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Impact of residential demand response on power system operation: A Belgian case study

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HIGHLIGHTS

- Demand response (DR) provides an efficient means to integrate RES and avoid surplus.
- DR decreases the loading and amount of start-ups of peak and mid-peak power plants.
- DR leads to lower operational cost, higher reliability and lower emission level.
- More uncontrollable capacity in a generation portfolio increases DR benefits.
- Scheduling battery electric vehicles brings higher societal value than scheduling white goods.

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ABSTRACT

The future power system is characterized by more renewable and uncontrollable capacity at the supply side and an electrification of energy at the demand side. Both evolutions increase the need for flexibility in the power system. Although this flexibility can be triggered at the supply and demand side, the latter is often overlooked. In this perspective, this paper assesses the impact of the use of flexibility at the demand side, also referred to as demand response, on power system operation. A two-stage modeling approach is used which combines a day-ahead deterministic unit commitment model and an hourly simulation in real-time. This approach is tested for two alternative Belgian generation technology mix scenarios including a detailed representation of residential demand response. Hereby, realistic cycling patterns of white goods and mobility patterns of battery electric vehicles serve as an input. This approach allows to quantify operational benefits of demand response and to assess a potential introduction of demand response in power system operation. Results show that in general demand response contributes to a lower cost, higher reliability, and lower emission level of power system operation. Moreover, a higher amount of uncontrollable capacity increases these benefits and therefore the societal value of demand response.

1. Introduction

Power systems around the world are facing challenges. At the supply side, traditional power generation portfolios are complemented with renewable energy resources (RES). Power generation from RES is characterized by limited controllability, limited predictability, and variability. At the demand side, an electrification of energy is occurring. The integration of battery electric vehicles (BEVs) and heat pumps illustrates this.

Both the renewables integration and the electrification of energy use, complicate power system operation. Due to variability and limited predictability of power generation, difficulties arise to maintain the demand–supply balance. Moreover, as demand grows due to the electrification of energy use, additional generation capacity is needed to cover peak demand. Traditionally, the supply side provides flexibility to safeguard the demand–supply balance and to cover increased peak demand, while ignoring demand-side flexibility. During the last decade, interest in flexibility at the demand side has grown. Hereby, consumers react to system conditions by adapting their consumption patterns, referred to as demand response (DR) [1].

The use of DR in systems with a high integration of renewables is investigated in literature. In [2], power system operation with

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high wind penetration is modeled by means of unit commitment modeling. This allows including the effect of wind variability. Results show that DR can level out variations in wind power, leading to cost and emission reductions. These reductions are accomplished by load shifting and peak reduction [3]. In [4], it is shown by means of unit commitment modeling that DR brings a reduction in wind power curtailment. Also in [5], the impact of DR programs in a high wind penetration scenario is tested. A day-ahead unit commitment model is combined with a real-time dispatch model. Next to the variability, this allows to account for the wind prediction error. Results show that less wind power is curtailed due to DR. In [6], the role of residential, commercial, and industrial demand-side management for integrating wind power in the system is assessed. Results show that peak reduction mitigates operational problems caused by the variability of wind power generation.

Also the impact of the electrification is investigated in literature. In [7], the impact of plug-in hybrid electric vehicles on power system operation is investigated using a detailed unit commitment model. It is shown that total operating costs can be reduced up to 13 percent. In [8], different possible charging strategies are tested in a unit commitment and daily economic dispatch model. The latter allows accounting for the prediction errors associated with power generation from RES.

A further refinement of the inclusion of DR in system operation modeling is needed. At the generation side, technical characteristics of generation plants such as ramping rates, minimum output, and minimum up and down time are neglected in [7]. In [2] and [4], a day-ahead unit-commitment model is performed, ignoring real-time operation. Therefore, prediction errors associated with power generation from RES are not considered. At the demand side, shiftable demand is often determined as a percentage of peak demand without accounting for the underlying consumption patterns of specific appliances [4], and [7]. A more detailed approach is needed to reach a realistic quantification of operational benefits. The same applies for BEVs as realistic driving patterns and BEV characteristics contribute to a more realistic outcome. Next to including realistic demand and supply characteristics, the analysis needs to be performed on a full year of data. Otherwise, the implications of single events are overestimated.

This paper assesses the impact of an introduction of DR on system operation, focusing on plant operation, system reliability, emissions, and costs. A detailed modeling approach of both the supply and demand side is taken, allowing to obtain a realistic quantification of DR benefits. The approach is applied on a full year of data. The focus is on residential DR, including the scheduling of white good appliances and BEVs. White good appliances are referred to as white goods (WGs) and include washing machines, dishwashers and dryers. BEVs only include residential light-duty vehicles. Electric heating is not considered in this paper as this requires the integration of weather conditions [9].

