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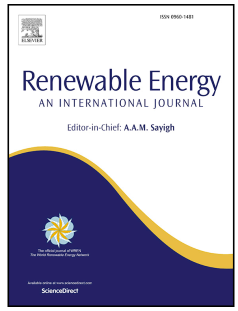

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Merit order or unit-commitment dispatch? How does thermal power plant modeling affect storage demand in energy system models?

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ABSTRACT

Flexibility requirements in prospective energy systems will increase to balance intermittent electricity generation from renewable energies. One option to tackle this problem is electricity storage. Its demand quantification often relies on optimization models for thermal and renewable dispatch and capacity expansion. Within these tools, power plant modeling is typically based on simplified linear programming merit order dispatch (LP) or mixed integer unit-commitment with economic dispatch (MILP). While the latter is able to capture techno-economic characteristics to a large extent (e.g. ramping or start-up costs) and allows on/off decision of generator units, LP is a simplified method, but superior in computational effort.

We present an assessment of how storage expansion is affected by the method of power plant modeling and apply a cost minimizing optimization model, comparing LP with MILP. Moreover, we evaluate the influence of wind and photovoltaic generation shares and vary the granularity of the power plant mix within MILP.

The results show that LP underestimates storage demand, as it neglects technical restrictions which affect operating costs, leading to an unrealistically flexible thermal power plant dispatch. Contrarily, storage expansion is higher in MILP. The deviation between both approaches however becomes less pronounced if the share of renewable generation increases.

Keywords: Renewable energy, storage demand, unit-commitment, economic dispatch, merit order, expansion planning

Contents

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1 Introduction

With growing shares of variable, renewable electricity (VRE) generation in power systems, ensuring sufficient flexibility will play a crucial role as the temporal and spatial mismatch between demand and supply increases. Definitions of flexibility are broad (see Ref. [1], [2], [8]), however, the term is commonly understood as the ability to decouple electricity demand and supply to balance variations in the net load [52] (which, in turn, is defined as the electricity load minus the generation from VRE). It is likely that the temporal variability of VRE generation will go along with an increase in storage demand to prevent the aforementioned temporal mismatch [3], [4], [13], [22], [43]. Moreover, higher shares of VRE generation will require a more flexible operation of thermal power plants to meet steeper net load ramps (see [52]).

1.1 Literature review

Model-based quantifications of future storage demand result in rather diverse ranges (see for example Kondziella and Bruckner [5] or Droste-Franke et al. [6]), depending on the spatial (I), temporal (II), and technological resolution (III) as well as the underlying modeling approach (e.g. for thermal power plant modeling in energy system models).

(I) Spatial resolution refers to the number of model-regions within an observation area. It affects the distribution of generation capacities, power demand as well as the transmission grid topology within the observation area. Required storage capacities have been derived for different observation areas and spatial resolutions[2], e.g. by Brown et al. [7] for a small exemplary region (1), for Texas in Denholm and Hand [8] (1), for California in Solomon et al. [9] (12), for Germany in Babrowski et al. [10] (400), for the U.S. Western Electricity Coordinating Council in Mileva et al. [11] (50), for Europe in Rasmussen et al. [12] (1) and Bussar et al. [13], [22], and for a worldwide analysis in Plessmann el al. [14] (1).

(II) The impact of temporal resolution (hourly vs. sub-hourly or the appropriate choice of representative time periods) in optimization models has been analyzed with regard to ramp flexibility and system costs [15], day-ahead utility scheduling through unit-commitment [16], [17], and for operation scheduling in energy scenarios with high shares of VRE generation [18], [53].

(III) In this study, technological resolution is referred to the way storage is considered in models. The literature ranges from representations of single generic storage [19–21], to storage categories (e.g. short-, mid-, long-term) [22], [23], or to more detailed modeling of actual technologies [24], [25], [43].

As shown, storage demand quantifications underlie various aspects and the understanding of such dependencies and quantifying the amount of storage demand is therefore essential for dimensioning future energy systems. Yet, the influence of assumptions in thermal power plant modeling on storage demand has not been considered so far.

Two main approaches of thermal power plant modeling in optimization models can be found in the literature: Detailed mixed integer linear programming (MILP) approaches that optimize the unit commitment and economic dispatch of the thermal power plant fleet and simplified linear programming (LP)where the dispatch of thermal power plants follows solely the merit order. Both approaches determine the optimal generation schedule, minimizing the operating costs of power plant dispatch, subject to device and operating constraints [26], [28], sometimes denoted as *operating, dynamic* or *unit-commitment constraints*. MILP however, includes integer (or binary) decision variables, allowing on/off consideration of single power plant units or groups, which again enables greater technological detail (e.g. part load efficiencies, ramping behavior, or minimum offline times).

The influence of increasing shares of VRE generation and their effect in different modeling approaches for thermal power plants has been analyzed for example by Brouwer et al. [27] or Abujarad et al. [28]. The former provide a comprehensive overview of how much VRE generation impacts reserve requirements, curtailments of VRE generation, displacement of thermal generator, and resource adequacy. [28] review different approaches for generation scheduling, such as heuristics (e.g. priority lists), mathematical methods (e.g. MILP or LP), or meta-heuristics (e.g. genetic algorithms), providing a qualitative assessment of their advantages and short-comings when considering increasing penetration levels of VRE and storage systems. [28] underscore the importance of storage as an additional flexibility option, that can enable improved power system reliability or smoothing of load patterns. As both [27] and [28] review the current state of research, they cannot, by definition, provide a quantitative assessment how electricity storage demand is affected by the modeling approach for thermal power plants.

Other studies specifically compare linear programming with unit-commitment. Abrell et al. [29] for example, compares various LP and MILP formulations for power plant start-ups and ramping, assessing its influence with regard to power plant dispatch and marginal prices of electricity generation. The latter is also research focus of Langrene et al. [30], who investigate the role of technological detail (*dynamic constraints*) in a MILP approach on marginal prices. Raichur et al. [31] analyze the influence of technological detail (*operating constraints*) in power plant modeling with regard to electricity generation associated emissions for two real power systems (New York, Texas). The study mainly relies on scenario data from the year 2010; it is therefore difficult to transfer their conclusions to power systems with higher shares of VRE generation. Through the implementation of an integrated utility dispatch and capacity expansion optimization tool, Palmintier [58] shows that the importance of technological detail (*operating constraints*) in power plant modeling increases with greater requirements for flexibility owing to higher shares of VRE generation. Neglecting such technical constraints within capacity expansion optimization can lead to sub-optimal generation portfolios. Poncelt et al. [53] compare the utility dispatch through LP (*merit-*

[2] The number of model-regions within the observation area is shown in brackets.

order model) with a MILP model, evaluating whether the influence of the temporal resolution or the influence of the technical detail in power plant modeling is more striking. The analysis is performed for different observation years which, in turn, are characterized by different shares of VRE generation up to 50%. Most recently, Stoll et al. [51] provide a broad comparison of a MILP power plant approach with LP for temporal resolutions of 1h or 5min and for differently sized energy systems (Colorado-based test system versus Western Interconnection model). Using PLEXOS [32], their analysis assesses the impact on production cost, VRE curtailment, CO_2 emissions, and generator starts and ramps. Though comprehensive in terms of evaluated modeling assumptions on various metrics, the study only analyzes the dispatch of an exogenous capacity mix with a relatively low share of VRE penetration (up to 30%). Moreover, the two compared energy systems also show several differences in the relative installed capacity of some technologies (e.g. coal fired power plants, gas turbines). By reason of the latter we argue that some effects therefore cannot be solely attributed to the power plant modeling approach.

1.2 Novelty and contribution

As energy system models become more diverse, their complexity grows, imposing new challenges with regard to computational effort and solution accuracy. As a result, the following questions arise: To which extent do simplifications affect the model's outcome? Under consideration of the model calculation times, which degree of detail is sufficient, without generating large errors? To the best knowledge of the authors, the influence of the modeling approach for thermal power plants on storage demand (i.e. storage expansion) and utilization, especially in highly renewable energy scenarios, has not yet been analyzed. We assume that dynamic behaviors and associated costs of thermal power plants—such as start-ups, ramping and minimum down times—might have an effect on storage demand. Furthermore, we think that a certain amount of resolution with regard to technical parameters of power plants and the number of represented units is needed since neglecting technical restrictions and aggregating too heavily might lead to a significant deviation from the optimal solution. We therefore quantify the future storage expansion in exemplary energy systems, emphasizing the influence of the modeling approach for thermal power plants, the degree of aggregation in a MILP unit-commitment clustering approach and the influence of different VRE and photovoltaic (PV) generation shares.

2 Methodology and data

2.1 The REMix model

We use the linear bottom-up optimization model REMix (**R**enewable **E**nergy **Mix**) which minimizes the total system costs of an energy system under perfect foresight. The system costs are comprised of the annuities of the overnight investment costs of capacity expansion as well the operating costs of the utility dispatch. The latter includes fuel, emission certificates as well as operation and maintenance costs (O&M). The model's decision variables are capacity dispatch and expansion, which are optimized for each model interval. A cross-sectoral approach enables the consideration of the transport, heat and power sector. In this particular application however, we only examine the latter. REMix is developed in the mathematical programming language GAMS [33] and solved with CPLEX [34]. An overview of the model functions is provided by Fig. 1, whereas a detailed model description including the mathematical framework can be found in [35], [45], [49], [56].

