year 2023 in MAF 2018 relative to MAF 2017

It is evident that substantial changes in the installed capacity of central-European countries occur when comparing the forecasts published in MAF 2018 to those of MAF 2017. In response to a written request, an entso-e representative stated that these changes were not the result of errors in the published data sets, but rather due to improved information availability. This reflects the uncertainty of the relevant input data for the investigated case study. Figure 12 illustrates the effect of the change in the data situation on the import surpluses or shortfalls of neighboring countries and the guaranteed import capacity in Germany at the peak load hour in the scenario year 2023.

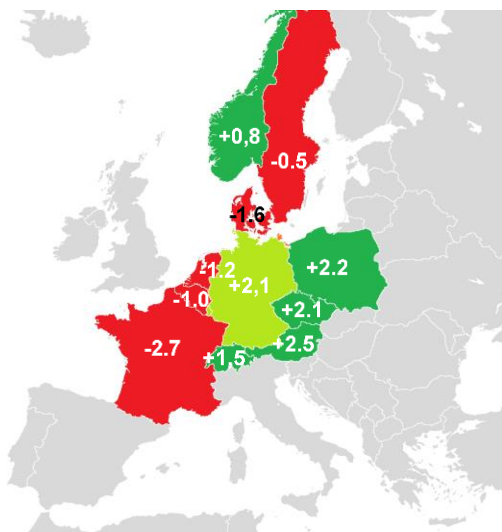

Figure 12. National power balances in GW as well as secured import capacity for Germany at peak load hour under consideration of bilateral NTCs, based on the new data set according to MAF 2018

It is evident that instead of the previously found import capacity of 7.6 GW (see Figure 3), only 2.1 GW of excess electricity available for import remains during peak load hours. This is taken as an example of the uncertainty of relevant input data. There are additional uncertainties regarding (1) the future electricity load on a domestic and international level, (2) developments of domestic supply capacity, and

(3) developments of transfer capacities. The effects of the change in input data on the modeling results are described as examples for both methods for the case of international capacity developments.

6.1 Modification of results: deterministic capacity balance

Figure 13 shows that the reduction in available import capacity from 7.6 GW to 2.1 GW substantially lowers the power surplus in the *base scenario* for 2023, but does not reverse the sign.

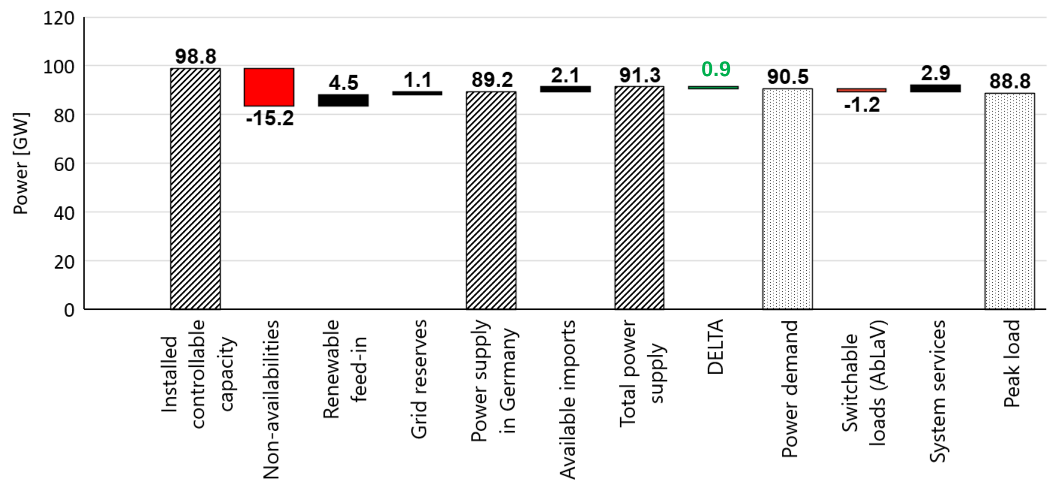

Figure 13: Deterministic capacity balance for Germany in year 2023, base scenario. Considering the new data according to MAF 2018

For the reduction scenario, Figure 14 shows that the existing power shortfall is increased from 1.0 GW (see Figure 9) to 6.5 GW when using the new data set according to MAF 2018. Here too, the effects of reduced import availability for the case study are directly reflected in deterministic capacity balance.