The remainder of this paper is structured as follows. Section 2 clarifies the operational model which is used to optimize system operation with DR. Section 3 elaborates on the data and assumptions for demand, DR, and generation. Results are highlighted in Section 4. Finally, Section 5 concludes.

2. Model

The impact of DR with WGs and BEVs on system operation is evaluated with the reliability and operation model for renewable energy sources (ROM-model). This model approximates real-life power system operation by combining two sequential stages: an optimization stage in day-ahead and an hourly simulation stage updating the economic dispatch in real-time. Each stage is documented below and visualized in Fig. 1. The model is solved in GAMS 24.0.1. using CPLEX 12.2 as a mixed integer problem solver.

2.1. Day-ahead optimization stage

2.1.1. Basic model description

In the optimization stage, a deterministic unit commitment and economic dispatch model is used to determine the optimal output of the thermal and hydro plants for the next day. This model contrasts with stochastic unit commitment models in which uncertainty is considered [10,11]. The specific mathematical formulation of the model used in this paper is extensively described in [2]. The model minimizes daily operational costs while meeting the demand–supply balance and the reserve requirements. Technical constraints for thermal units are considered. These include minimum and maximum output, maintenance, and ramping rates. Technical constraints for pumped storage units include bounds on the hydro reservoir and minimum and maximum output. The demand profile and the predicted power generation profile from RES are considered as an input. Also power generation from biomass plants and combined heat and power plants (CHPs) are modeled as an input, as generation from these plants is considered as uncontrollable from system operator point of view.

2.1.2. Inclusion of residential demand response

Within the day-ahead optimization stage, DR with WGs and BEVs is introduced. Contrary to the use of price elasticities [12–14], this is done by optimizing the consumption patterns of the appliances themselves. Hereby, the scheduling of appliances is modeled as a centralized decision making process taking into account behavioral constraints.

For WGs, the model allows to integrate DR with different types of appliances, such as washing machines or dryers. The hourly load pattern of each appliance type can be shifted in time according to its shifting potential. The load pattern shift for each type must be balanced within one day. A detailed model description of the inclusion of WGs is provided in [2]. The main mathematical formulation is added in appendix.

For BEVs, the model allows to integrate different types of cars with different types of usage and connection profiles. Several technical characteristics of BEVs and their batteries are considered: specific energy consumption when driving, battery capacities, grid-to-battery and battery-to-wheel efficiencies, maximum state of charge, and maximum charging power. When BEVs are scheduled, the energy requirements related to the mobility patterns must be satisfied. The inclusion of DR with BEVs is extensively described in [8,15]. The main mathematical formulation is added in appendix.

2.2. Hourly simulation stage in real-time

In the hourly simulation stage, two events are introduced which require corrective actions in order to meet the demand–supply balance. First, forecast errors of power generation from RES is integrated based on the difference between day-ahead predicted and real-time power generation. Second, forced outages on thermal units are simulated based on forced outage rates of power plants. Three main actions can be performed to restore the demand–supply balance. First of all, operation reserves kept available from the optimization stage are assigned. Secondly, quick start thermal units are deployed. As a last resort, generation surplus or energy not served is triggered. This leads to a revised output of thermal and hydro plants.