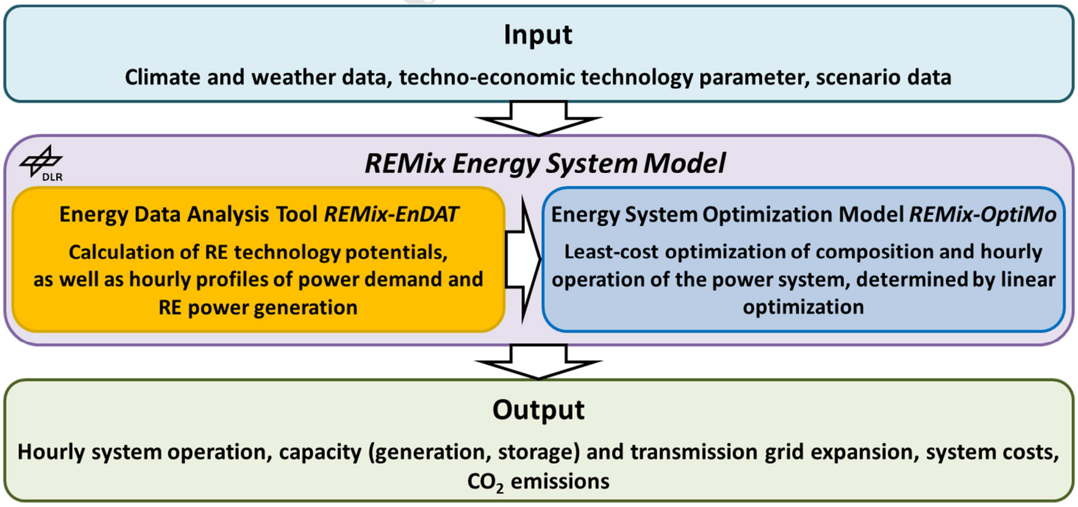


Fig. 1: Principal structure of the REMix optimization model based on [36].

2.2 Power plant modeling in REMix

REMix provides two different methods for thermal power plant modeling: A MILP unit-commitment approach with economic dispatch and a LP merit order method, described subsequently.

The MILP method is based on a piecewise unit-commitment approach as described by Carróin and Arroyo [37]. At the highest level of detail it allows a generation unit specific consideration of the following techno-economic parameters: part load and temperature dependent efficiencies (via a piecewise linear production cost approach), minimum load rates, ramping processes and associated costs, minimum offline and online times, increased fuel usage and respectively increased costs owing to power plant start-ups, different cooling methods influencing the internal consumption (parasitics) of a power plant. Moreover, each power plant (or power block) is characterized by its construction year which allows the consideration of power plant decommissioning based on their technical life-time and construction year based efficiencies. For all MILP model runs a relative MILP gap of 0.01% was used. A more detailed description of this modeling approach can be found in the work of Fichter et al. [38].

The LP approach relies on the merit order and economic scheduling. As for MILP, the dispatch optimization is based on the operating costs (fuel and variable O&M costs, CO_2 allowance certificate costs), including the efficiencies of each technology. Ramping costs are incorporated via costs of power change in terms of wear and tear (€/MW_{el}), whereas the power plant's parasitics are implemented via the ratio of net to gross efficiency. Similar to the MILP approach, power plant technologies are described by their life-time and construction year to include decommissioning and learning curves in terms of efficiencies.

MILP modeling is a suitable method to consider each power plant or power block of an energy system in detail. For complex power systems however, the approach struggles with long calculation times. A self-evident solution to this problem is to reduce the number of binary variables by aggregating single power plants into groups with similar techno-economic parameters. Though computationally efficient, the approach fails to consider minimum load rates and start-up costs properly [58]. All power plants within one group are either on or off, due to the binary variable which describes the unit-commitment for each time step (see [b] in Fig. 2). In consequence, the method systematically underestimates the flexibility of the power plant fleet.

We therefore apply a clustering approach (grouped integer modeling) as described by Palmintier [58], which replaces the binary decision variables with integer commitment variables. The value of the latter describes the number of power plants (or power blocks) within each cluster. Opposed to the classical MILP method (binary variable), the grouped integer modeling allows each power plant to start or ramp down individually (see [a] in Fig. 2).

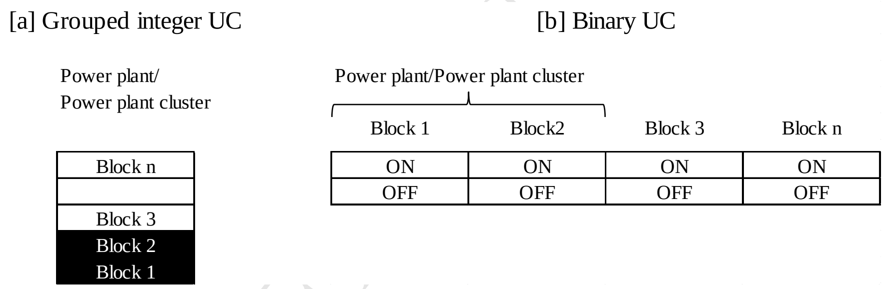


Fig. 2: Comparison of the classical unit-commitment (UC) approach which uses a binary start/stop decision variable [a] and the group integer modeling approach [b]. Figure is adapted from [58].

In this analysis, we use the power plant portfolio of Germany based on the Platts World Electric Power Plants Database (WEPP) of the year 2010 [39] and aggregate each power plant into different groups (cluster) based on their technology type and plant size. We subsequently obtain 15 clusters (see Tab. 1) with an overall installed capacity of 96.18 GW. The clusters encompass fossil fired (lignite, coal, natural gas) and nuclear power plants. Furthermore, we distinguish by technology-specific, typical power plant sizes, i.e. capacity ranges: large, midsize, and small. Within natural gas fired power plants we additionally distinguish between gas turbines and combined cycle power plants (CCGT). All other techno-economic data for fossil and nuclear fired power plants as well as the assumptions regarding fuel prices and CO_2 emission costs can be found in Sec. 2.3.

Tab. 1: Cluster with regard to thermal power plant technology type and plant size.

Technology group	Capacity group	Capacity range [MW]	Number of blocks [-]	Installed capacity [MW]
Nuclear	Large	> 800	17	20,400
Nuclear	Midsize	-	-	-
Nuclear	Small	-	-	-
Lignite	Large	> 800	4	3,800
Lignite	Midsize	400 ≤ 800	18	9,900
Lignite	Small	< 400	74	7,40
Coal	Large	> 550	12	9,000
Coal	Midsize	350 ≤ 550	20	8,000
Coal	Small	< 350	116	11,600
CCGT	Large	> 350	15	6,750
CCGT	Midsize	150 ≤ 350	26	6,500
CCGT	Small	< 150	237	4,740
Gas turbine	Large	> 150	2	400
Gas turbine	Midsize	50 ≤ 150	57	3,990
Gas turbine	Small	< 50	370	3,700
Total			968	96,180

2.3 Scenario assumptions

As the main research focus lies in the analysis of the influence of different conceptual approaches in thermal power plant modeling on storage demand, we do not model a real world energy scenario, but a simplified, hypothetical case study. All dispatch optimizations of the VRE and thermal power plants rely on exogenous capacity mixes, while the storage capacity is endogenously determined by capacity expansion. LP modeling is used for VRE and storage dispatch as well as storage capacity expansion. The thermal power plant modeling on the other hand distinguishes between unit-commitment with economic dispatch (MILP) and simplified merit order dispatch (LP). We assume a single node power system with no transmission to other regions or transmission constraints within the region ("copper plate"). The optimization period is divided into 8,760 hourly chronological time-steps of one observation year. We predefine shares of VRE generation and the ratio of PV-to-VRE electricity generation, subsequently denoted α and β, as described for example in [40–44], [52]. The VRE share α describes the ratio of theoretical annual electricity generation from VRE in relation to the annual electricity demand (see Eq. 2.1). The actual VRE share resulting from the optimization can be lower than the theoretical share owing to curtailments of VRE or storage losses. In this analysis, VRE curtailments are not restricted or associated with any costs. The theoretical PV-to-VRE ratio β is defined in Eq. 2.2.

$$\propto = \frac{\sum_{t=1}^{t=8760} P_{Wind}(t) + \sum_{t=1}^{t=8760} P_{PV}(t)}{D} * \Delta t \qquad 2.1$$

$$\beta = \frac{\sum_{t=1}^{t=8760} P_{PV}(t)}{\sum_{t=1}^{t=8760} P_{Wind}(t) + \sum_{t=1}^{t=8760} P_{PV}(t)} \qquad 2.2$$

where

$P_{Wind}(t)$	Theoretical electricity generation from wind power in each time step *t* [GWh/h]
$P_{PV}(t)$	Theoretical electricity generation from PV power in each time step *t* [GWh/h]
Δt	Length of one time step [h]
D	Annual electrical demand [GWh]

We analyze three main and two sub-scenarios for each main scenario. The main scenarios distinguish between each other by the VRE share α (0.33, 0.66, 1.00), whereas the sub-scenarios are characterized by different PV-to-VRE ratios β (0.4, 0.6).

Exogenously pre-defined generation capacities include all thermal power plants (clustered as described in Sec. 2.2) as well as all PV and wind power capacities, subject to α and β. For the sake of comparing the influence of the power plant modeling approaches, the installed thermal power plant capacity per cluster is identical in all scenarios, although higher VRE shares most likely would imply a change in the power plant portfolio. To derive the cost optimal dispatch of VRE, REMix requires the potential, technology-specific, hourly renewable electricity generation as input. These potential renewable generation time-series are a result of the REMix sub-model EnDAT (**En**ergy **D**ata **A**nalysis **T**ool) and rely on solar irradiation and wind speeds of the weather year 2006, including technical constraints as well as the characteristic curves of wind power plants and PV systems (see [45]). These profiles are scaled with VRE capacities to reach the theoretical VRE share α and the PV-to-VRE ratio β (see Tab. 2). The optimized VRE input is derived from the potential generation less the curtailments.

Tab. 2: Exogenous installed PV and wind capacities for all considered scenarios.

Scenario	PV [GW]	Wind [GW]
$\alpha = 0.33\ \beta = 0.4$	51	63
$\alpha = 0.33\ \beta = 0.6$	76	42
$\alpha = 0.66\ \beta = 0.4$	101	126
$\alpha = 0.66\ \beta = 0.6$	152	83
$\alpha = 1.00\ \beta = 0.4$	153	191
$\alpha = 1.00\ \beta = 0.6$	230	127

For modeling thermal power plants, the analysis includes three fuel price and emission certificate cost variations (see Tab. 3). In the cited sources of Tab. 3, for fuel prices and CO_2 costs, the *low* cost scenarios are used in the scenarios with α = 0.33, *medium* cost scenarios for α = 0.66 and *high* cost scenarios for α = 1.00.

