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Article

Day-ahead market modelling of large-scale highly-renewable multi-energy systems: analysis of the North Sea region towards 2050

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Abstract: This paper proposes a mathematical model to simulate Day-ahead markets of large-scale multi-energy systems with high share of renewable energy. Furthermore, it analyses the importance of including unit commitment when performing such analysis. The results of the case study, which is performed for the North Sea region, show the influence of massive renewable penetration in the energy sector and increasing electrification of the district heating sector towards 2050, and how this impacts the role of other energy sources such as thermal and hydro. The penetration of wind and solar is likely to challenge the need for balancing in the system as well as the profitability of thermal units. The degree of influence of the unit commitment approach is found to be dependent on the configuration of the energy system. Overall, including unit commitment constraints with integer variables leads to more realistic behaviour of the units, at the cost of increasing considerably the computational time. Relaxing integer variables reduces significantly the computational time, without highly compromising the accuracy of the results. The proposed model, together with the insights from the study case, can be specially useful for system operators for optimal operational planning.

Keywords: Energy System; Large Scale; Day Ahead Market; Operational Planning; Unit Commitment

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1. Introduction

Due to climate change and environmental concerns, energy systems including all energy vectors such as heating, transportation and agriculture, are converting to electricity-based energy usage. The European Commission has the vision of decarbonising the whole energy system by 2050 [1]. Denmark in this direction has the ambition to completely phase-out coal by 2030 [2]. Renewable based electricity generators such as hydro, wind, solar, or biomass are replacing the carbon-based generators. Many of these renewable energy sources are inherently variable in nature such as wind, solar, or micro-hydro. Consequently, increasing the share of such variable renewable energy (VRE) sources in electricity systems increases the variability and uncertainty in the full energy system.

Maintaining a stable and secure operation in the electricity system with large share of VRE can be very challenging for the power system operators. Major challenges involved in operational planning are estimation of operational reserves [3], or determining the ramp requirements and flexibility for the generators. This information is then used to mitigate the impact of variability in the electric power system.

Operational planning should include co-optimisation of all the sectors to avoid infeasibilities and sub-optimal solutions. For example, estimation of reserves from combined heat and power (CHP) units while only performing optimisation of electrical power systems can create infeasibilities for the units in real-time due to heating constraints, and thereby, challenging the security of the system. Exploiting the synergies of multi-energy analysis can also include, for instance, planning maintenance of the units considering the needs of the different parts of the energy sector.

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The operation of the system generally takes place in real life through different energy markets. Examples of these market for electricity are day-ahead (DA), intra-day, or balancing markets. This paper focuses on simulating the operation of the DA market.

When simulating the operation of the DA market, it is generally relevant to consider the unit commitment (UC) problem [4]. Different UC modelling approaches have been researched for many years [4–6]. Mixed integer programming (MIP) is a widely used methodology for UC. However, MIP based methods are computationally expensive. Lagrangian relaxation offers saving in computational time without compromising accuracy [7].

Simulation of DA operation of large-scale multi-energy systems considering UC constraints is computationally challenging. In the literature, either such a problem has been handled for a small system (for example, a 6 bus system in [8]) or compromise has been made in terms of simulation horizon (24 hours in [9]), technologies involved (such as only for electrical systems), or scenario years analysed. Recently, UC based studies have also been applied for multi-carrier energy systems, but again the application has been limited to small test systems [10]. Performing these operational planning studies for short term can lead to infeasible solutions and is otherwise sub-optimal for reasons such as unable to consider long-term constraints, for example yearly schedule of hydro reservoirs. The integration of VRE has also been limited in the sense of modelling the details of weather dependencies.

An analysis of the available literature concerning relevant features for the scope of this paper is shown in Table 1. It can be observed that there is no available literature which can handle all the features.

Table 1. Coverage of existing literature.

The analysis included:	[5]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]	[21]	[22]	[23]
a large-scale system		✓	✓	✓	✓				✓	✓	✓	✓		✓	✓	✓		✓
several scenario years																		
annual storage scheduling						✓			✓	✓		✓			✓			✓
full year hourly results							✓	✓	✓		✓	✓	✓	✓	✓	✓		✓
multi-energy markets					✓				✓	✓			✓			✓		✓
influence of Unit Commitment	✓					✓	✓	✓			✓	✓	✓	✓			✓	
planned maintenance scheduling							✓				✓	✓			✓			
renewable energy sources				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

The novelty of this paper involves developing a methodology to integrate all the features mentioned in Table 1 to simulate the DA market and using the developed methodology to provide analysis and recommendations for future scenarios of very large power systems. The efficacy of the developed methodology is applied for case studies of large-scale energy systems of North Sea countries for 2020, 2030 and 2050 energy scenarios including detailed representation of renewable variations. The computational and practical challenges in modelling and implementation for such a large system are discussed. The computational cost and accuracy of results for different UC modelling approaches are also compared. Even though the existing literature has investigated deeply the UC problem, introducing such analysis for the context of this study (large scale, different scenario years, multi-energy system) can be relevant to understand the advantages and disadvantages of the UC approach when simulating the DA market.

The paper is structured as follows. Section 2 explains the mathematical model-based methodology applied to model the DA market operation. Since the scale of the problem is large in terms of technologies, geography and time period, special considerations need to be taken to reduce computational complexity as described in Section 3. Section 4 presents the case study. Section 5 shows the results and discusses the limitations of the study while section 6 summarizes the conclusions.

2. Mathematical modelling

The methodology used in this paper to simulate the DA market can be split in four stages: DA optimisation (section 2.1), VRE simulations (section 2.2), storage and planned maintenance optimisation (section 2.3), and stochastic outage simulations (section 2.4). The stages are linked as shown in the

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flow chart of Figure 1. The sensitivity cases studied in this paper, which focus on the UC modelling approach, are presented in section 2.5.