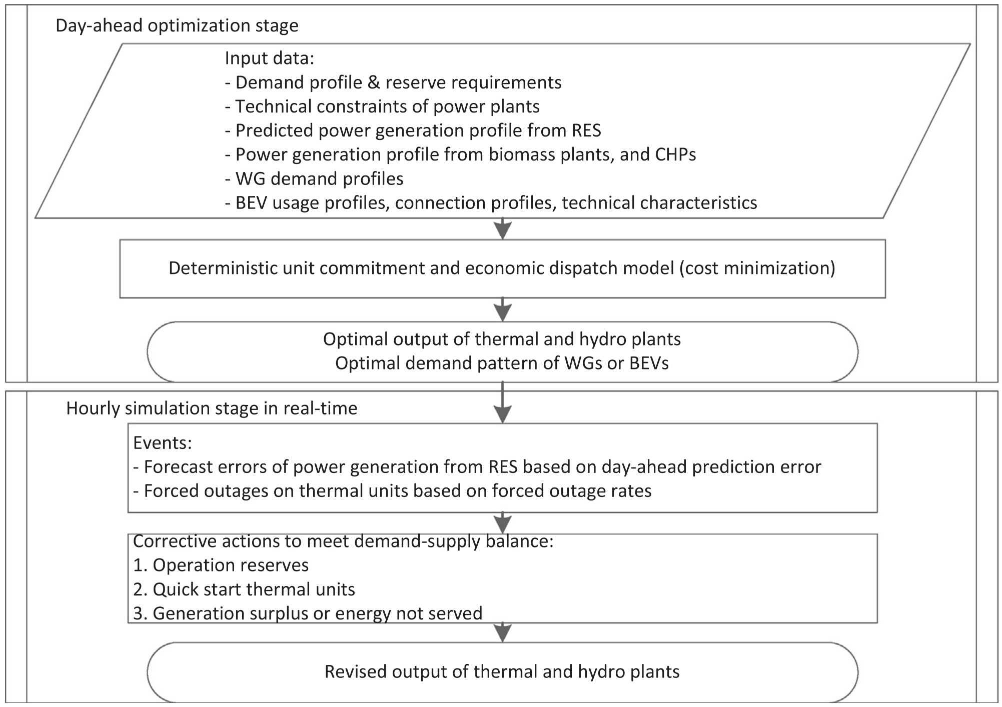

Fig. 1. Flowchart of the ROM-model.

3. Data and assumptions

The impact of DR with WGs and BEVs on system operation is assessed within two alternative power generation portfolios for a one year period. The first portfolio contains the Belgian power generation portfolio of 2012, while the second portfolio consists of the projected Belgian portfolio in 2025. In what follows, data and assumptions on both the demand and supply side are discussed.

3.1. Demand

Demand in Belgium is based on hourly load data from 2012, provided by ENTSO-E [16]. Yearly demand sums to 84.59 TW h/year. The average, maximum, and minimum hourly demand amounts 9.63 GW h/h, 14.19 GW h/h, and 6.24 GW h/h respectively. Demand in 2012 and 2025 are assumed identical.

3.1.1. White goods

Residential demand partly arises from consumption with WGs. These are split up in three types: washing machines (WMs), dryers (DYs), and dishwashers (DWs). Average load patterns for all Belgian white goods are depicted in Fig. 2. These patterns are deducted from total demand and modeled separately. In order to derive the Belgian load pattern for each appliance, the following parameters are used: the number of times appliances are cycled, the starting times of the cycles, and the consumption profiles of the cycles. Based on [17] and statistics from the federal public service [18], over 9 million WGs are present in Belgium and the number of cycles a day amounts to 2.51, 0.65, and 1.85 million cycles for washing machines, dryers, and dishwashers respectively. Starting times of appliances are derived from [19]. Realistic consumption cycles are attained from measured profiles from a large-scale pilot project named LINEAR [20]. This leads to a total yearly consumption of 1.93 TW h of which 0.53, 0.60, and 0.80 is attributable to WMs, DYs and DWs respectively. This exceeds 2% of total yearly electricity demand. It is assumed that all WG cycles can be used for load shifting purposes. While this is an overestimation, it allows results to be comparable with the scheduling of BEVs. A shifting potential of 4 h for both forward and backward shifting is assumed [21].

3.1.2. Battery electric vehicles

As the current Belgian demand does not include a significant amount of BEVs, power consumption of these has to be added to demand representing the electrification of energy. In both the 2012 and 2025 scenario, the amount of Belgian light-duty vehicles is assumed to be 5.41 million based on federal public service statistics [22], of which 8% or over 430 000 vehicles are BEVs [23]. Three

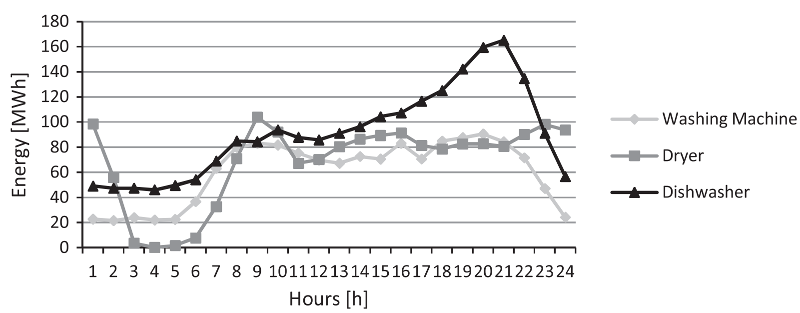

Fig. 2. Average daily load patterns of unscheduled Belgian white goods.

types of vehicles are considered: subcompact, midsize, and large vehicles. Each type has its own technical battery characteristics as depicted in Table 1.