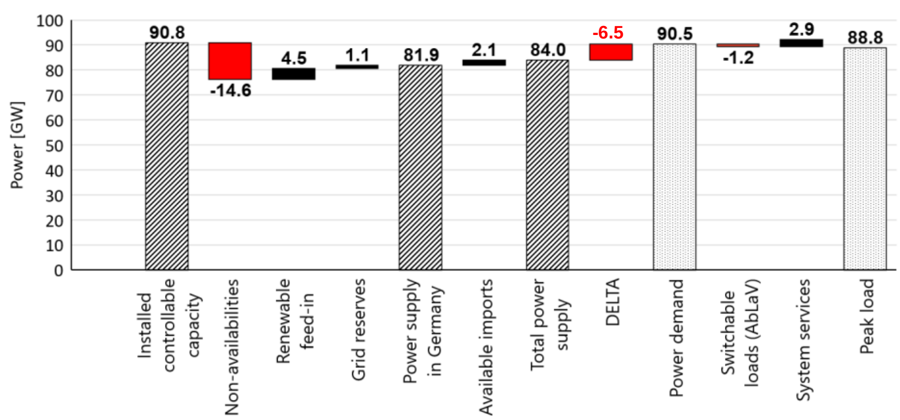

Figure 14: Deterministic capacity balance for Germany in year 2023, reduction scenario. Considering the new data according to MAF 2018

6.2 Modification of results: probabilistic simulation model

So far, I have presented the effects of the changed data basis on the results of the investigated case study using deterministic capacity balances. This section will evaluate the new results on the basis of the probabilistic simulation model.

Figure 15 and Table 4 summarize the results obtained by probabilistic simulation based on the new input data.

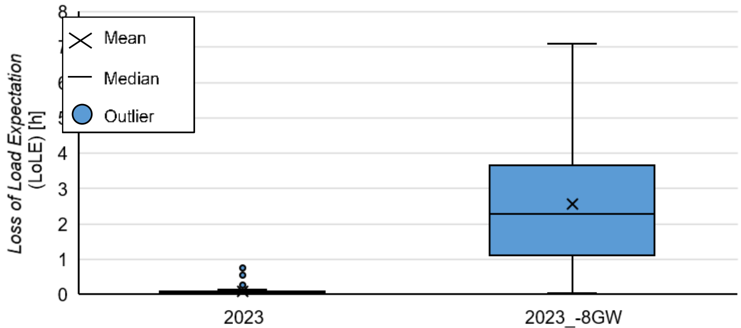

Figure 15: Presentation of the results of the probabilistic simulation model in boxplots, base scenario (left) and reduction scenario (right), consideration of the new data set according to MAF 2018.

Table 4: Loss of Load Expectation (LoLE) in h, determined by probabilistic simulations based on new input data according to MAF 2018

	Base scenario	Reduction scenario
Maximum	0.8	7.1
Third quantile (Q3, 75%)	0.1	3.5
Mean	0.1	2.6
Median (Q2, 50%)	0.0	2.3
First quantile (Q1, 25%)	0.0	1.2
Minimum	0.0	0.0

There are now substantial changes for the *base scenario* when the new input data is applied. In accordance with the results of the deterministic power balance (see Figure 14), even for worst-case weather years a *LoLE* of less than one hour can be expected. However, the absolute level of security of supply is unlikely to be maintained and an influence of the weather conditions on the supply security becomes apparent.

The changes in the results for the *reduction scenario* are much more severe: While a maximum *LoLE* of 2.3 h was to be expected even in worst-case weather years using the old data basis based on the MAF 2017, *LoLEs* of up to 7.1 h in the worst-case and 2.6 h emerge on basis of the new MAF 2018 input data set. This indicates a significant deterioration in the supply security situation for the case study under investigation.

In contrast to the deterministic capacity balance, the probabilistic simulation does not allow the direct traceability of the effects. The results also show that a tipping point is reached in the *reduction scenario* causing the model results to react highly sensitively to changes in the input data. The complexity of the model as well as the *a-priori* unforeseeable and highly non-linear relationship between input and output data makes it difficult to interpret the results depending on the uncertainties on the input data side.

7 A comprehensive guideline through complexity

Based on the application of both modeling approaches to assess security of electricity supply to a case study and the discussion regarding uncertain input data, in the following paragraphs I first conduct a comprehensive comparison of the two modeling approaches. I then abstract and generalize the findings by introducing a mathematical framework to derive the optimal *Level of Detail (LoD)* of a modeling approach in the field of energy sciences that provides most insights for the interpreters of the results and offer a guideline to reach this level.