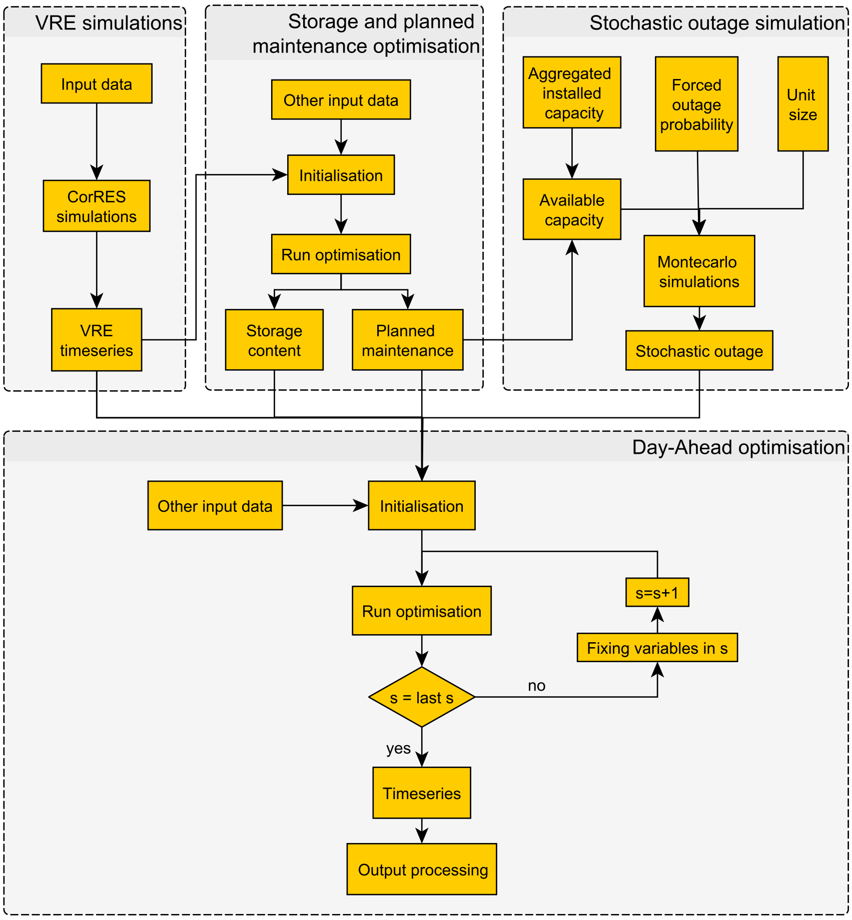

Figure 1. Flow chart of the methodology.

The optimisations and simulations, except for the VRE simulations, are performed with the energy system model Balmorel [24], an energy system tool, deterministic, open source [25], with a bottom-up approach. It has been traditionally used to model the electricity and district heating sectors, although it is being developed to increase its capabilities and include more sectors [26].

The temporal representation used is composed of years $y \in \mathbb{Y}$, which are disaggregated into seasons $s \in \mathbb{S}$ (in this paper days), which are composed of time steps $t \in \mathbb{T}$ (in this paper hours).

The geographical representation used is composed of countries, which are composed of regions $r \in \mathbb{R}$, which are disaggregated into areas $a \in \mathbb{A}$. Regions are built to represent copperplate zones for electricity transmission, whereas areas represent copperplate zones for heat transmission.

2.1. Day-Ahead optimisation

The DA optimisation of the energy markets is performed in a daily basis to replicate the behaviour of the spot market of electricity. This means that consecutive dispatch optimisations of 24 hours are performed. The results are linked from day to day, which means that operational decisions made in previous days can have a limiting effect on the operation on the following days, depending on the flexibility of the units.

The storage content at the beginning of each day for the DA optimisation, as well as the planned maintenance, is fixed from the storage and planned maintenance optimisation. Additionally, the availability of the units within the day is also affected by stochastic outage, which together with the

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planned maintenance determine the final availability of the units to participate in the markets. Detailed mathematical formulation of the problem can be found in appendix A of [27]. For the sake of space limitation, only a few equations are shown here.

2.1.1. Objective function

The objective function constitutes of all operational costs of the studied system in the studied time steps and during the solving phase the value of the objective function is minimized (Equation 1). The time steps considered in this optimisation correspond to one day. In this paper, the costs have been aggregated into to variable operational and maintenance costs, and emission tax costs. Fixed operational and maintenance costs which depend on the installed capacity are also included in the objective function as a parameter. The disaggregation of these costs can be found in equations A2-A6 of [27].

$$\min \sum_{y \in \mathbb{Y}} c_y^{vom} + c_y^{emi} + C_y^{fom} \tag{1}$$

2.1.2. System constraints

There are two main system constraints that need to be fulfilled in every time step. One of them is the electricity balance, in which the use of the electricity storage is optimized, and where most of the electricity demand is considered inelastic, except for the use of electricity to heat in district heating networks:

$$\begin{aligned} &\sum_{a \in \mathbb{AR}} \left(\sum_{g \in \mathbb{EL}} p^{el}_{g,a,y,s,t} - \sum_{g \in \mathbb{STO}, g \in \mathbb{EL}} stol_{g,a,y,s,t} - \sum_{g \in \mathbb{PTOH}} d^{f}_{g,a,y,s,t} \right) \\ &= D^{el}_{r,y,s,t} + \sum_{r' \in \mathbb{R}} \left(x_{r,r',y,s,t} - x_{r',r,y,s,t} \cdot (1 - xloss) \right) \\ &\qquad \forall r \in \mathbb{R}, y \in \mathbb{Y}, s \in \mathbb{S}, t \in \mathbb{T} \end{aligned} \tag{2}$$

The other system constraint is the heat balance, where the use of heat storage is optimized and the heat demand considered inelastic:

$$\sum_{g \in \mathbb{HEAT}} p^{h}_{g,a,y,s,t} - \sum_{g \in \mathbb{STO}, g \in \mathbb{HEAT}} stol_{g,a,y,s,t} = D^{h}_{a,y,s,t} \qquad \forall a \in \mathbb{A}, y \in \mathbb{Y}, s \in \mathbb{S}, t \in \mathbb{T} \tag{3}$$

Ancillary services in the electricity sector were not included to simplify the problem.