In order to take into account realistic driving behavior in the Belgian vehicle park, 200 representative BEVs and their accompanying driving patterns are considered based on measured driving patterns of light-duty vehicles [24]. Total Belgian yearly power consumption of BEVs sums to 1.78 TW h. This exceeds 2% of total yearly electricity demand. The average load pattern in the unscheduled BEV charging scenario is depicted in Fig. 3. Hereby, it is assumed that BEVs are plugged in at each location when they are not driving. As soon as a BEV is plugged in, it starts charging until the battery reaches maximum state of charge or until the BEV departs again. With scheduled charging the timing and quantity of charging is optimized over the period when the BEV is not driving.

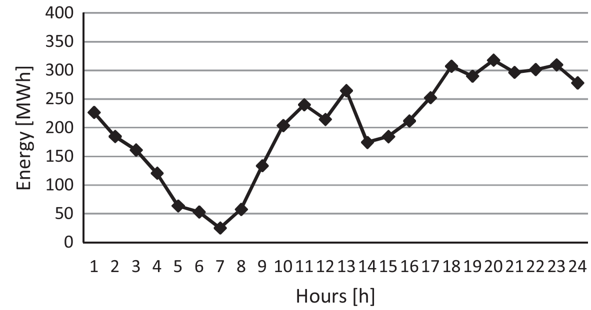

Fig. 3. Average daily load pattern of unscheduled charging of BEVs.

3.2. Power generation portfolio

3.2.1. Installed capacity

The current and future installed capacity in Belgium is based on data from ENTSO-E [26] and the Belgian Transmission System Operator (TSO) [27]. These capacity data are adjusted in two ways. Firstly, current and future installed wind and solar power capacity is revised according to renewed estimations from Belgian regulators [28,29]. Secondly, a full nuclear phase out is assumed by 2025 according to the Belgian TSO [30]. Apart from covering demand, both power generation portfolios need to provide reserves. An approximation of the Belgian reserve requirements is based on ENTSO-E and amounts to 870 MW and 970 MW for 2012 and 2025 respectively [26]. Interconnection capacity and its cross-border flows are not included in the analysis. Also the transmission grid is considered as a copper plate as no internal congestions are considered.

Total installed capacity in 2012 and 2025 amounts to 20.30 GW and 22.25 GW respectively. As depicted in Fig. 4, the 2012 portfolio is characterized by plants operating on a mix of primary energy sources. Gas and nuclear capacity make up the main part. This is complemented with solar, wind, hydro, biomass, coal, and oil capacity. Towards 2025, nuclear, coal, and oil capacity is phased out. Moreover, renewable integration becomes even more significant as more wind, solar, and biomass capacity is installed. These renewables make up almost 50% of total installed capacity. Installed capacity of gas power plants also rises due to an increase in combined cycle gas turbines and combined heat and power plants (CHPs).

3.2.2. Technical characteristics

Over 50 different thermal plants using different fuel types are present in Belgium. Capacities and fuel types of these plants are provided by the Belgian TSO [31]. Based on the capacities, the technical characteristics of plants are derived according to Table 2. Five different technologies are considered: pressurized water reactors (PWRs), steam power plants (SPPs), combined cycle gas turbines (CCGTs), gas turbines (GTs), and internal combustion engines (ICEs). Except for start-up costs, probability of maintenance and forced outage rate, all technical characteristics of the first four technologies are based on [32] and consistent with [33]. Start-up costs are based on [34], except for PWRs for which this characteristic is retrieved from [32]. The probability of maintenance and the forced outage rate are based on [35] for PWRs and on historic data from the Belgian TSO [36] for the other technologies. Technical characteristics of ICEs are retrieved from [34].

Power generation from run-of-river plants is assumed to be stable at 50% of capacity. Pumped storage units are assumed to produce at an efficiency of 80% [37]. The reservoir level allows power generation at full capacity for 5–6 h.

Power generation data for solar, wind, biomass, and CHP plants are based on data from the Belgian TSO [27]. For wind power, both day-ahead predictions and real-time power generation data are included to account for the prediction error. Power generation from biomass is included based on historical output data, while CHPs are considered as must-run plants with an unavailability rate of 14% in consistency with GTs. Towards 2025, all uncontrollable power generation data is scaled towards its respective installed capacity.

3.2.3. Fuel costs and carbon content

Fuel costs and the carbon content of fuels are listed in Table 3. Fuel costs are expressed in €/MW $h_{thermal}$, except for uranium which is given in €/MW $h_{electric}$. Emission costs are set at 15 €/tCO_2 [33].

4. Results

This section describes results obtained from the Belgian case study for a whole year. As DR is the driver of operational benefits, the scheduling of WGs and BEVs is addressed first. Afterwards, the impact of scheduling on power system operation is evaluated.