7.1 Comparison of modeling approaches used in the case study

I organize the following comparison according to relevant modeling steps: from the first (implicit) assumptions, to the analysis of effects of uncertain input data and discussions on potential model expansion.

(Implicit) assumptions

For deterministic capacity balances, it is implicitly assumed that the peak load hour represents the system's critical state. This might not be the case for energy systems with high shares of renewable supply, where hours with high *residual load* might be more critical for the supply of electricity. Further, the implicit significance level of $\alpha = 95\%$ for the calculation of capacity margins gives the results of deterministic capacity balances a stochastic character that is often not mentioned. In fact, the available capacity used in deterministic capacity balances represents a point on the probability distribution (i.e. the available capacity at a probability of 95%) during peak load hour used in probabilistic simulations. It can thereby be defined as a reduced *submodel* of the more complex approach with a lower *Level of Detail (LoD)*. Probabilistic simulation models also use (implicit) assumptions: potential grid bottlenecks on a national level are neglected (so-called copper plate assumption), international power flows are limited by bilateral NTCs, the number of countries under consideration is often limited to reduce complexity and modeling effort, and the probability of weather years is assumed to follow a uniform distribution. Thus, probabilistic simulation models abstract from physical load flows and from changes in the probability distribution of weather years (e.g. due to climate change). Overall, both methods abstract from the real-world system, but probabilistic simulation models depict a more comprehensive picture as deterministic capacity balances can be defined as submodels of such simulations.

Data collection and preparation

To conduct deterministic capacity balances, comprehensive data acquisition on future installed capacities and loads is required. This constitutes a substantial part of the modeling effort. Further, capacity credits need to be derived using probabilistic methods. Input data can be directly used for the modeling procedure as it only needs to be summed and compared for the capacity balances. For probabilistic simulation models, additional time series on the feed-in of renewables, electricity loads, and the probability for non-availability of generator units need to be acquired. Further, comprehensive data preparation is needed to use input data at the interfaces provided by the model.

Model implementation

Deterministic capacity balances require a negligible implementation effort, since the modeling is essentially limited to setting up spreadsheet calculations of the input data. Implementing probabilistic simulation models, on the other hand, comes with considerable effort. This can e.g. be concluded from the considerably higher number of required variables and equations to mathematically describe the model. Several person-months of programming work must be scheduled and the corresponding cost needs to be considered when deciding to implement complex probabilistic simulations.

Model runs

When conducting model runs, a similar picture emerges: whereas deriving deterministic capacity balance comes with virtually no effort, considerable effort is required for each run of the probabilistic simulation model due to its high computing time per run. Further, the hardware requirements of complex probabilistic simulation models comprise high-performance computing clusters, while spreadsheet calculations needed for the deterministic capacity balance can be performed using standard hardware at no additional cost. For probabilistic simulation models, a trade-off between additional effort for implementing efficient model formulations, approximations, and metamodeling approaches and the effort per model run exists (see Nolting et al., 2020). Here it needs to be decided if additional costs to reduce runtime are overcompensated by the additional benefit of a better executability of the model.

Visualization and interpretation of results

For deterministic capacity balances, the visualization of results also comes with virtually no effort, as the main results can be plotted using rather straightforward balances. Moreover, the main outcome of deterministic capacity balances can be reduced to one figure: the *Remaining Capacity Margin (RCM)*. This allows for an easy interpretation, and therefore the results of deterministic capacity balances are particularly useful for a non-scientific audience. The main outcome of probabilistic simulation models can also be reduced to key figures (such as the *Loss of Load Expectation LoLE),* but their interpretation is more complex: e.g. the *LoLE* only represents the expected shortage duration per weather year, but different weather years are considered in probabilistic simulations, so a probability distribution of results emerges. Boxplots can be used to visualize this distribution, but statistical knowledge is required to interpret the results. Thus, explaining the results of probabilistic simulation models to an audience without in-depth knowledge of statistics might lead to misinterpretations.

Performing sensitivity analyses and investigating the effects of uncertain input data

For deterministic capacity balances, the effects of potential inaccuracies of input data on the model outcome can directly be seen in the model. The number of potential sensitivity analyses is not limited by the modeling effort. For probabilistic simulation models, however, the number of sensitivity analyses is limited by the considerable amount of resources required per model run. This becomes even more severe, as the effects of uncertain input data cannot directly be seen in the model. When the system reaches a *tipping point*, probabilistic simulation models become increasingly *ill-conditioned* causing the model output to react in an unpredictable way to changes in the input data.