2.1.3. Technological constraints

Generation technologies in the model are split in three categories: dispatchable generation units, pure storage units, and VRE units. Dispatchable technologies include electricity-only, combined heat and power, boilers, heat pumps, geothermal, and hydroelectric power with reservoirs. These units are subject to several technical constraints. The operation of these technologies depends on the available units in each time step and specific technical characteristics of each type. The equations relevant for each of these technologies are described from A-29 to A-48 in the report [27]. Those storage units that do not receive inflow except from the active loading are defined as pure storage units. Examples of these technologies are hydro pumping, electric batteries, hot water tanks, or pit heat storage. The relevant equations for these units are equations A-49 to A-71 in [27]. Non-dispatchable technologies included are solar PV, solar heating, wind onshore and offshore, and hydro-run-of-river. The equations limiting their production are A-72 and A-73 in [27]. Furthermore, electricity trade is allowed between regions, which are assumed to be copper plates, and is limited to the available transmission capacity between the regions in each time step. The relevant equation limiting their operation is A-74 in [27]. Heat trade between areas is not allowed.

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2.2. Modelling of renewable generation including fluctuations

The CorRES model [28] is used for simulating the VRE generation time series used as inputs for Balmorel. CorRES is based on data from the weather research and forecasting model [29]. In addition to modelling the spatiotemporal dependencies in wind and solar PV generation, CorRES allows modelling of VRE technology development impacts on the VRE time series. For the presented case study, the assumed VRE technology developments towards 2050 are described in [30]. The resolution of the simulated VRE generation time series is hourly; data are aggregated to the regions used in Balmorel.

2.3. Storage and planned maintenance optimisation

When simulating the DA market, it is important to capture that some of the decisions that market participants take are based on future expectations of market prices, rather than just planning for the next 24 hours. Planned maintenance and use of storage are part of these long-term decisions. In this paper, these two decisions are obtained by performing a full year dispatch optimisation. Planned maintenance and storage content at the beginning of each season are saved and forced in the DA optimisation. Planned maintenance is also used in the stochastic outage simulation to calculate the available capacity for production that can suffer an unexpected outage.

The formulation is similar to the one in section 2.1, with a few exceptions. The time steps considered in this optimisation correspond to one year. All the equations can be found in [27]. In this paper only some equations are shown.

2.3.1. Available units

The availability of the units due to planned maintenance is endogenised in this optimisation. Planned maintenance decisions influence the availability factor of the units when simulating the DA market.

$$\frac{FC_{g,a,y}}{US_g^{gen}} - n_{g,a,y,s}^{nav,pm} \geq n_{g,a,y,s,t}^{av,on} \qquad \forall g \in \mathbb{GD}, a \in \mathbb{A}, y \in \mathbb{Y}, s \in \mathbb{S}, t \in \mathbb{T} \tag{4}$$

Additionally, the maximum number of units on maintenance is limited by the total number of units:

$$\frac{FC_{g,a,y}}{US_g^{gen}} \geq n_{g,a,y,s}^{nav,pm} \qquad \forall g \in \mathbb{GD}, a \in \mathbb{A}, y \in \mathbb{Y}, s \in \mathbb{S} \tag{5}$$

2.3.2. Yearly maintenance requirement

The following equation makes sure the minimum maintenance time per technology is respected in each year:

$$\sum_{s \in \mathbb{S}} n_{g,a,y,s}^{nav,pm,su} \cdot SL_s = MMT_g \cdot \frac{FC_{g,a,y}}{US_g^{gen}} \qquad \forall g \in \mathbb{GD}, a \in \mathbb{A}, y \in \mathbb{Y} \tag{6}$$

2.3.3. Uninterrupted maintenance

Maintenance is assumed to take place uninterrupted, i.e. in consecutive seasons:

$$\sum_{s'=1}^{MMT_g} n_{g,a,y,s-s'}^{nav,pm,su} \leq n_{g,a,y,s}^{nav,pm} \qquad \forall g \in \mathbb{GGG}, a \in \mathbb{A}, y \in \mathbb{Y}, s \in \mathbb{S} \tag{7}$$

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2.3.4. Logical conditions

The number of units on maintenance depends on the units starting or stopping maintenance:

$$n^{nav,pm}_{g,a,y,s} - n^{av,pm}_{g,a,y,s-1} = n^{nav,pm,su}_{g,a,y,s} - n^{nav,pm,sd}_{g,a,y,s} \qquad \forall g \in \mathbb{GGG}, a \in \mathbb{A}, y \in \mathbb{Y}, s \in \mathbb{S} \tag{8}$$

In order to reflect the discrete nature of the generation units that are part of the energy system, the following variables are restricted to be integer variables. As mentioned in section 3.2, this constraint is relaxed however due to computational complexity in the optimisation.

$$n^{av,on}_{g,a,y,s,t}, n^{nav,pm}_{g,a,y,s}, n^{nav,pm,su}_{g,a,y,s}, n^{nav,pm,sd}_{g,a,y,s} \in \mathbb{Z}^+ \qquad \forall g \in \mathbb{GGG}, a \in \mathbb{A}, y \in \mathbb{Y}, s \in \mathbb{S}, t \in \mathbb{T} \tag{9}$$

2.4. Stochastic outage simulations

Unexpected operational problems can lead to making units unavailable until the problem is fixed, which can influence market prices. Hence, it is relevant to capture these occurrences. Using as input parameters the total capacity of a unit type in each area, the size of a single unit, the planned maintenance (if previously calculated), and the probability of suffering an outage, Monte carlo simulations are performed for each time step and unit in the system to simulate these outages. The outcome from these simulations is then fed to the DA optimisation, and the relevant variables fixed. This approach is applied to all units excepts to VRE ones, since their availability is part of the time series used. The formulation can be found in equations A-85 and A-86 of [27].

2.5. Sensitivity cases: unit commitment modelling approaches

To analyse the importance of the UC modelling approach when modelling the DA market, three different sensitivity cases of UC modelling approaches are studied in the DA optimisations: 1) adding UC constraints with integer commitment variables (UC-MIP), 2) adding UC constraints with relaxed commitment variables (UC-RMIP), and 3) not adding constraints nor corresponding commitment variables (NO-UC).