4.1. Residential demand response

4.1.1. Scheduled WG consumption patterns

To be able to assess the impact of residential DR on yearly power system operation, firstly the unscheduled and scheduled consumption patterns of WGs for 2012 are discussed. While on average 15% of the total WG consumption volume is reduced during peak moments, daily shifting patterns widely vary over the year. Fig. 5 compares the unscheduled WG consumption pattern and the spreading of scheduled WG consumption. To attain the spreading of scheduled consumption, all daily consumption patterns are bundled. Afterwards, a distribution is made for each specific hour over all days. Hourly median values of scheduled consumption are represented by the white line. The intervals around the median capture a percentage of the total amount of observations and visualize the spreading of the hourly white good

Table 1
Technical characteristics of BEVs.

	Subcompact BEV	Midsize BEV	Large BEV	Refs.
Specific consumption (kW h/km)	0.16	0.19	0.25	[24]
Battery capacity (kW h)	20.8	31.2	41.6	[24]
Grid-to-battery efficiency (%)	90	90	90	[24]
Battery-to-wheel efficiency (%)	90	90	90	[24]
Maximum state of charge (% of battery capacity)	95	95	95	[8]
Maximum charging power (kW)	4	4	4	[25]

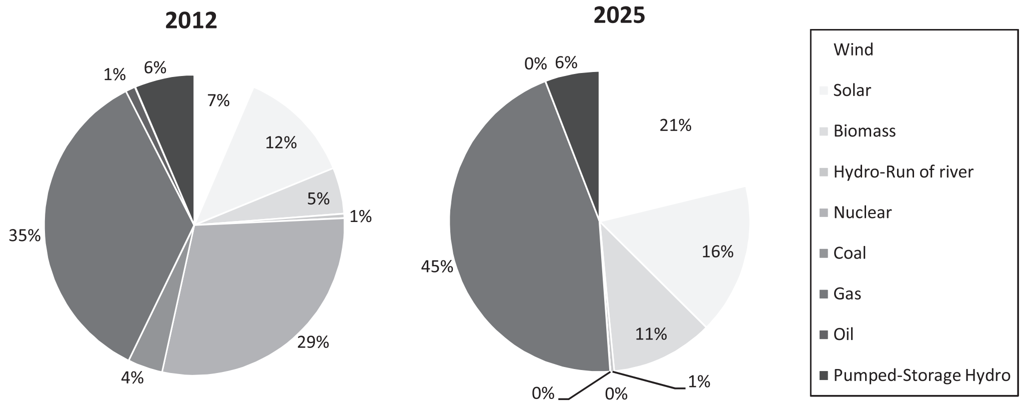

Fig. 4. Installed capacity in Belgium in 2012 and 2025.

Table 2
Technical characteristics of power plants.

Technology	Min. output (% of P_{max})	Max. output [% of P_{max}]	Efficiency at min. load (%)	Efficiency at max. load (%)	Up and down ramp (% of P_{max}/h)	Start-up costs (€/MW)	Maintenance (% of hours)	Forced outage rate (% of hours)
PWR	40	100	100	100	40	15	13	1
SPP	30	100	33	40	40	34	2	6
CCGT	45	100	53	60	100	73	7	2
GT	20	100	25	32	100	10	9	5
ICE	60	100	40	42	100	10	9	5

Table 3
Fuel prices and carbon content.

Fuel	Fuel costs (€/MW h)	Carbon content (tCO_2/MW h)	Refs.
Crude oil	48	0.63	[34,38]
Coal	10	0.85	[34,39]
Natural gas	23	0.34	[32,34]
UO_2	7	0.00	[40]

consumption. For example, the 0–10% interval shows the spreading of the 10% lowest consumption values for each specific hour. It can be seen that WG consumption shows a large day-to-day variation, as demand and uncontrollable generation patterns differ between days. Therefore, cost minimization leads to different WG consumption patterns. In general, appliances are often shifted from the morning and the evening towards the late afternoon and the night. This leads to demand reductions of up to 150 MW h/h. Although shifting often leads to new peaks in total white good consumption, shifted demand typically fills valleys when total demand is considered. Although not visualized in this paper, average shifting patterns in 2025 are similar to the average shifting patterns in 2012. Nevertheless, variability of shifting patterns is higher in 2025 due to wind and solar power variability.

4.1.2. Scheduled BEV consumption patterns

On average, 50% of the total BEV consumption volume in 2012 is reduced during peak moments. While unscheduled charging mainly takes place during daytime, scheduled charging shifts cycles towards the night as depicted in Fig. 6. Therefore, scheduled charging mainly occurs at home. Charging is mainly reduced during peak moments at noon and in the evening. During these moments, total BEV consumption is often reduced to a level of 0 MW h/h. This can amount to a 300 MW h/h reduction. Similarly to WG scheduling, scheduled charging creates new peaks on the level of BEV consumption. As these new peaks occur mainly during nighttime, shifted consumption fills valleys when total demand is considered. Compared to scheduled charging in 2012, shifts in the average BEV consumption pattern is less profound in 2025. Moreover, the variability of shifting patterns is higher. This results from more variability due to wind and solar capacity.