<u>*Sustainable model maintenance and potential model expansions*</u>

While deterministic capacity balances only require regular updates of the database with regard to expected installed capacity and load, the maintenance of the comprehensive program code needed for probabilistic models comes at high effort and cost. Therefore, this effort needs to be considered beyond the implementation and runtime of models when choosing the adequate modeling approach.

Potential model expansions for capacity balances comprise the investigation of hours with peak *residual load* beyond the focus on peak load. For probabilistic simulation models, the scope can be expanded by considering more details on the physical load flow on inter-national and intra-national levels.

7.2 General mathematical model to derive the optimal *Level of Detail (LoD)*

The aim of the following section is to abstract from the findings based on the model comparison in the field of assessments of security of electricity supply so as to derive a general mathematical framework to define the *optimal Level of Detail (LoD*)* of a modeling approach. While the idea behind the framework is based on the model comparison and the case study as shown above, it is intended to stand on its own and its generalizability is ensured by the fundamental nature of the findings.

As the *Level of Detail (LoD)* determines the accuracy in which the system under investigation is depicted in the model, it indirectly defines the level of complexity of the modeling approach: the more granular the scale of representing a complex system, the more complex the resulting model. To find the optimal level of detail LoD^*, the net benefit of a modeling approach needs to be maximized. As shown in the case study, more detailed modeling approaches allow for the investigation of more complex research questions. Thus, the benefit $\beta(LoD)$ of a model at a given *LoD* can be defined as the ability to depict the system's behavior closely and to answer prevailing research questions at a given level of complexity. $\frac{d\beta(LoD)}{dLoD} = \beta'(LoD) > 0$ holds, as the usefulness of a model to provide insights on the system and to answer complex research questions increases with LoD. Further, $\frac{d^2\beta(LoD)}{dLoD^2} = \beta''(LoD) < 0$ because the marginal benefits of increasing the level of detail towards answering more complex research questions decrease with the prevailing LoD (a 100% representation of real-world system would not generate any added value). The exact functional relation $\beta(LoD)$ depends on the modelers' and interpreters' preferences and the structure of the underlying system and does not need to be known for the abstract analysis as presented here.[6]

On the other hand, an increasing LoD also comes with costs $c(LoD)$, as found in section 7.1. These costs comprise financial expenditures, the need for additional human resources, and an abstract cost linked to the worse traceability of complex models. This can be expressed as follows:

$$\begin{aligned} c(LoD) = {} & c_{data\ collection\ and\ preparation}(LoD) + c_{model\ implementation}(LoD) \\ & + c_{model\ runs}(LoD) + c_{interpretation\ of\ results}(LoD) \\ & + c_{sensitivity\ analyses}(LoD) \\ & + c_{worse\ traceability}(LoD) + c_{model\ maintanance}(LoD) \end{aligned} \tag{1}$$

Again, the exact functional relation $c(LoD)$ depends on the modelers' and interpreters' preferences and the structure of the depicted system. In general, the derivation of $c(LoD)$, is positive as the cost of a modeling approach strictly increases with the level of detail:

$$\frac{dc(LoD)}{d(LoD)} = c'(LoD) > 0 \tag{2}$$

However, $\frac{d^2c}{dLoD^2} = c''(LoD) > 0$ holds, as the additional cost for depicting details over-proportionally increases with the *LoD* of the prevailing model. Overall, the following optimization problem can be defined and solved:

$$\max_{LoD} \beta(LoD) - c(LoD) \tag{3}$$

$$\rightarrow \ \beta'(LoD) - c'(LoD) = 0 \tag{4}$$

$$\leftrightarrow \ \beta'(LoD^*) = c'(LoD^*) \tag{5}$$

Accounting for the decreasing marginal benefit ($\beta''(LoD) < 0$) and the increasing marginal cost ($c''(LoD) > 0$), this results in the conclusion that the optimal level of detail LoD^* is reached when the

[6] To reflect the modelers' and interpreters' preferences regarding *LoD*, e.g. *Discrete Choice Models* can be used to determine individual utility functions that reflect $\beta(LoD)$.

marginal benefits of increasing the model's level of detail $\beta'(LoD^*)$ correspond to the marginal cost of doing so $c'(LoD^*)$. Eq. 5 reflects the conflict between the goal of parsimony and needed *LoD* as introduced in Section 1. Overall, I have mathematically proven that not the most detailed (and thus, the most complex) model maximizes net benefit, but the one, that reflects a *Level of Detail* where the marginal benefit of increasing model complexity is equivalent to the marginal cost linked to increased complexity, given the modelers' and interpreters' preferences and the structure of the depicted system.