3. Special considerations for Long-term Operational Planning of Large-Scale Energy System

3.1. Unit commitment assumptions

Introducing UC in the optimisation allows for an improved representation of conventional generation, at the cost of increasing considerably computational complexity due to the use integer variables. Solving a large-scale MIP problem can be intractable. To deal with this problem, one can either relax the integer variables, or limit the technologies modelled with integer variables. In this paper, the second approach is considered so the impact of the different optimisation approaches can be evaluated. The technologies modelled with UC integer variables are almost all type of fuel-based thermal plants, i.e. gas turbines, steam turbines, combined cycle turbines and boilers. Engines were not included since they are very fast and their size is generally much smaller than other generators, making their impact negligible. The rest of the technologies, i.e. hydro reservoirs, other storage, P2H, and VRE, were not modelled with UC variables to reduce the complexity of the problem.

3.2. Simplifications in storage and planned maintenance optimisation

Optimal planning of maintenance is solved as a relaxed mixed integer problem (RMIP), including all days of the years but with 1 every 3 hours to reduce complexity. Planned maintenance is only computed for the units modelled with UC (see section 3.1).

4. Case Study: The North Sea offshore grid

The study case used in this paper corresponds to the offshore grid scenario presented in [30], developed as part of the North Sea Offshore Network - Denmark project. The scenario focuses on the following countries: Norway, Great Britain, Netherlands, Belgium, and Germany. The sectors included are the electric and district heating sectors. The study case shows towards 2050 a high share of VRE, transmission interconnection, and partial electrification of the district heating sector in the countries in focus. The capacity development (Figure 2) was highly influenced by the assumptions on increasing CO_2 EU ETS price: 5.93, 75.16, and 127.77 2015€ /ton in 2020, 2030, and 2050 respectively. More details about the scenario can be read in [30], [31], and [32].

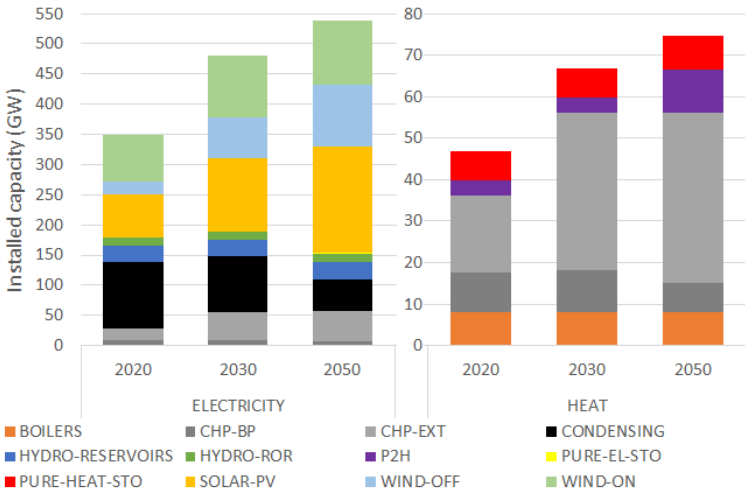

Figure 2. Installed capacity in the countries in focus (GW). The types considered are heat boilers, CHP back pressure (CHP-BP), and CHP extraction (CHP-EXT), electricity-only thermal units (condensing), hydro reservoirs, hydro run-of-river (ROR), P2H, other electricity storage (PURE-EL-STO), heat storage (PURE-HEAT-STO), solar PV, wind offshore (WIND-OFF) and wind onshore (WIND-ON).

5. Results and discussion

First, section 5.1 focuses on key results obtained from the storage and planned maintenance optimisations. Section 5.2 presents the results from the Day-Ahead optimisations, focusing on the influence of VRE penetration and the UC modelling approach. The limitations of the study are discussed in section 5.3. Costs and prices are in €$_{2012}$.

5.1. Storage and planned maintenance optimisation

5.1.1. Planned maintenance

The share of installed capacity under planned maintenance of district heating units burning waste in Denmark is shown in Figure 3. Units burning waste tend to show high capacity factors, and hence, the scheduling of their maintenance is of relevance. The results show that most of the planned maintenance takes place during summer, which is when the district heat demand is lowest. For CHP units, by 2020 most of the maintenance takes place in July (89%), and towards 2050, a larger share of the maintenance takes place in earlier months. The fact that in 2050 maintenance in May is 34% of the total could be linked to solar PV generation, since in Denmark the production of this technology is highest in this month, favoring the use of electricity-to-heat (P2H), and hence, leading to less need for CHP units to be operative. For district heating boilers, no significant difference towards 2050 is observed.

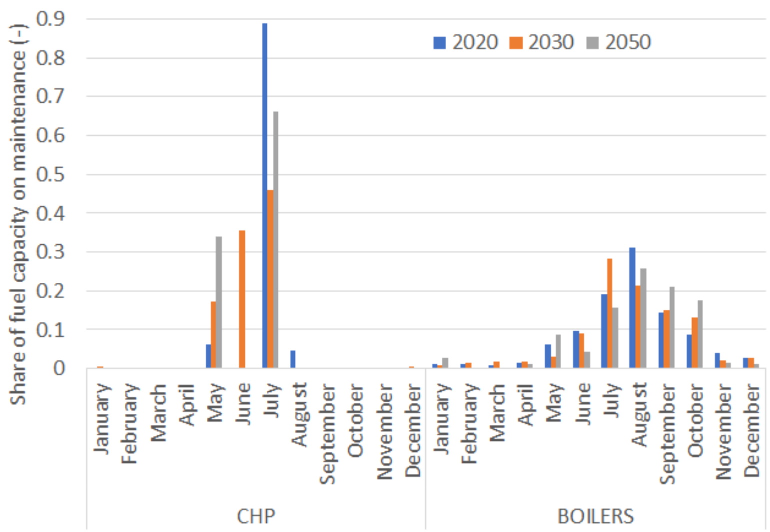

Figure 3. Share of capacity on maintenance of district heating units burning waste in Denmark.

5.1.2. Planned storage use

The aggregated planned energy content along the year of hydro reservoirs in Norway is shown in Figure 4. The minimum value of each profile has been subtracted. The results show that reservoirs are mainly filled during the summer and discharged during winter. The maximum energy content is higher in 2020 than in 2030 and 2050. This is a result of storing less energy in the reservoir during the year, which is linked to using hydro energy for balancing VRE. These results strengthen the importance of performing full year optimisations.