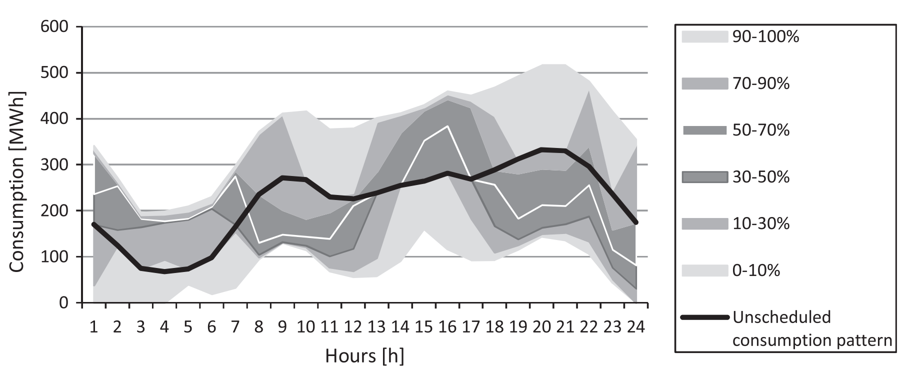

Fig. 5. Distribution of daily white good consumption in 2012.

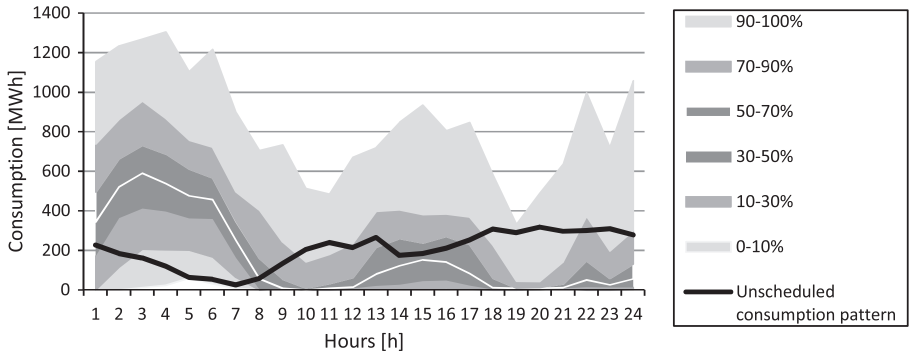

Fig. 6. Distribution of BEV charging patterns in 2012.

4.2. Impact of residential demand response on power system operation

4.2.1. Power plant operation

Demand response influences power plant operation within the current and future Belgian portfolio. To assess this influence, first power plant operation within two reference scenarios is evaluated. These reference scenarios consist of the 2012 and 2025 power generation portfolio in which no DR is present. Afterwards, the impact of DR is discussed. Distinction is made between WG and BEV scheduling as the impact is assessed in separate simulations.

The share of yearly power generation from different primary energy sources within the two reference scenarios is visualized in Fig. 7. For clarity reasons, power generation from oil and run-of-river hydro plants is omitted. These account for less than 1% of power generation. In 2012, over 50% of demand is covered by power generation from nuclear plants, while 28% is produced from gas plants. Wind mills, solar panels, and biomass plants contribute 14% of power generation. In 2025, significant changes in power generation shares occur. Nuclear and coal plants are phased out, while power generation from gas plants increases substantially due to an increase in CCGTs and CHP plants. Also power generation from wind mills, solar panels, and biomass more than doubles. As power generation from wind mills and solar capacity increases, hourly ramping also increases. Comparing both power generation portfolios, the increase in uncontrollable power generation is noteworthy. While in 2012 uncontrollable power generation amounts 24%, this increases to 54% in 2025.

When taking a look at power plant operation of different technologies, PWRs and SPPs are typically used as base load units. CCGTs are operated as mid-peak plants, while GTs, ICEs, and pumped storage units are used during peak moments.

Residential DR affects annual power generation of different power plants. In what follows, the focus is on CCGTs, GTs, and pumped storage units, as DR influences these mid-peak and peak units the most. This is visualized in Fig. 8. Hereby, annual generation of technologies within each scenario is compared with its reference scenario. Three main observations can be derived. Firstly, WG scheduling decreases annual generation from mid-peak and peak units. Secondly, BEV introduction increases the loading of those units. An exception is the decrease of GT loading in 2012. This is largely outset by an increased CCGT loading. Finally, the increased loading due to BEV introduction is reduced by scheduling BEVs. In other words, the scheduling of BEVs decreases the impact of a BEV introduction.