Tab. 3: Fuel price scenarios for each fuel type.

Fuel type	Cost scenario[b]	Fuel costs [€/MWh_{th}]	CO_2 costs [€/t CO_2]	Source
Coal	Low	77	27	[46][a]
Lignite	Low	60	27	[46][a]
Natural gas	Low	76	27	[46][a]
Uranium	Low	3.3	27	[47]
Coal	Medium	117	60	[46][a]
Lignite	Medium	86	60	[46][a]
Natural gas	Medium	113	60	[46][a]
Uranium	Medium	3.3	60	[47]
Coal	High	136	75	[46][a]
Lignite	High	100	75	[46][a]
Natural gas	High	131	75	[46][a]
Uranium	High	3.3	75	[47]

[a] Price path A.
[b] *Low* cost scenario uses the values of the year 2020, *medium* of the year 2040 and *high* of the year 2050 of the cited sources.

High fuel prices might trigger a reduction in the number of CO_2 emissions certificates since they can lead to a decrease in the utilization of thermal power plants. As a result, decreased utilization of thermal power plants will increase the number of available emission certificates which lowers their costs. However, in this analysis, we do not consider such inter-dependencies for the cost assumptions. The techno-economic parameters of thermal power plants for the LP and MILP modeling approach can be extracted from Tab. A 1 and Tab. A 2 in the Appendix. Note that the MILP modeling approach requires more parameters, as its degree of detail is much higher than the LP approach.

The model uses an hourly load profile of Germany for the electricity demand, based on the load profiles from 2006 of the European Network of Transmission System Operators for Electricity (ENTSO-E) [48] and are scaled with an annual electricity demand of 500 TWh.

For storage expansion the model is only allowed to invest in one representative technology, whose techno-economical parameters are loosely orientated on the characteristics of stationary lithium-ion-batteries (Li-ion), assuming a significant decrease of power (converter) and energy (storage unit) related investment costs. The expansion of storage is based on a LP approach in all model runs. REMix optimizes the storage dispatch and furthermore allows for an individual and independent dimensioning of the storage converter size (kW_{el}) and the storage unit capacity (kWh_{el}), implying no pre-defined storage-unit-to-converter ratio (E2P). The E2P value describes the time in hours the storage needs for a complete cycle with its nominal power and allows an identification whether a storage technology is mainly used for short, mid or long-term applications. A detailed description of the methodology for storage modeling is provided in Scholz et al. [49], whereas the main techno-economic parameters are shown in Tab. 2. No constraints regarding the technical potential (both maximum installable converter power and storage capacity) for Li-Ion were assumed.

Tab. 4: Techno-economic parameters for stationary Li-ion batteries as the representative storage technology [50], [57].

Parameter	Unit	Li-ion
$\text{Invest}_{converter}$	[€/kW_{el}]	50
$\text{Invest}_{storage}$	[€/kWh_{el}]	101
Amor. time converter	[a]	25
Amor. time storage	[a]	25
Interest-rate	[-]	0.07
$O\&M_{fix}$	[% Inv./a]	0.009
$O\&M_{var}$	[€/kWh_{el}]	0.00001
η_{charge}	[-]	0.93
$\eta_{discharge}$	[-]	0.93
Self-discharge rate	[1/h]	0.00007
Availability	[-]	0.98

3 Results and discussion

3.1 Storage expansion and utilization

Fig. **3** illustrates the amount of storage capacity expansion (in terms of converter power) and storage utilization (in terms of annually discharged electricity) that results when comparing the MILP and LP power plant modeling approach over the scenarios with different VRE shares α, while the PV share is fixed (β = 0.40).

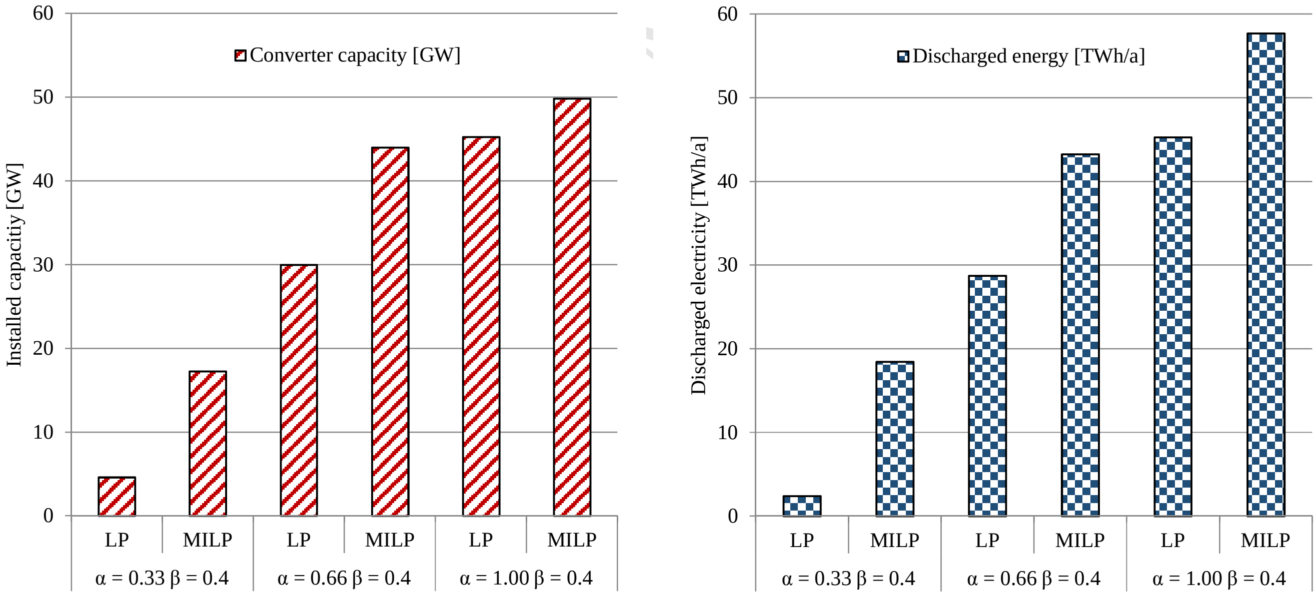


Fig. 3: Storage converter capacity expansion (GW) and storage utilization in terms of annually discharged energy (TWh/a) compared over the scenarios ($\boldsymbol{\beta = 0.4}$) with increasing VRE share (α) and over the different modeling approaches (MILP, LP) for power plants.

The following observations can be made:

i. Storage expansion and utilization increase with increasing VRE share α, as the growing temporal mismatch between generation and demand has to be balanced in some way. While one option is storage, VRE over-generation also can be balanced through curtailments.
ii. Storage expansion and utilization is always higher when using MILP modeling compared to LP. This observation also holds for the scenarios with a PV share β of 0.6 (see Fig. A 1 in the Appendix).
iii. With increasing VRE share α the differences between LP and MILP in terms of storage expansion and utilization decrease.

While observation i is trivial and fostered by the high shares of VRE, observations ii and iii seem to be influenced by the modeling approach for thermal power plants as all others parameters are almost identical. We subsequently analyze the differences in system dispatch and annual utilization.

3.2 Simulation of system dispatch

Fig. 4 compares the system dispatch between the LP and MILP approach in the scenarios with a VRE share of 0.33 and a PV share β of 0.4. Note that in the following analysis all capacity groups of a thermal power plant technology (cluster, see Tab. 1) are aggregated by technology type.

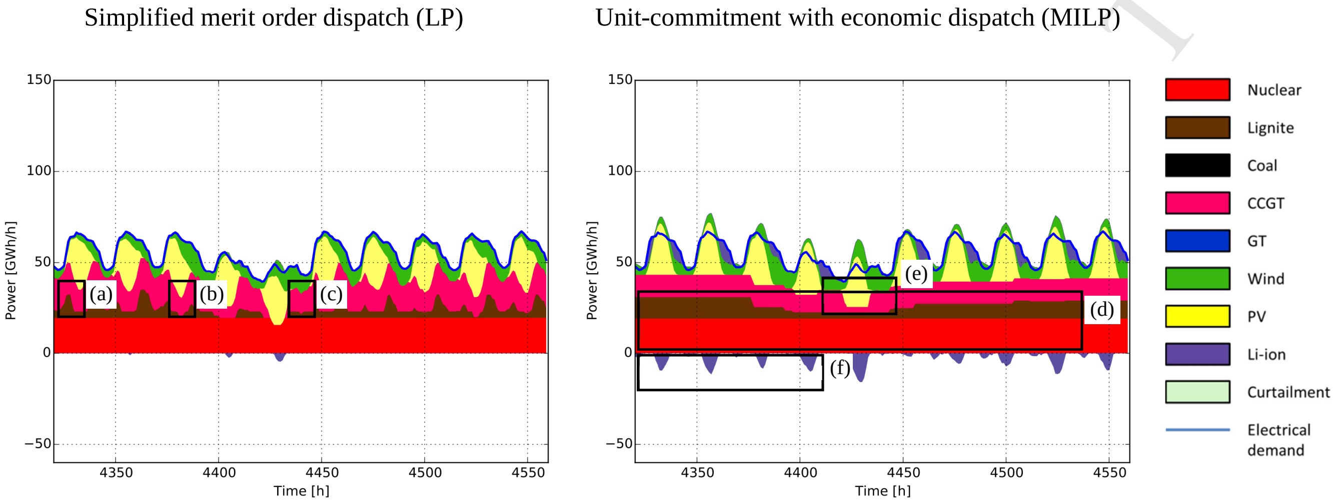


Fig. 4: Comparison of the hourly electricity generation of the simplified merit order dispatch (LP) and unit-commitment with economic dispatch (MILP) power plant modeling approach for the hours 4320 – 4560 for the scenario with a VRE share of 0.33 and a PV share $\boldsymbol{\beta}$ of 0.4. The latter's in brackets refer to the observations described in the text below.