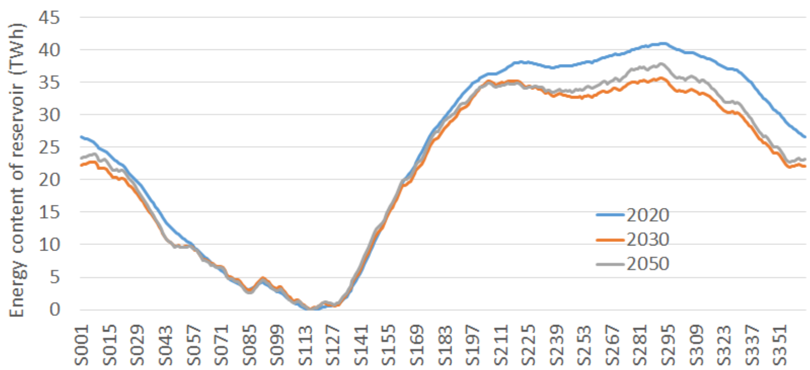

Figure 4. Planned energy content along the year of hydro reservoirs in Norway (TWh). The minimum value of each profile has been subtracted.

5.2. Day-Ahead optimisation

5.2.1. Annual production

The aggregated generation of electricity and heat per year, scenario, and technology in the countries in focus for different UC approaches is depicted in Figure 5. The penetration of VRE in the electric sector towards 2050 is remarkable, at the expense of decreasing the use of thermal technologies. The results show that the share of CO_2 free generation increases from 64% in 2020 to 91%, which is linked to the assumed VRE penetration. On the heating side, the generation of P2H units increases towards 2050 at the expense of thermal units. Introducing UC constraints increases slightly the aggregated production of thermal power units and reduces VRE generation.

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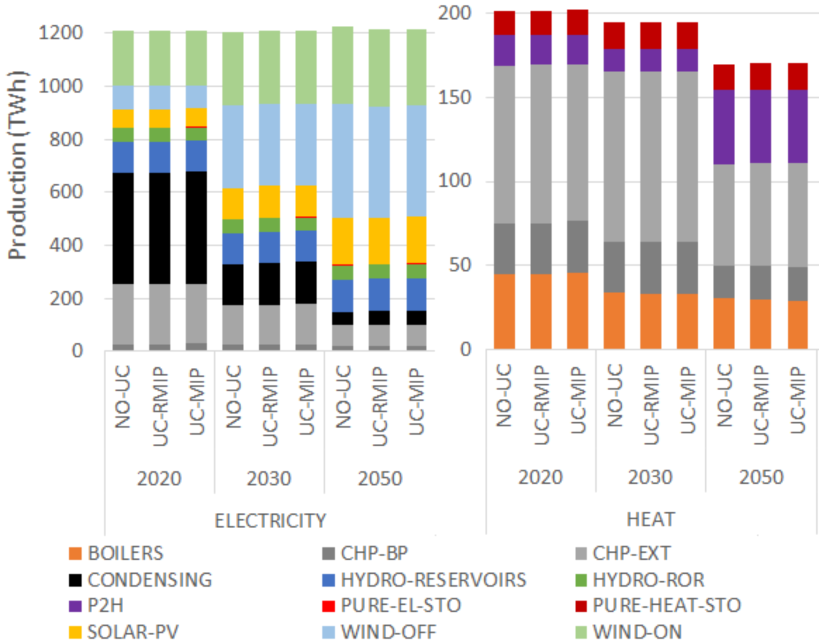

Figure 5. Production development per commodity, year, technology type, and UC approach (TWh).

The average capacity factor of thermal power units for electricity with/without heat generation is shown in Figure 6 for the UC-MIP approach. The difference with NO-UC and UC-RMIP is negligible. The electricity capacity factor is calculated with rated electricity generation capacity, whereas the heat one uses rated heat generation capacity. The results show that towards 2050, the average electricity capacity factor decreases for CHP back pressure units, CHP extraction units and electricity-only units, especially for the last two types. The heat capacity factor also tends to decrease. These results suggest that massive penetration of VRE might challenge the profitability of thermal units towards 2050.

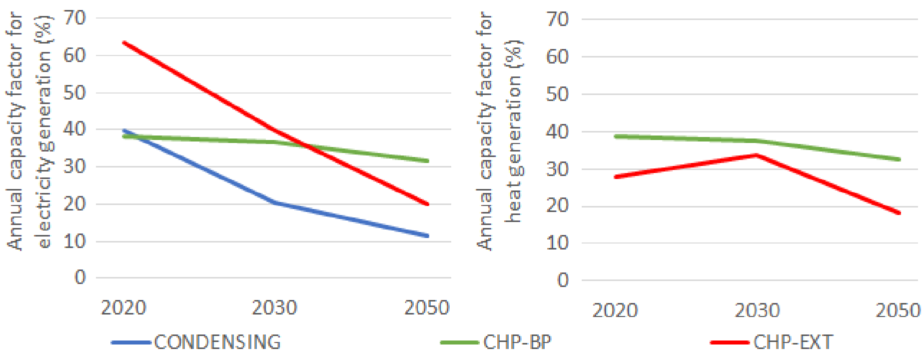

Figure 6. Average capacity factor development of thermal power units for electricity (left) and heat (right) generation using UC-MIP. The difference with NO-UC and UC-RMIP is negligible.

5.2.2. System costs

The disaggregated operational costs development in the countries in focus per UC approach is shown in Table 2. The total operational costs increase in 2030 with respect to 2020, and decrease in 2050 compared to 2030. This development is linked to VRE penetration and CO_2 tax assumptions. By 2030, there is still considerable fossil generation, leading to high CO_2 tax costs. By 2050, even though the CO_2 tax is higher than in 2030, there is much less fossil generation, which together with further VRE penetration leads to considerably less variable costs. Using UC-RMIP leads to much closer results to UC-MIP than using NO-UC, although the difference decreases towards 2050, again due to less fossil generation. Not including UC constraints, i.e. using NO-UC, underestimates both variable and CO_2 costs since it overestimates the flexibility of the units when ignoring relevant costs such as start-up.

Table 2. Disaggregated operational costs (billion €).