7.3 Stepwise approach towards finding the optimal *Level of Detail (LoD)*

Having introduced a general, abstract mathematical framework to define the optimal *Level of Detail (LoD)* of a modeling approach, I now introduce a stepwise approach towards finding this optimal model design. As this optimum strongly depends on the use case (i.e., the guiding research questions), the approach is based on guiding questions that need to be answered individually. I distinguish three steps as follows:

(1) *Determine additional benefit by increasing the modeled level of detail ($\beta'(LoD)$)*

- To what extent does adding further details provide additional insights?
- Is it sufficient to depict the system's overall emergent behavior to answer the prevailing research question and to provide insights for decision makers from policy and industry or are additional details and a bottom-up modeling needed?
- What preferences towards model complexity do the interpreters of the results have?
- Who is the audience for the results? Does the audience have the possibility and desire to interpret the results of complex modeling approaches?

(2) *Determine dependence of cost on level of detail ($c'(LoD)$)*

- How costly is increasing the level of detail, considering all steps of the modeling chain?
- Is the necessary data available at reasonable cost and sufficient accuracy?
- How complex is the investigated system? Will increasing the *LoD* substantially increase the model's complexity?

- Is the system close to a *tipping point* where increased model complexity might hinder necessary sensitivity analyses and lead to a worse traceability of results?
- Might increasing the complexity of the modeling approach detract from relevant insights due to a worse traceability of the results back to the input data?

(3) *Determine optimal model choice that reflects both the preferences and the cost structure (LoD*)*

- Starting from the simplest possible modeling approach and step-wise increasing the *LoD*: Do the additional benefits of increasing model complexity still overcompensate the cost regarding time, effort and worse traceability of the results?
- Can more straightforward research questions be answered using simpler models to gain a good overview?

8 Conclusion and policy implications

Starting with a comparison of two different modeling approaches to assess security of electricity supply as a case study, I generalized the findings by introducing a mathematical framework that defines the optimal *Level of Detail* (*LoD*)* of a modeling approach. Further, I demonstrated a stepwise approach towards finding this optimal level of complexity based on guiding questions for individual applications.

Overall, I find that complex research questions (e.g., with an intrinsically probabilistic character) require more sophisticated and detailed modeling approaches that come with a higher degree of complexity, as they need to depict a higher share of the real-world system's complexity. To provide an overview of the system's emergent behavior, rather simple approaches are suitable and more complex ones do not *per se* allow for a higher quality of results. Of even greater concern is that highly sophisticated models are often said to provide more reliable outputs, but their dependency on the quality of input data is higher (i.e., $c_{worse\ traceability}(LoD)$ increases), as the case study demonstrated for assessments of the security of electricity supply.

I summarize this as the *complexity dilemma*: the more sophisticated the prevailing research question, the higher the number of details of the underlying system need to be depicted, leading to more complex models. However, the accuracy of complex models highly depends on the quality of input data.

Uncertainties regarding necessary input data for complex models, in turn, are rather high, in particular with regard to future scenarios. Thus, answering complex research questions focusing on future developments is only possible to a limited extent and high levels of uncertainty need to be considered. Complex models cannot compensate for this, and less detailed modeling approaches are sometimes more suitable considering (1) the underlying research question, (2) the quality and availability of necessary input data, and (3) the audience for the results.

My results have substantial policy implications as they suggest not to unconditionally rely on the accuracy of most complex models for decision making: time-intensive and complex modeling approaches do not guarantee reliable predictions of the future when data uncertainties occur. It is *a priori* difficult to predict all consequences of market interventions in complex energy systems even using complex models. Thus, I suggest to use flexible, market-based mechanisms for the integration of externalities to avoid situations in which planned-economy approaches based on model outputs lead to undesired outcomes due to the complex behavior of the modeled energy system. I hypothesize that model outputs can serve as indications for needed market interventions but should not directly be seen as a basis for planned-economy system planning due to the *complexity dilemma*. Investigating this hypothesis and deriving additional valued of flexible policy options opens space for future research on the general applicability of system models in the field of energy sciences and the benefits of flexible market mechanisms that might be used to circumvent the *complexity dilemma* by adjusting to changing real-world conditions.

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