We see that the LP modeling approach overestimates the flexibility of thermal power plants in comparison to the MILP methodology, mainly owing to neglecting technical restrictions, such as minimum load rates or ramping constraints. As shown in Fig. 4, especially the flexibility of lignite fired power plants is overestimated in the LP approach, as they are able to ramp very rapidly (a), are not restricted by any minimum up or down times (b) and are not characterized with minimal load rates of the power plants (c). The specific operating expenditure costs (OPEX) result in the following merit order of power plant dispatch (sorted OPEX of power plant clusters): Nuclear, Lignite, CCGT, Coal, Gas turbines. Slight changes in the merit order can occur depending on the scenario and its assumed CO_2 prices, fuel costs and improvements of efficiency (see Tab. A 3 in the Appendix). Moreover, since we categorize power plants into different capacity groups (see Tab. 1), the merit becomes more diverse (see Fig. A 2 in the Appendix).

In contrast, the MILP approach shows a more realistic dispatch of the thermal power plants, where base-load power plants, such as nuclear systems, mainly provide electricity at a constant level with little to no power changes (d), while lignite fired power plants and CCGT are more flexible in their dispatch (e), operating as mid and peak-load power plants. Additionally, Fig. 4 indicates a significant higher utilization of storage capacities (f). In Fig. 4 and all following dispatch plots, storage charging is illustrated by negative y-values, while storage discharging is shown by positive y-values.

Fig. 5 illustrates the generation share σ similar as defined in [53] (see Eq. 3.1) for thermal power plants, renewable energy systems and storage, comparing LP and MILP over the different renewable shares in the scenarios. Moreover, the figure illustrates the differences between MILP and LP with regard to the generation share (see Eq. 3.2), which is denoted by $\Delta\,\sigma$ and defined as the deviation of the technology-specific generation share σ between the MILP and LP approach in percent.

$$\sigma_x = \frac{\sum_{t=1}^{t=8760} P'_x(t)}{\sum_x \sum_{t=1}^{t=8760} P'_x(t)}, \forall x \in X \qquad 3.1$$

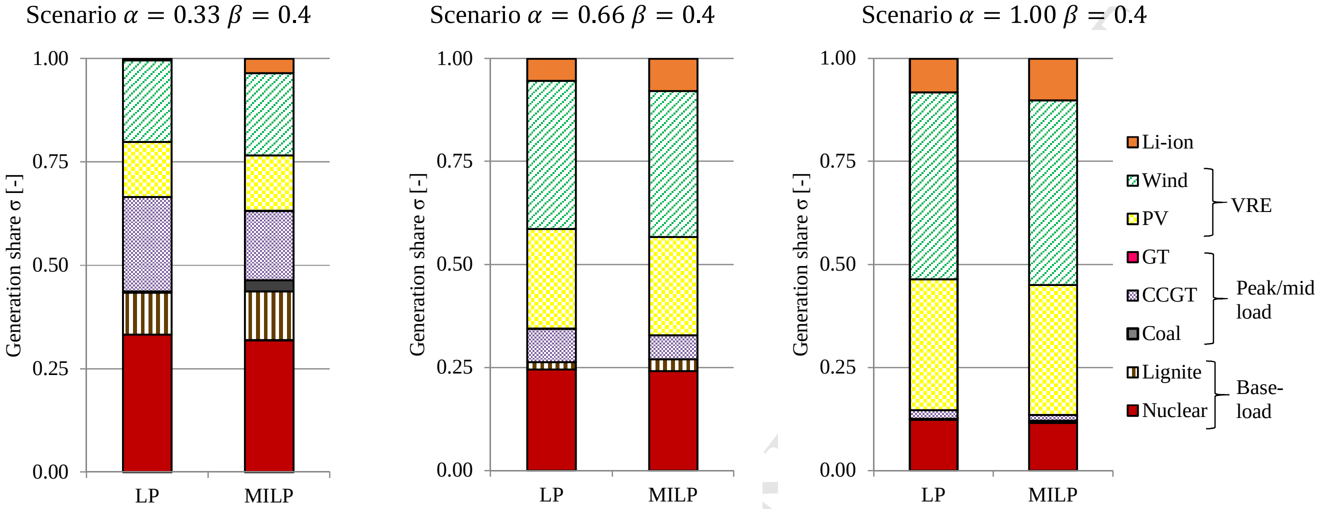
where

x	Technology index
$P'_x(t)$	Actual electricity generation from technology x in each time step t [GWh/h]
Δt	Length of one time step [h]
D	Annual electrical demand [GWh]

$$\Delta\,\sigma_x = \;|\sigma_x^{LP} - \sigma_x^{MILP}\;| * 100, \forall x \in X \qquad 3.2$$

where

x	Technology index
σ_x^{LP}	Generation share in LP approach of technology x
σ_x^{MILP}	Generation share in MILP approach of technology x



Technology	$\Delta\,\sigma$ [%]
Li-Ion	3.1
VRE	0.2
Mid/peak-load	6.0
Base-load	2.7

Technology	$\Delta\,\sigma$ [%]
Li-Ion	2.5
VRE	0.9
Mid/peak-load	2.2
Base-load	1.1

Technology	$\Delta\,\sigma$ [%]
Li-Ion	2.0
VRE	0.8
Mid/peak-load	0.7
Base-load	0.5

Fig. 5: Comparison of technology-specific generation shares $\boldsymbol{\sigma}$ in the scenarios with different VRE share α, comparing the simplified merit order dispatch (LP) to the unit-commitment with economic dispatch (MILP) modeling approach. Li-ion refers to the share of discharged electricity within the observation year. Moreover, the deviation of the generation share between LP and MILP is expressed as percentage and denoted $\Delta\,\boldsymbol{\sigma}$.

Within each scenario, the ratio of thermal to renewable generation does not differ significantly due to α. Furthermore, the ratio of PV share is similar in each scenario due to β. Distinct variations however can be observed in the composition of the generation share of thermal power plants and, as a result, the utilization of Li-ion storage:

(1) σ LP < σ MILP for base-load power plants (nuclear, lignite) in all scenarios.

(2) $\Delta\,\sigma$ for all thermal power plants and storage decreases with increasing VRE share α.

(1) In LP the stronger simplifications of operating constraints allows relatively inflexible base-load power plants to ramp up or down more frequently, and, for the scenario with low VRE share (α = 0.33), typically observed continuous operation of base-load power plants occurs only for the technology with the lowest operating costs (in this case electricity generation from nuclear power plants (see Fig. 4)). Slightly higher operating costs, as for lignite fired power plants, will results in a more discontinuous dispatch, following the characteristics of the hourly electrical demand. In scenarios with the highest VRE share (α = 1.00) even nuclear power plants are operating in a flexible way as a consequence of high VRE generation and a low or even negative net load as depicted in Fig. 6 (a).

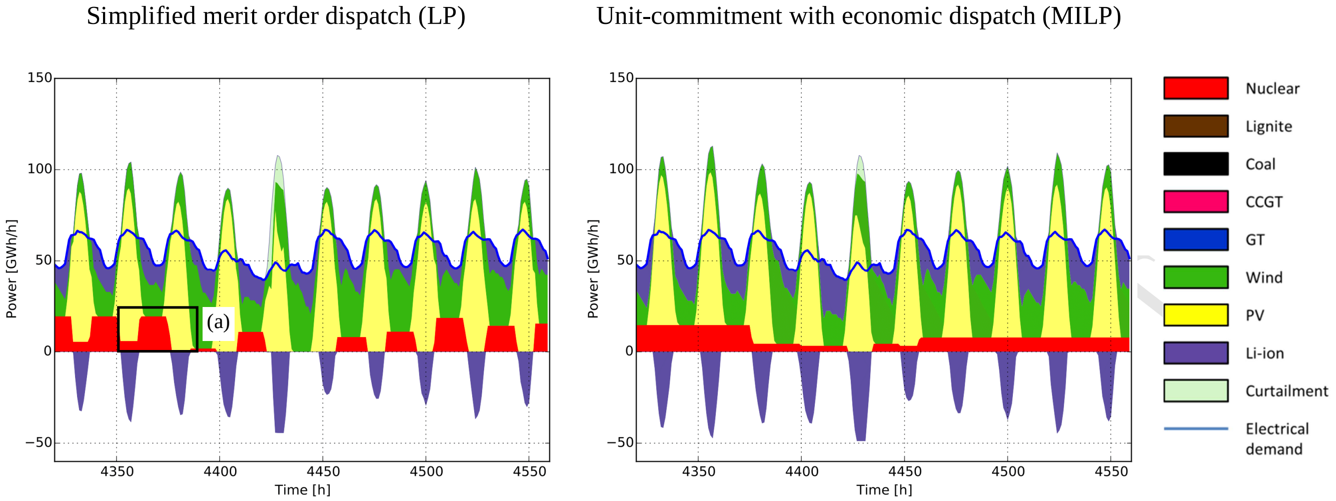


Fig. 6: Comparison of the hourly electricity generation of the simplified merit order dispatch (LP) and unit-commitment with economic dispatch (MILP) power plant modeling approach for the hours 4320 – 4560 for the scenario with a VRE share of 1.00 and a PV share of 0.4. The latter in brackets refers to the observations described in the text above.

In contrast, the dispatch consideration in the MILP approach is characterized by a higher utilization of storage, enabled by higher storage converter capacity expansion (see Sec. 3.1, enumeration ii). This enables more continuous operation of base-load power plants with less ramping events and results in higher generation shares of base-load power plants in MILP. The effect is illustrated in Fig. 7, which shows the dispatch of all utilities for the scenario α = 0.66, β = 0.4 and the hours 0 – 240. In the LP approach for example, lignite and coal fired power plants are able to follow the load in the hours 110 – 115 (a), whereas in MILP, we observe that charging of storage ensures a continuous operation of lignite and coal fired power plants as well as CCGT (b). In some hours (c), the generation from power plants (in this case CCGT) even exceeds the electrical load. In these situations the model favors the continuous dispatch through storage utilization over a flexible operation of the power plant, which again leads to the higher storage utilization (and expansion, see Fig. 3) for the UC approach.