Year	Modelling approach	Fixed costs	Variable costs	Emission costs	Total
2020	NO-UC	8.2	12.3	1.8	22.4
	UC-RMIP	8.2	13.6	1.9	23.7
	UC-MIP	8.2	14.1	1.9	24.2
2030	NO-UC	9.6	13.5	6.3	29.4
	UC-RMIP	9.6	14.4	6.5	30.5
	UC-MIP	9.6	14.7	6.6	30.9
2050	NO-UC	10.6	8.5	6.1	25.2
	UC-RMIP	10.6	9.0	6.2	25.8
	UC-MIP	10.6	9.1	6.3	26.0

5.2.3. Hourly electricity balance

The hourly electricity balance for four representative days for the years 2020, 2030, and 2050, for Great Britain and with the UC-MIP approach, is depicted in Figure 7. The prices are derived from the dual variable of the electricity balance equation (Equation 2). The graph includes aggregated generation and demand per type, as well as electricity prices. The penetration of VRE replaces most thermal generation towards 2050. Such a large penetration of VRE energy highlights the need for proper planning of balancing resources towards 2050, since forecast errors could challenge the correct operation of the system.

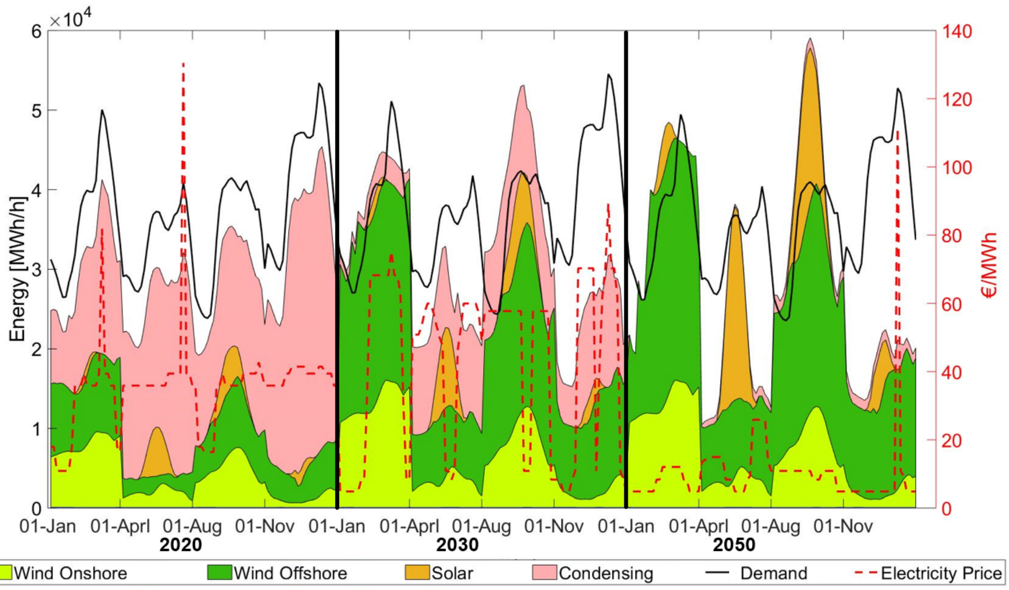

Figure 7. Hourly dispatch and electricity prices for 4 representative days of each year in GB using UC-MIP.

5.2.4. Electricity prices

The influence of the UC approach in the cumulative probability curves for the electricity prices in each year, for the region DK1 is shown in Figure 8. The influence of the optimisation approach decreases towards 2050, which is explained with the decrease of thermal power capacity and use towards 2050, since they are the ones affected by the different UC approaches. UC-MIP leads to overall higher prices in all price-range due to forcing discrete block sizes to be on/off for thermal units. The number of hours with very low prices (where VRE curtailment sets the price), are higher with

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UC-RMIP, and especially with UC-MIP. These low prices generally correspond to those hours where it is cheaper (or the only feasible way) to increase the use of more expensive generation units, rather than starting/shutting them. In the mid-range prices, the prices for UC-RMIP tend to be the lowest, which can be explained in a similar way to VRE curtailment, but instead, what it is being "curtailed" is the next available cheaper generator. On the high-range prices, NO-UC underestimates high prices, which can be explained with the non-consideration of restrictive constraints like minimum-on/off time, minimum production, and ramping. The order of magnitude of the prices is highly influenced by the CO_2 tax assumption development (section 4).

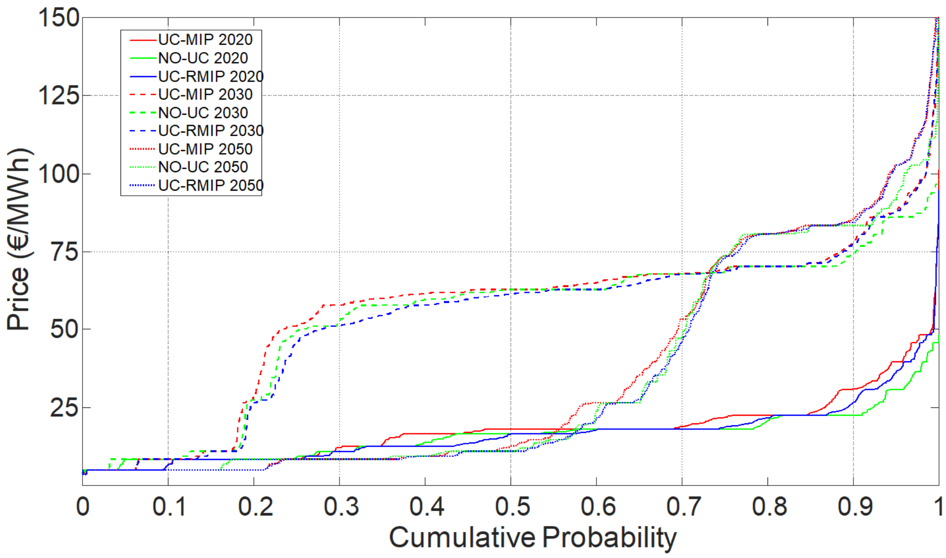

Figure 8. Probability distribution function of the hourly electricity price in DK1 for each year and UC modelling approach.

5.2.5. Curtailment

The influence of the UC approach on curtailment for different technology types in the countries in focus per year are shown in Table 3. Not considering UC costs leads to less curtailment. On the other hand, wind offshore is curtailed more often than onshore due to operation costs assumptions, i.e. variable costs for offshore are more expensive than for onshore. The impact of not considering UC costs on curtailment increases towards 2050, when there is higher VRE penetration.