Similar effects occur during the peak moments of the year. In Fig. 9, load duration curves of CCGTs and GTs are visualized. These depict the highest 300 h of loading for each technology, covering different power plants. Due to decreased controllable generation capacity, mid-peak and peak plants run longer at full load in 2025 compared to 2012. Demand response, both with WGs and BEVs, decreases the hours mid-peak and peak technologies operate at full capacity. Moreover, in 2012 maximum GT loading is never attained under the scheduled BEV scenario.

DR also influences the frequency of starting up mid-peak and peak plants within a year (Fig. 10). In both 2012 and 2025, the amount of start-ups of CCGTs and GTs decreases when WGs are scheduled. This decrease can go up to 180 start-ups of CCGTs in 2012, corresponding to 15% of the reference start-ups. When unscheduled BEV charging is introduced, the amount of start-ups goes up. This increase is reduced when BEVs are scheduled. For example, in 2012 the amount of start-ups with CCGTs decreases with 437 or 33% compared to the unscheduled BEV scenario. Except for base load technologies, similar reductions in start-ups are found for other technologies. This illustrates that although the amount of flexible residential demand is limited compared to total demand, residential DR influences the amount of start-ups to a large extent.

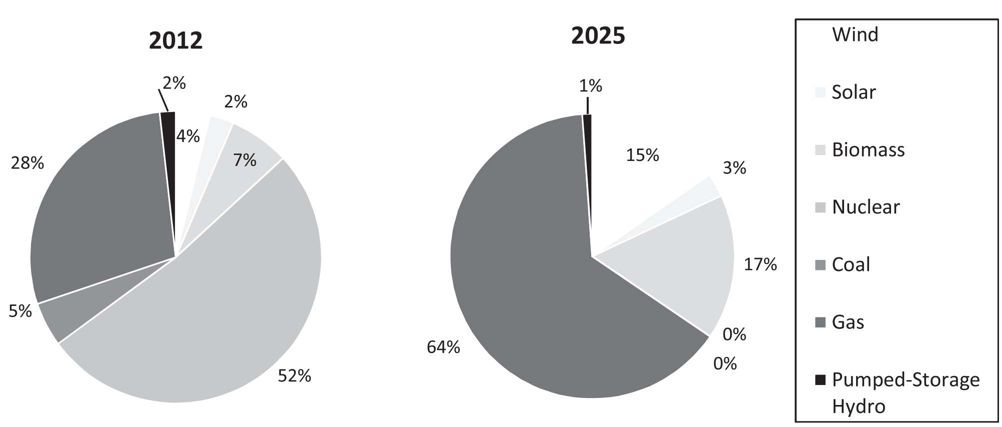

Fig. 7. Share of yearly power generation from different primary energy sources in Belgium in 2012 and 2025.

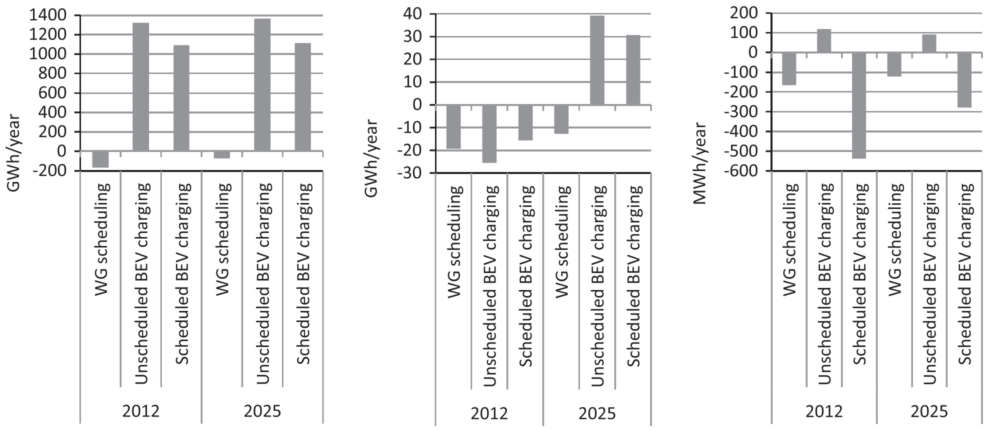

Fig. 8. Annual generation difference of CCGTs (left), GTs (middle), and pumped storage plants (right) compared to the 2012 and 2025 reference scenarios.