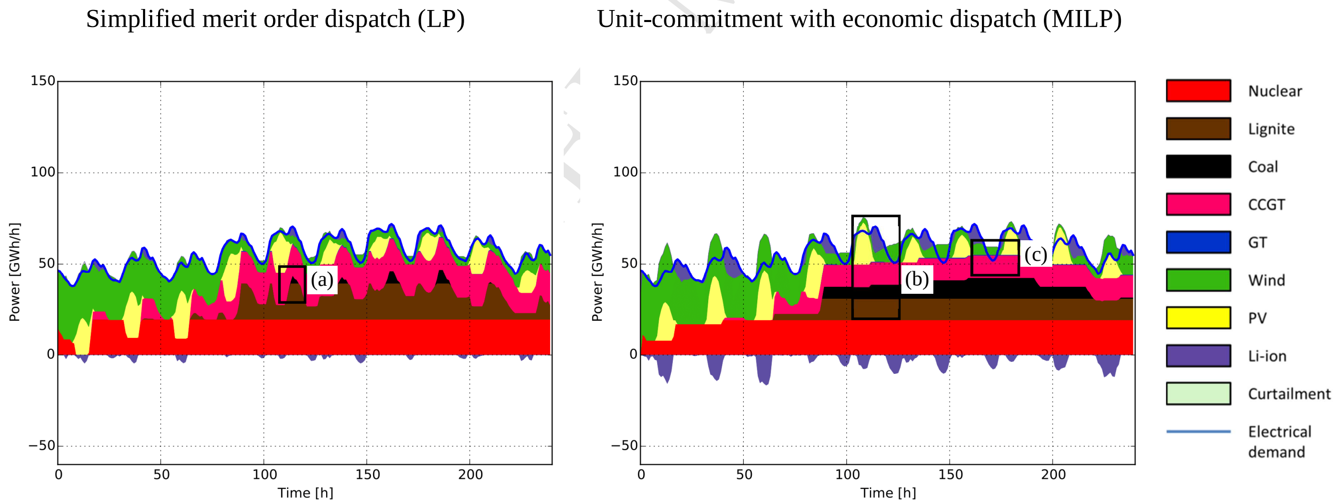


Fig. 7: Comparison of the hourly electricity generation of the simplified merit order dispatch (LP) and unit-commitment with economic dispatch (MILP) power plant modeling approach for the hours 0 – 240 for the scenario with a VRE share of 0.33 and a PV share $\boldsymbol{\beta}$ of 0.4. The latter's in brackets refer to the observations described in the text above.

(2) We already noticed that, when comparing LP and MILP, the differences in storage capacity expansion and utilization decrease with increasing VRE share α (see Sec. 3.1, enumeration iii). This observation is in line with the results shown in Fig. 5, where $\Delta\sigma$ decreases with increasing VRE share α. In other words, the amount of discharged electricity of Li-Ion storage converges between MILP and LP if the amount of renewable electricity generation increases. Similar observations can be made for base, mid and peak-load power plants. On one hand, thermal power plants become less important (i.e. their generation shares decrease) with higher VRE shares (i.e. increasing α). On the other hand, the dispatch patterns of thermal base and peak-load power plants also change with higher α. While scenarios with low shares of VRE are characterized by continuous dispatch of power plants with low operating costs (i.e. base-load), enabled through storage utilization, in scenarios with higher VRE shares, mid and peak-load power plants almost completely disappear, as the renewable generation is sufficient to cover the electric load.

More specifically, generation from coal disappears in scenario with α = 0.66, whereas the generation from almost all lignite capacities disappears in the scenario with α = 1.00. In these high-share VRE scenario, flexibility is mainly provided by storage utilization, whereas nuclear power plants remain the only base-load technology, characterized by a more flexible dispatch (see Fig. 6, (a)).

3.3 Influence of power plant portfolio granularity

Next, we test whether the influence of the MILP approach on storage expansion and utilization is dependent on the flexibility of the power plant portfolio within the system (i.e. the number of power block). In our analysis we showed that—when incorporating endogenous storage expansion and dispatch into the optimization problem—the importance of a detailed MILP unit-commitment modeling approach decreases with increasing VRE shares. However, this might change if the assumed power plant portfolio only consists of a limited number of power blocks/units (as for example in small regions or countries). Consequently, the relative influence of technical constraints might increase as the system is less flexible. Likewise, the decreased flexibility might foster greater storage expansion and utilization.

Since in LP the number of blocks (Nb) can be considered unlimited, as the size of one block is infinitely small, LP is the most flexible system (see e.g. Fig. 4). Nevertheless, the reference power plant portfolio in the MILP approach (see Tab. 1) is already quite flexible, as it contains a rather high number of blocks (968) which enables numerous possible combinations of on and offline power blocks. To assess the influence of the power plant portfolio granularity, we lower the number of power blocks from 968 of the reference case to 485, 20 and 5 blocks as shown in Fig. 8. The overall installed capacity remains identical in all scenarios (see Tab. A 4 in the Appendix).

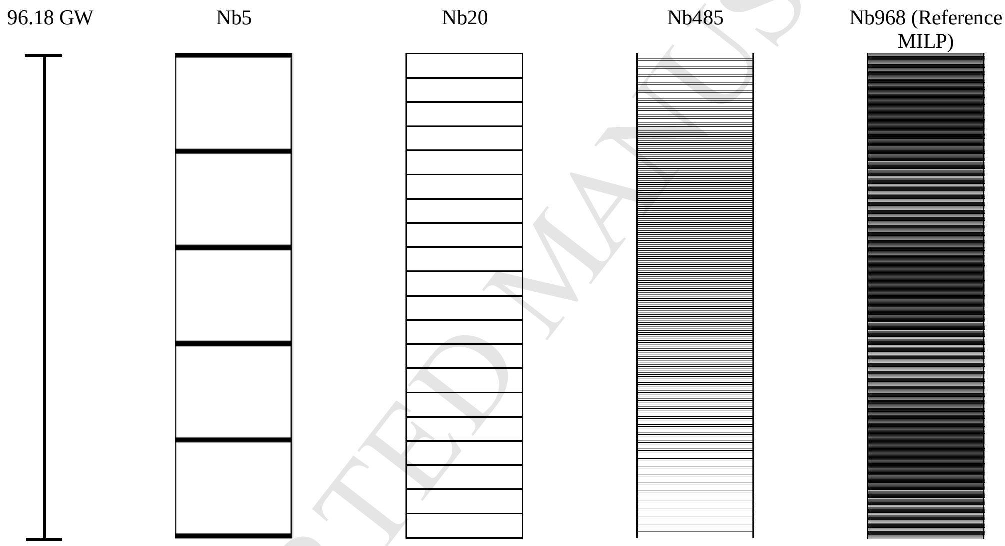


Fig. 8: Power plant granularity in terms of number of blocks. The exact number of blocks for each power plant cluster can be extracted from Tab. A 4.

To illustrate the effects of different granularities of the power plant portfolio, Fig. 9 shows the dispatch for two extreme cases: a capacity mix with 968 blocks (Nb968) and 5 blocks (Nb5). As expected, the inflexibility of Nb5 causes increased storage utilization at some hours (a), whereas in the system with 968 blocks, lignite power plants and CCGT provide flexibility during the same hours, preventing most of the storage charging (b). Again, we see that CCGT operates as mid-load generation owing to the OPEX cost assumptions.

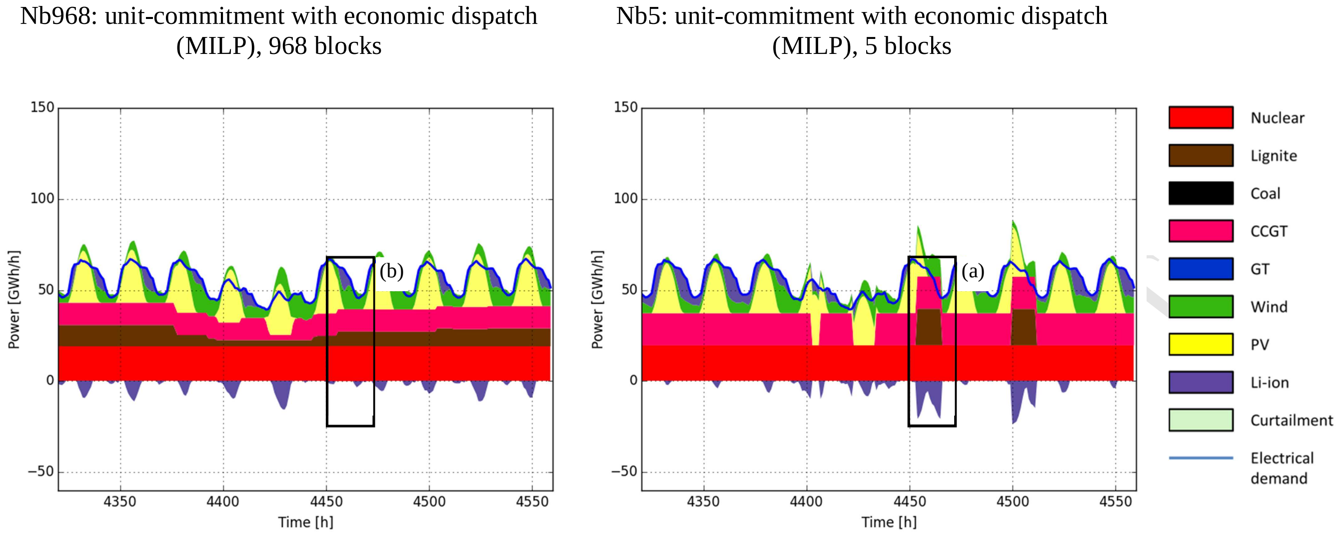
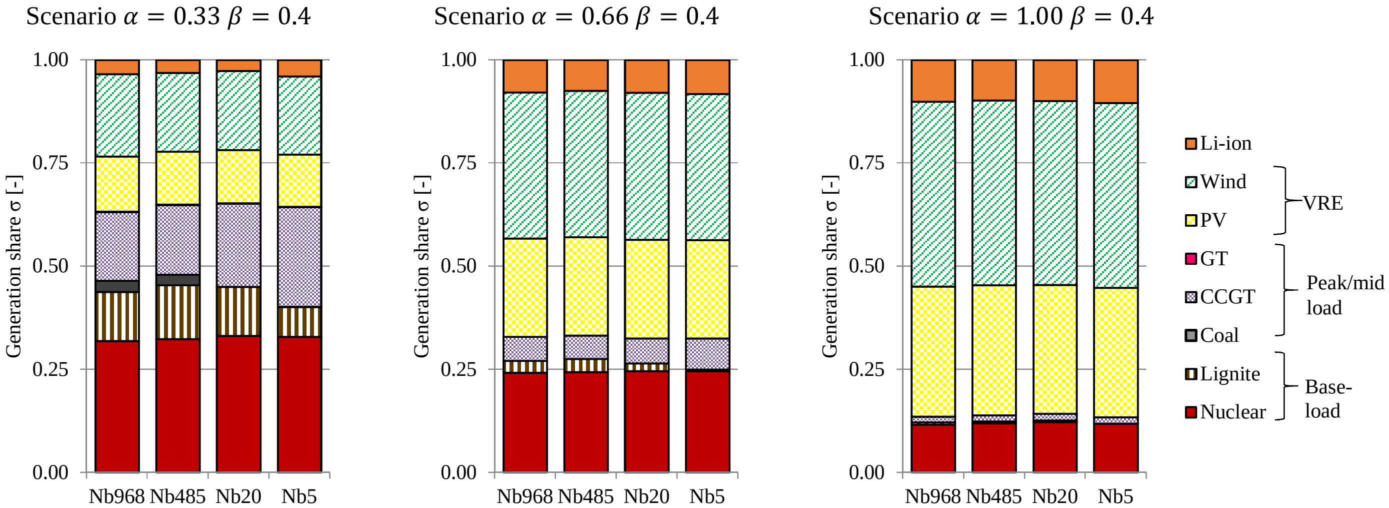