Table 3. Influence of UC approach in aggregated yearly curtailment per technology type in the countries in focus. Difference with respect to UC-MIP approach (TWh).

Technology type	NO-UC			UC-RMIP		
	2020	2030	2050	2020	2030	2050
Wind offshore	-0.9	-4.3	-13.9	0	0	0
Wind onshore	-0.3	0	-0.1	0	0	0
Total	-1.2	-4.3	-14	0	0	0

5.2.6. Average revenue of wind and solar PV units

The influence of the UC approach on the variability of the average revenue per energy unit sold in each region and year from the operation in the DA market for wind and solar PV units is shown in Figure 9. The results show a decrease in the variability of the average revenue across countries towards 2050, mainly due to grid expansion, which remarks the importance of large-scale energy system analysis. Solar PV's average revenue is higher in 2020 and 2030 than wind unit's, but slightly smaller in 2050. With a UC-MIP approach, average revenues are slightly higher for both technologies. The yearly levels of average revenue are directly linked to the DA price development.

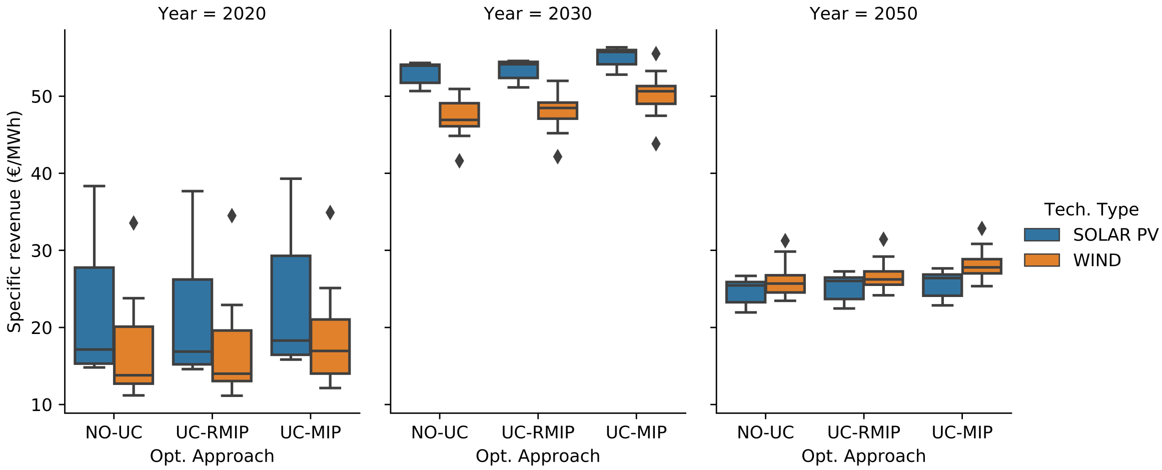

Figure 9. Regional variability of the average revenue per energy unit sold of wind and solar PV units in DA market towards 2050. Influence of UC modelling approach.

5.2.7. Electricity-only thermal plant operation

The influence of the UC approach in the utilization factor of electricity-only thermal generation units using natural gas or nuclear fuels is shown in Table 4. The results show a decrease in utilization for all the considered units towards 2050. Units burning natural gas half their capacity factor with respect to 2020 in 2030 and stay almost constant by 2050. Nuclear power capacity factor also decreases considerably towards 2050. The UC approach impacts the utilization of nuclear power by 2050, overestimating its flexibility when using NO-UC. These results are influenced by the decrease of nuclear power in the system towards 2050, and the increasing penetration of VRE. This result challenges the profitability of these thermal units towards 2050.

Table 4. Influence of UC modelling approach and year in annual capacity factor of electricity-only thermal generation units for different fuels (/%).

	NATURAL GAS			NUCLEAR		
Modelling approach	**2020**	**2030**	**2050**	**2020**	**2030**	**2050**
NO-UC	17.1	7.6	7.6	95.2	85.5	55.1
UC-RMIP	18.0	8.6	7.7	93.5	87.0	61.5
UC-MIP	19.7	9.2	8.0	94.8	87.4	62.6

The impact of the UC modelling approach on hourly nuclear operation, highly affected by UC constraints, is shown in Figure 10, which shows the hourly operation of nuclear power plants for four consecutive days in Great Britain. The figure depicts that towards 2050, with higher VRE penetration, unless UC costs and constraints are considered, nuclear units start up and shut down with high frequency, which might be extremely challenging, and maybe unrealistic. These results strengthen the importance of multiple scenario year analysis as well as the UC modelling approach used.

5.2.8. Computational time

The influence of the UC modelling approach on the computational time of the DA optimisation of each full year is shown in Table 5. The computational time required to solve the UC-MIP case is much higher than the others, which decreases significantly towards 2050 since the number of thermal power

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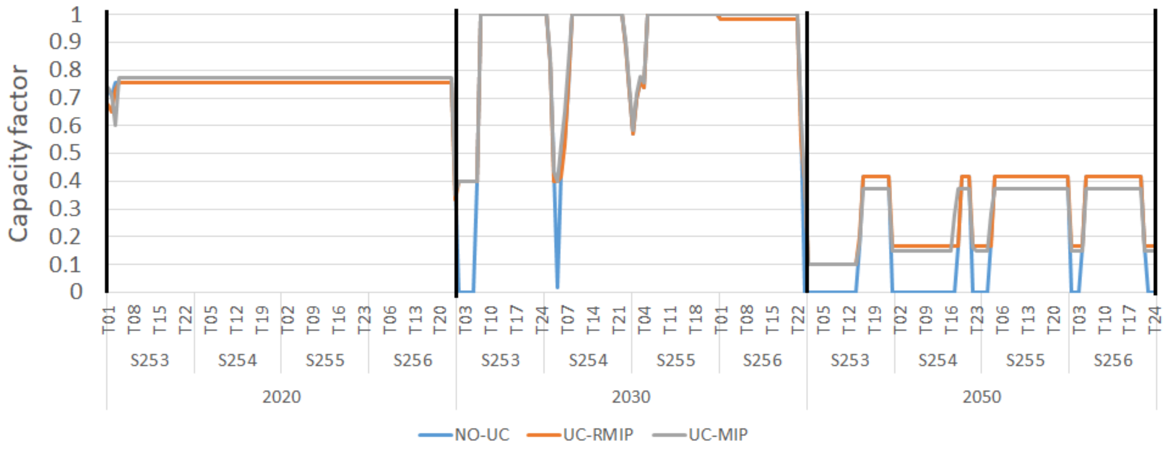

Figure 10. Hourly capacity factor of nuclear power in four consecutive days in Great Britain in different scenario years. Impact of UC modelling approach.

plants is considerably reduced in this scenario. Using UC-RMIP leads to closer computational times to NO-UC than to UC-MIP.