Fig. 9: Comparison of the hourly electricity generation of the unit-commitment with economic dispatch (MILP) power plant modeling approach consisting of 968 and 5 blocks. The figure shows the time period of hour 4320 – 4560 for the scenario with a VRE share of 0.33 and a PV share $\boldsymbol{\beta}$ of 0.4. The latter's in brackets refer to the observations described in the text above.

Fig. 10 depicts the annual, technology-specific generation shares σ dependent on the power plant portfolio granularity (Nb968-Nb5) over the scenarios of different VRE shares α and for the PV share β=0.4. We define the most granular capacity mix (Nb968) as benchmark and subsequently derive the deviation of generation shares of less granular capacity mixes ($\Delta\,\sigma^{Nb485}$, $\Delta\,\sigma^{Nb20}$, $\Delta\,\sigma^{Nb5}$).



Technology	$\Delta\,\sigma^{Nb485}$	$\Delta\,\sigma^{Nb20}$	$\Delta\,\sigma^{Nb5}$	$\Delta\,\sigma^{Nb485}$	$\Delta\,\sigma^{Nb20}$	$\Delta\,\sigma^{Nb5}$	$\Delta\,\sigma^{Nb485}$	$\Delta\,\sigma^{Nb20}$	$\Delta\,\sigma^{Nb5}$
Li-Ion	0.8	0.7	1.0	0.4	0.1	0.4	0.3	0.1	0.3
VRE	1.3	1.1	1.6	0.0	0.2	0.1	0.0	0.5	0.1
GT	-	-	-	-	-	-	-	-	-
CCGT	0.2	3.5	7.4	0.1	0.3	1.8	0.1	0.2	0.1
Coal	0.2	2.6	2.6	-	-	-	-	-	-
Lignite	1.2	0.1	4.6	0.3	0.9	2.5	0.0	0.2	0.5
Nuclear	0.5	1.2	4.6	0.1	0.3	0.4	0.3	0.6	0.3

Fig. 10: Comparison of technology-specific generation shares $\boldsymbol{\sigma}$ in the scenarios with different VRE share α, comparing the unit-commitment with economic dispatch (MILP) modeling approach, containing different numbers of blocks. Li-ion refers to the share of discharged electricity within the observation year. Moreover, the deviation of the generation share between LP and MILP is expressed as percentage and denoted $\Delta\,\boldsymbol{\sigma}$.

As shown on an hourly basis in the dispatch plots (Fig. 9), the effect of increasing storage utilization with decreasing number of blocks is also consistent on an annual basis to compensate the inflexibility of the power plant capacity mix. Additionally, instead of providing flexibility through the combinations of on and offline power blocks (as in NB968), Nb5 provides flexibility by the technical ability of mid and peak-load power plants to follow the net load. This is reflected by higher generation shares σ of CCGT in the less flexible scenarios (Nb5, Nb20). In contrast, the generation shares of lignite fired power plants decreases over higher Nb, as their technical ability to provide flexibility is insufficient to follow the temporal variability of VRE generation. The described effects are visible for all scenarios, but becomes less pronounced (decreasing $\Delta\,\sigma$) with increasing VRE share α. In other words, under the premises of model endogenous storage expansion, MILP approaches are particularly important if the analysis focusses on smaller regions (i.e. a limited number of thermal blocks) in combination with low shares of VRE. This also applies for larger energy systems, where the model user heavily aggregates the number of blocks. In turn, the aggregation of power blocks and the importance of MILP is less important in high share VRE scenarios.

3.4 Comparison to the state of research

Our results corroborate some findings of the existing research. In terms of the deviation of the thermal power plant generation shares between the two modeling approaches (LP versus MILP), our results are in line with the work of Poncelt et al. [53], as $\Delta\,\sigma$ (*Generation mix error merit order dispatch* in [53]) is relatively low (max. 6.0%, see Fig. 5). Our model results also indicate an increased utilization of storage in the MILP approach as shown by Stoll et al. [51]. This is especially the case in scenarios with low shares of VRE generation.

Differences exist, however, with regard to the importance of MILP depending on the VRE share α, and, more specifically, the trend of $\Delta\,\sigma$ over the different VRE shares α. Palmintier [58] finds that, in contrast to the results presented in this paper, the importance of operating detail in thermal power plant modeling increases with higher shares of VRE generation (and stricter CO_2 emission limits). The latter can be explained since [58] performs an integrated optimization of dispatch and capacity expansion which leads to different initial power plant portfolios, whereas the analysis at hand uses identical generation portfolios, only optimizing their dispatch and storage expansion. Similar to [58], the results of Poncelt et al. [53] show an increase of $\Delta\,\sigma$ with increasing α, i.e. detailed power plant modeling which considers operating constraints becomes more important with higher VRE shares. However, two important assumptions distinguish our work from [53]. First, the present analysis conducts optimization calculations up to a theoretical VRE share of 100%, whereas VRE shares in [53] reach 50% in the year 2050. Yet, the importance of power plant modeling might decrease as the share of thermal generation in highly renewable scenarios also decreases. Second, [53] do not include storage expansion as a flexibility option in their calculations. Consequently, all balancing of the intermittent VRE generation has to be provided by dispatchable power plants. As flexibility requirements increase with higher VRE shares (e.g. in terms of hourly or multi-hour ramp requirements, see e.g. [52]), technical constraints with regard to the dispatchability of power plants (as considered in the MILP approach) have a great influence and explain $\Delta\,\sigma$ between the LP and MILP approach in Poncelet et al. [53].

4 Conclusions

We examined the influence of thermal power plant modeling (simplified merit order dispatch (LP) versus unit-commitment with economic dispatch (MILP)) on storage demand, using the cost minimizing capacity expansion and dispatch model REMix. The analysis was conducted for scenarios with different shares of PV and wind power generation, ranging from 33% up to 100% of theoretical generation share with regard to the annual power demand.

We found that LP systematically overestimates the flexibility of thermal power plants, thus leading to lower storage expansion and utilization compared to MILP in all scenarios. If endogenous storage expansion is considered in the capacity planning and dispatch optimization (and flexibility provision does not solely rely on the existing power plant portfolio), MILP modeling is superior in terms of realistic storage consideration. Power plants are restricted by minimum load rates or ramping constraints, consequently fostering an increase in storage utilization to ensure continuous operation of the thermal units. However, we also found that, owing to the decreasing share of thermal power plants that are modeled either by LP or MILP, the differences of LP and MILP in storage expansion and utilization as well as the generation shares of thermal power plants merely decrease with increasing variable renewable energy (VRE) shares. This leads to the conclusion that a high degree of detail in power plant modeling becomes less important in scenarios with high shares of VRE if network constraints are neglected.

Similar relations were observed for smaller energy systems with a lower number of available generation units. For low share VRE scenarios and in the case of very few units, significant deviations with the highly granular energy system become visible, especially for nuclear and lignite power plants as well as for combined cycle power plants. The differences in storage utilization are rather small. Again, the differences become less distinct with increasing share of VRE.

There are limitations of our analysis and future work should carefully consider these. First, we used storage expansion and dispatch of a single technology as a proxy for flexibility demand. However, other options are possible and, for example, enable balancing of intermittent renewable generation through spatial balancing (i.e. shifting of electricity from one point in time to another by the electricity grid) or through changes of the electric load curve (i.e. demand response). As the fundamental functionalities of these alternative flexibility options vary quite heavily from the ones of storage, power plant modeling might have different effects as our results show. Moreover, the hourly resolution of the REMix model does not capture sub-hourly flexibility requirements, such as frequency control.

Second, both in LP as well as in MILP, storage capacity expansion relies on linear programming. Similar to LP and as described in Sec. 3.2 the approach is not able to consider on/off behavior of single storage units or to capture some techno-economic characteristics as it would be possible with mixed-integer methods. For storage these constraints are heavily technology dependent, e.g. batteries include limitations in terms of depth of discharge or cycle stability, whereas pumped hydro storage are restricted by minimum storage levels or turbine power [54], [55]. Similar to the argumentation of power plant granularity in Sec. 3.3, the necessity of mixed-integer storage modeling depends on the granularity of the overall installed storage capacity and hence the typical capacity size of one storage unit. In this sense, mixed-integer approaches might be desirable for large scale storage technologies and in smaller energy system, whereas linear programming is likely to be sufficient in large energy systems in combination with smaller storage units.

Third, we solely considered electricity and do not model interactions to other energy related sectors, such as the transportation or heat sector. Especially the latter might be affected by assumptions of power plant modeling, as some units operate as Combined Heat and Power Plants (CHP). In combination with heat storage, CHP units have the potential to operate in a more flexible way as shown in [56].

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Nomenclature

Indices

$x \in X$	Technologies
$t \in T$	Time

Parameter

α	Annual theoretical power generation share of photovoltaic and wind power systems with regard to the annual

	power demand [-]
β	Annual theoretical power generation share of photovoltaic systems with regard to the overall theoretical power generation from variable, renewable systems [-]
Δt	Length of one time step [h]
$P_{Wind}(t)$	Theoretical electricity generation from wind power in each time step t [GWh/h]
$P_{PV}(t)$	Theoretical electricity generation from photovoltaic systems in each time step t [GWh/h]
D	Annual electrical demand [GWh]
$P'_x(t)$	Actual electricity generation from technology x in each time step t [GWh/h]
σ_x	Actual generation share of technology x [-]
σ_x^{LP}	Generation share in simplified merit order dispatch (LP) approach of technology x [-]
σ_x^{MILP}	Generation share in unit-commitment and economic dispatch (MILP) approach of technology x [-]
$\Delta\,\sigma_x$	Generation share difference between economic dispatch and unit-commit [%]

Abbreviations

LP	Linear programming
MILP	Mixed-integer programming
UC	Unit-commitment
VRE	Variable, renewable electricity
REMix	Renewable Energy Mix
O&M cost	Operating and maintenance costs
WEPP	World Electric Power Plants Database
PV	Photovoltaic
OPEX	Operating expenditures
CCGT	Combined cycle gas turbines
Nb	Number of power blocks within a power plant or power plant cluster
CHP	Combined heat and power plant

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Appendix

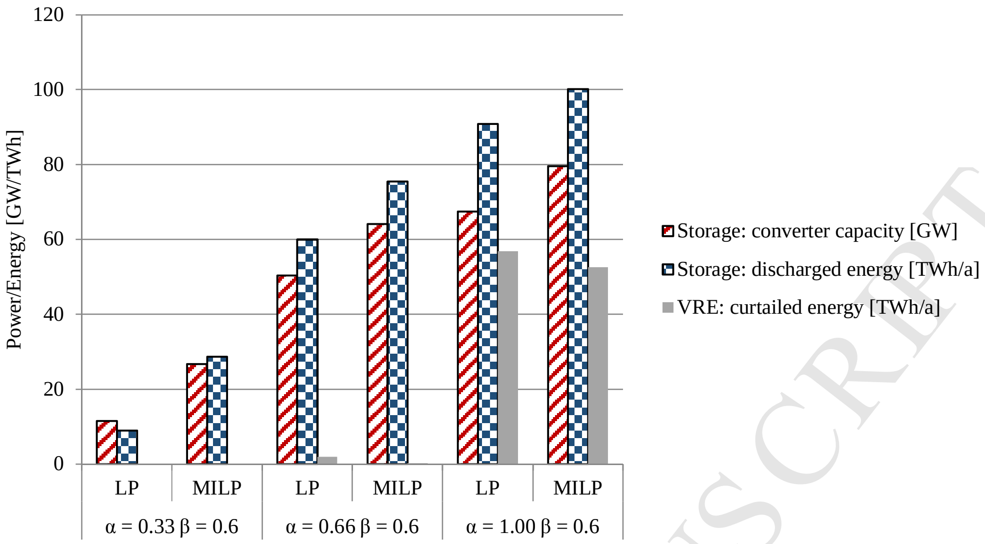

Fig. A 1: Storage converter capacity expansion (GW) and storage utilization in terms of annually discharged energy (TWh/a) compared over the scenarios (PV share $\boldsymbol{\beta}$ of 0.6) with increasing VRE share (α) and over the different modeling approaches (MILP, LP) for power plants.

Tab. A 1: Techno-economic parameters of thermal power plant clusters for the LP modeling approach.

Power plant cluster	η_{gross} [-][a]	η_{net} [-][b]	O&M$_{var}$ [€/kWh]	Wear & tear costs [€/kW][c]
Nuclear large	0.324	0.309	0.00171	0.0015
Nuclear midsize	0.324	0.309	0.00171	0.0015
Nuclear small	0.324	0.309	0.00171	0.0015
Lignite large	0.433	0.406	0.00358	0.0015
Lignite midsize	0.395	0.370	0.00358	0.0015
Lignite small	0.373	0.350	0.00358	0.0015
Coal large	0.414	0.379	0.00358	0.0015
Coal midsize	0.415	0.380	0.00358	0.0015
Coal small	0.405	0.371	0.00358	0.0015
CCGT large	0.461	0.453	0.00288	0.0005
CCGT midsize	0.517	0.508	0.00288	0.0005
CCGT small	0.493	0.484	0.00288	0.0005
Gas turbine large	0.400	0.395	0.01236	0.0005
Gas turbine midsize	0.289	0.285	0.01236	0.0005
Gas turbine small	0.358	0.354	0.01236	0.0005

[a] η_{gross} is based on [58].
[b] As [58] does not provide data for η_{net}, we use the ratio of η_{gross} to η_{net} provided by [57]. Note however that [57] do not differentiate between capacity groups and includes only technology-specific efficiencies. In consequence, the ratio of η_{gross} to η_{net} in this table is identical within each technology group.
[c] Based on [67]. For nuclear power plants we use the values of *Advanced Nuclear* of [67], for lignite and coal power plants the values of *Advanced Pulverized Coal Facility*, for gas turbines *Conventional Combustion Turbine* and for CCGT *Conventional Natural Gas Combined Cycle*. To conclude to €, we assume an exchange rate of 1.3US $/€ and an inflation rate of 2% p.a. .

Tab. A 2: Techno-economic parameters of thermal power plant clusters for the MILP modeling approach. $\eta@P_{max}$ describes the efficiency at maximal power; $\eta@P_{min}$ the efficiency at minimum load of the unit. Load $rate_{min}$ is defined as the minimal load rate of the unit relative to the gross capacity.

Power plant cluster	$\eta@P_{max}$ [a]	$\eta@P_{min}$ [b]	Load $rate_{min}$ [-] [c]	Fuel cons. start $[MWh_{th}/MW_{el}]$ [d]	Auxiliary power $cooling_{min}$ [e] [MW]	Auxiliary power $others_{min}$ [e] [MW]	Minimum on-line time [h]	Minimum off-line time [h]	$O\&M_{var}$ $[k€/GWh_{el}]$ [f]	Startup costs [k€/GW] [g]	Ramping costs [k€/GW] [g]
Nuclear large	0.3240	0.2786	0.50	2.27	6.10	32.00	48	48	1.71	6.6	2.53
Nuclear midsize	0.3240	0.2786	0.50	2.27	104.10	32.00	48	48	1.71	6.6	2.53
Nuclear small	0.3240	0.2786	0.50	2.27	104.10	32.00	48	48	1.71	6.6	2.53
Lignite large	0.4325	0.3720	0.40	3.08	3.20	57.00	12	12	3.58	6.52	2.53
Lignite midsize	0.3950	0.3397	0.40	2.05	2.00	60.76	12	12	3.58	5.01	2.83
Lignite small	0.3725	0.3204	0.40	2.05	0.50	91.20	12	12	3.58	5.01	3.13
Coal large	0.4137	0.3558	0.40	3.08	2.50	57.00	12	8	3.58	6.52	2.53
Coal midsize	0.4150	0.3569	0.40	2.05	1.40	60.76	12	8	3.58	5.01	2.83
Coal small	0.4052	0.3484	0.40	2.05	0.50	91.20	12	8	3.58	5.01	3.13
CCGT large	0.4612	0.2652	0.30	0.14	0.30	16.50	8	4	2.88	1.56	0.60
CCGT midsize	0.5171	0.2973	0.30	0.14	0.20	21.95	8	4	2.88	1.56	0.60
CCGT small	0.4928	0.2834	0.30	0.14	0.00	27.51	8	4	2.88	1.56	0.60
Gas turbine large	0.4000	0.1520	0.20	0.062	0.00	16.50	0	1	12.36	0.78	2.80
Gas turbine midsize	0.2895	0.1100	0.20	0.062	0.00	21.95	0	1	12.36	0.78	2.10
Gas turbine small	0.3585	0.1362	0.20	0.062	0.00	27.51	0	1	12.36	0.78	1.40

[a] Based on [58].

[b] Based on [59–61], [63].

[c] Based on [61–63].

[d] Based on [68]. Assumed to be warm start.

[e] All other parasitics, excluding cooling. Based on [63–66].

[f] Based on [67]. For nuclear power plants we use the values of *Advanced Nuclear* of [67], for lignite and coal power plants the values of *Advanced Pulverized Coal Facility*, for gas turbines *Conventional Combustion Turbine* and for CCGT *Conventional Natural Gas Combined Cycle*. To conclude to €, we assume an exchange rate of 1.3US $/€ and an inflation rate of 2% p.a.

[g] Based on [68]. For nuclear power plants internal assumptions were used.

Tab. A 3: Total specific operating expenditures (OPEX) disaggregated into the cost components CO_2 and fuel costs as well variable operation and maintenance costs ($O\&M_{var}$) over the scenarios with different VRE shares for the LP approach. Note that the total OPEX in this table do not include wear & tear costs as they are a result of the optimization.