Table 5. Influence of year and UC modelling approach on the sum of computational time of all DA optimisations (seconds)[1].

Modelling approach	2020	2030	2050	Average
NO-UC	1263	1656	1168	1361
UC-RMIP	11026	18579	16220	15273
UC-MIP	106976	96435	55514	86308

5.3. Limitations of the study

The simplifications undertaken to reduce the complexity of the problem limit the findings of this study.

The flexibility of technologies for which UC constraints were not applied could have been overestimated, especially for hydro power units.

Further work should include adequacy analysis and/or ancillary services requirements in the simulations. Both of these aspects can be highly relevant for the correct operation of the system, especially towards 2050 with more VRE penetration. Furthermore, future research should also include stronger sector coupling, since it can influence considerably the generation of VRE technologies and the need for flexibility ([33], [23],[26]) .

The full-year foresight assumed for the planned maintenance and storage optimisation can be unrealistic due to the high uncertainty on, e.g. weather. Performing the analysis with several weather years and/or performing stochastic optimisation would help understand the role of uncertainty in the results. In this paper, for simplification, a unique weather year was used (2012), and stochastic features are mainly modelled through unplanned outages.

6. Conclusions

This paper proposes a mathematical model to simulate Day-ahead markets of large-scale multi-energy systems with high penetration of renewable energy towards 2050. Furthermore, it

[1] In UC-MIP runs, a relative gap of 0.00001, and a time limit of 660 seconds was assumed for each day of the year. The solver used was CPLEX. The optimisations are performed in High Performance Computing clusters (10 nodes were used). More information on https://www.hpc.dtu.dk/?page$_i d = 2520$

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analyses the influence of UC modelling on the results. The results highlight the importance of analysing multiple scenario years with long time series, including several sectors, as well as the value of not restricting the analysis to small scale.

The results for the studied case of the North Sea region show how the penetration of VRE towards 2050 challenges thermal units' traditional operation in the electricity and district heating sectors towards 2050. Furthermore, the high penetration of wind and solar is likely to challenge the need for balancing in the system, and hence, flexibility will be very important towards 2050.

The influence of the UC approach is found to be dependent on the scenario year. Generally, including UC constraints with integer variables leads to more realistic behaviour of the units, at the cost of increasing considerably the computational time. Relaxing integer variables reduces significantly the computational time, but medium-level prices are underestimated. Not including UC constraints leads to underestimation of costs, VRE curtailment, VRE's average revenue per energy unit sold, as well as price volatility. It also overestimates the flexibility of the thermal units. Hence, depending on the purpose of the analysis, it is recommended to think carefully on which UC modelling approach to use and acknowledge the limitations. When the focus is on prices and revenues, using UC constraints with integer variables is preferable, otherwise, relaxing the integer variables is encouraged.

The proposed model, together with the insights obtained from the study case, can be specially useful for system operators, who can use this model to perform operational planning studies towards 2050.

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Nomenclature

Acronyms

VRE	Variable Renewable Energy
VRE	Variable Renewable Energy
CHP	Combined Heat and Power
$P2H$	Power-to-Heat
DA	Day Ahead
UC	Unit Commitment
MIP	Mixed Integer Linear Programming
$RMIP$	Relaxed Mixed Integer Linear Programming

Sets

$g \in \mathbb{GGG}$	Generation and pure storage units
$y \in \mathbb{Y}$	Years
$s \in \mathbb{S}$	Seasons
$t \in \mathbb{T}$	Time steps
$a \in \mathbb{A}$	Areas
$r \in \mathbb{R}$	Regions
$ar \in \mathbb{AR}$	Areas in regions

Subsets

$\mathbb{STO} \subset \mathbb{GGG}$	Pure storage units
$\mathbb{GD} \subset \mathbb{G}$	Dispatchable generation units
$\mathbb{PTOH} \subset \mathbb{HO}$	Electricity to heat generation units
$\mathbb{EL} \subset \mathbb{GGG}$	Technologies delivering electricity to consumers
$\mathbb{HEAT} \subset \mathbb{GGG}$	Technologies delivering heat to consumers

Parameters

$FC_{g,a,y}$	Installed input fuel consumption capacity [MW]
$xloss$	Transmission loss [-]
$US^{gen}_{g,a,y,s,t}$	Unit size of input fuel capacity of a generation unit [MW/unit]
C^{fom}	Fixed annual cost [€]
SL_s	Season length [days]
MMT_g	Minimum maintenance time [days]
$D^{el}_{y,r,s,t}$	Exogenous gross electricity consumption rate [MW]
$D^{h}_{a,y,s,t}$	Exogenous gross heat consumption rate [MW]

Positive decision variables

$p^{el}_{g,a,y,s,t}$	Net delivered electricity [MW]
$p^{h}_{g,a,y,s,t}$	Net delivered heat [MW]
$d^{f}_{g,a,y,s,t}$	Fuel consumption rate [MW]
$stol_{g,a,y,s,t}$	Storage loading rate [MW]
$x_{r,r',y,s,t}$	Transmission flow [MW]
$n^{av,on}_{g,a,y,s,t}$	Units available for generation on [-]
$n^{nav,pm}_{g,a,y,s,t}$	Units not available for generation on planned maintenance [-]
$n^{nav,pm,su}_{g,a,y,s,t}$	Units not available for generation starting up planned maintenance [-]
$n^{nav,pm,sd}_{g,a,y,s,t}$	Units not available for generation shutting down planned maintenance [-]
$c^{vom}_{g,a,y}$	Variable operational and maintenance annual cost [€]
$c^{CO_2}_{g,a,y}$	Carbon dioxide tax annual cost [€]

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