VRE share α [-]	Technology	CO_2 costs [€/t CO_2]	Fuel costs [€/MWh_{th}]	η_{net} [-]	CO_2 costs [€/MWh_{el}][a]	Fuel costs [€/MWh_{el}]	$O\&M_{var}$ [€/MWh_{el}]	Total OPEX [€/MWh_{el}]
0.33	Nuclear large	27	3.3	0.309	0.00	10.68	1.71	12.39
0.33	Nuclear midsize	27	3.3	0.309	0.00	10.68	1.71	12.39
0.33	Nuclear small	27	3.3	0.309	0.00	10.68	1.71	12.39
0.33	Lignite large	27	60.0	0.406	26.57	147.78	3.58	177.94
0.33	Lignite midsize	27	60.0	0.370	29.16	162.16	3.58	194.90
0.33	Lignite small	27	60.0	0.350	30.83	171.43	3.58	205.83
0.33	Coal large	27	77.0	0.379	23.85	203.17	3.58	230.60
0.33	Coal midsize	27	77.0	0.380	23.79	202.63	3.58	230.00
0.33	Coal small	27	77.0	0.371	24.37	207.55	3.58	235.49
0.33	CCGT large	27	76.0	0.453	12.02	167.77	2.88	182.67
0.33	CCGT midsize	27	76.0	0.508	10.71	149.61	2.88	163.20
0.33	CCGT small	27	76.0	0.484	11.25	157.02	2.88	171.15
0.33	GT large	27	76.0	0.395	13.78	192.41	12.36	218.55
0.33	GT midsize	27	76.0	0.285	19.10	266.67	12.36	298.13
0.33	GT small	27	76.0	0.354	15.38	214.69	12.36	242.43
0.66	Nuclear large	60	3.3	0.309	0.00	10.68	1.71	12.39
0.66	Nuclear midsize	60	3.3	0.309	0.00	10.68	1.71	12.39
0.66	Nuclear small	60	3.3	0.309	0.00	10.68	1.71	12.39
0.66	Lignite large	60	86.0	0.406	59.05	211.82	3.58	274.46
0.66	Lignite midsize	60	86.0	0.370	64.80	232.43	3.58	300.81
0.66	Lignite small	60	86.0	0.350	68.50	245.71	3.58	317.80
0.66	Coal large	60	117.0	0.379	53.00	308.71	3.58	365.29
0.66	Coal midsize	60	117.0	0.380	52.86	307.89	3.58	364.34
0.66	Coal small	60	117.0	0.371	54.15	315.36	3.58	373.09
0.66	CCGT large	60	113.0	0.453	26.70	249.45	2.88	279.03
0.66	CCGT midsize	60	113.0	0.508	23.81	222.44	2.88	249.13
0.66	CCGT small	60	113.0	0.484	24.99	233.47	2.88	261.34
0.66	GT large	60	113.0	0.395	30.62	286.08	12.36	329.06
0.66	GT midsize	60	113.0	0.285	42.44	396.49	12.36	451.29
0.66	GT small	60	113.0	0.354	34.17	319.21	12.36	365.74
1.00	Nuclear large	75	3.3	0.309	0.00	10.68	1.71	12.39
1.00	Nuclear midsize	75	3.3	0.309	0.00	10.68	1.71	12.39
1.00	Nuclear small	75	3.3	0.309	0.00	10.68	1.71	12.39
1.00	Lignite large	75	100.0	0.406	73.82	246.31	3.58	323.70
1.00	Lignite midsize	75	100.0	0.370	81.00	270.27	3.58	354.85
1.00	Lignite small	75	100.0	0.350	85.63	285.71	3.58	374.92
1.00	Coal large	75	136.0	0.379	66.25	358.84	3.58	428.67
1.00	Coal midsize	75	136.0	0.380	66.08	357.89	3.58	427.55
1.00	Coal small	75	136.0	0.371	67.68	366.58	3.58	437.84
1.00	CCGT large	75	131.0	0.453	33.38	289.18	2.88	325.44
1.00	CCGT midsize	75	131.0	0.508	29.76	257.87	2.88	290.52
1.00	CCGT small	75	131.0	0.484	31.24	270.66	2.88	304.78
1.00	GT large	75	131.0	0.395	38.28	331.65	12.36	382.28
1.00	GT midsize	75	131.0	0.285	53.05	459.65	12.36	525.06

1.00	GT small	75	131.0	0.354	42.71	370.06	12.36	425.13

[a] The following specific emission factors were assumed [t CO_2/MWh_{th}]: uranium = 0.00, lignite = 0.40, coal = 0.33, natural gas = 0.20.

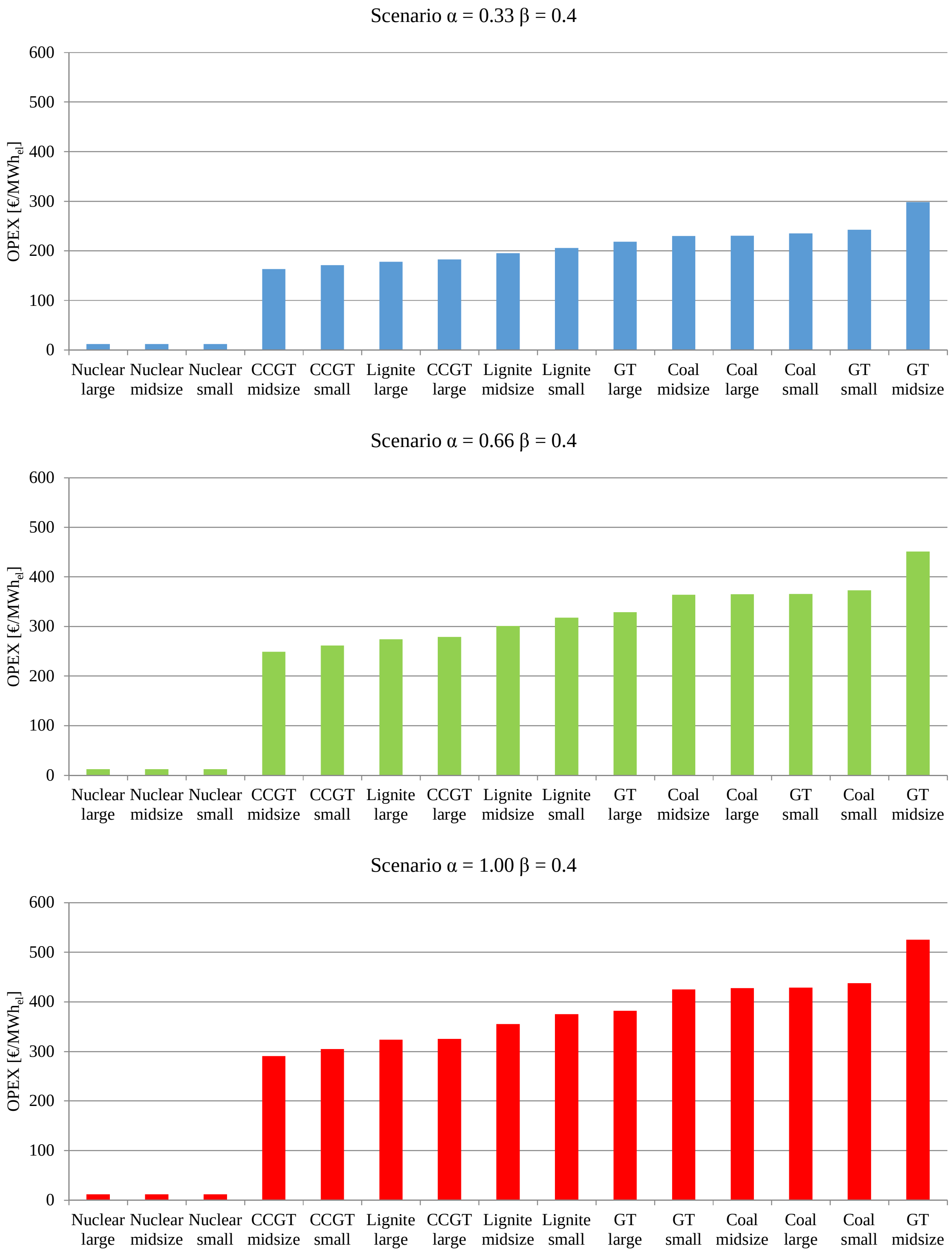

Fig. A 2: Merit order for the scenarios differing in their VRE share α for all power plant groups in the LP approach.

Tab. A 4: Cluster with regard to power plant technology type and plant size for the scenario with reduced number of blocks (485, 20, 5).

Technology group	Capacity group	Capacity range [MW]	Number of blocks [-]			Installed capacity [MW]
			485	20	5	
Nuclear	Large	> 800	8	1	1	20,400
Nuclear	Midsize	-	-	-	-	-
Nuclear	Small	-	-	-	-	-
Lignite	Large	> 800	2	1	-	3,800
Lignite	Midsize	400 ≤ 800	9	1	1	9,900
Lignite	Small	< 400	37	1	-	7,40
Coal	Large	> 550	6	1	-	9,000
Coal	Midsize	350 ≤ 550	10	1	1	8,000
Coal	Small	< 350	58	2	-	11,600
CCGT	Large	> 350	8	1		6,750
CCGT	Midsize	150 ≤ 350	13	1	1	6,500
CCGT	Small	< 150	119	3	-	4,740
Gas turbine	Large	> 150	1	1	-	400
Gas turbine	Midsize	50 ≤ 150	29	1	1	3,990
Gas turbine	Small	< 50	185	5	-	3,700
Total			485	20	5	96,180

Highlights

- Mixed integer unit-commitment with economic dispatch (MILP) and simplified linear programming merit order dispatch (LP) for thermal power plants are compared with regard to electricity storage demand and utilization in a least cost optimization model.
- The analysis relies on different hypothetical energy scenarios with different shares of variable renewable electricity (VRE) generation and photovoltaics to wind power ratios as well as different granularities of the thermal power plant capacity mix.
- Users of optimization models for future energy scenarios should carefully deliberate their choice of thermal power plant modeling in order to consider storage expansion and utilization appropriately.
- MILP approaches were found to be superior in lower share VRE scenarios and/or in thermal capacity mixes with a limited number of thermal generation units.
- LP in contrast is sufficient in highly renewable and granular capacity mixes.