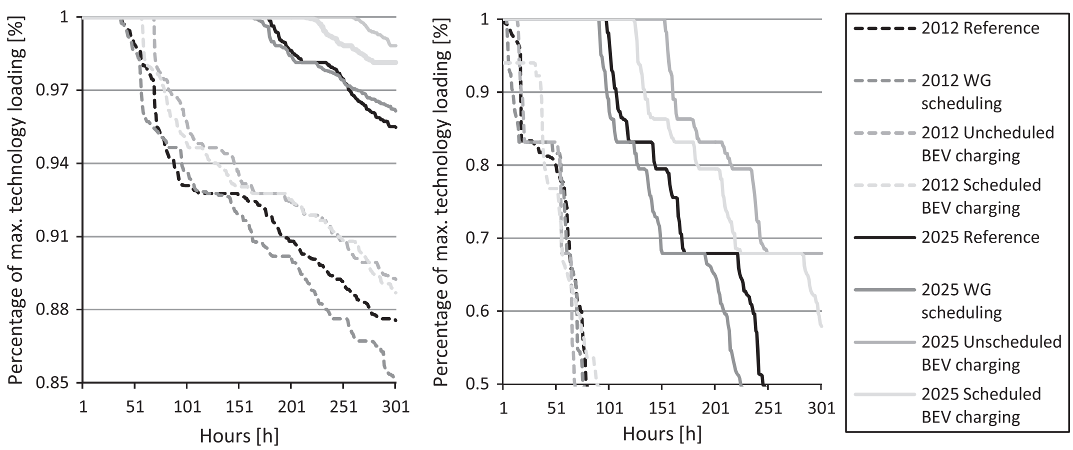

Fig. 9. Load duration curve of CCGTs (left) and GTs (right) for the top 300 h of the year in different scenarios.

4.2.2. Reliability

As plant operation is modified by DR, power system reliability is also affected. This impact is visualized in the first two rows of Table 4. Reliability is expressed by energy not served (ENS) and loss of load expectation (LOLE). While ENS describes the total amount of electricity demand which could not be delivered, LOLE defines the number of hours in which it is expected that demand cannot be met. As interconnection capacity is not considered, ENS and LOLE should be interpreted with care. While these parameters provide insights in system reliability, actual reliability will be higher as interconnection capacity is available.

Results show that ENS and LOLE are a lot higher in 2025 compared to 2012. This results from the underlying generation portfolio and reserve requirements in both years. In 2012, controllable capacity and reserve requirements are high enough to cover variations in RES, CHPs, and demand. ENS only occurs during forced outages of multiple large power plants. In 2025, demand cannot be met during 200 h. Although this number is distorted due to the exclusion of cross-border flows, it illustrates that the increase in wind, solar, biomass, CHP, and CCGT capacity and the limited increase in reserve requirements are not sufficient to fully cover the phase out of nuclear and coal capacity. This leads to a capacity constrained portfolio in which controllable capacity is not always able to cover demand peaks. Together with limited predictability of wind power, this is the main reason of ENS.

It can be noticed that ENS not necessarily decreases when demand response is introduced. This is a consequence of two counteracting effects. On the one hand DR contributes to peak shaving, reducing ENS when total capacity is constrained, such as in 2025. In this case, DR with white goods decreases ENS with 1% compared to the reference case. Scheduling of BEVs also reduces ENS by 7% or 13.25 GW h compared to unscheduled charging. On the other hand, DR results in a decreased number of committed power plants in the day-ahead optimization stage. This can result in a decrease of flexibility from committed plants on top of the reserve requirements as plants are running closer to their capacity limits. This can lead to more ENS in the real-time simulation stage. Although the impact is small, this effect leads to an ENS increase in 2012.

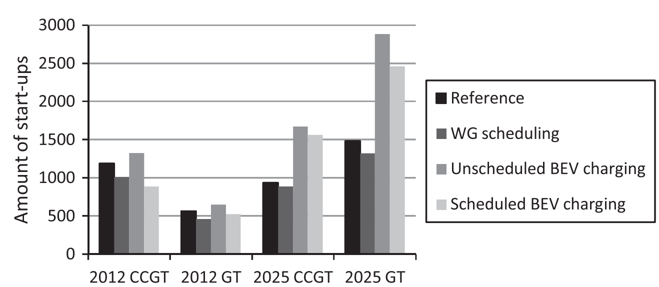

Fig. 10. Amount of start-ups of CCGTs and GTs in different scenarios.

Table 4
Reliability, emissions, and costs in different portfolios.

	2012 Power generation portfolio				2025 Power generation portfolio			
	Reference	WG scheduling	Unscheduled BEV charging	Scheduled BEV charging	Reference	WG scheduling	Unscheduled BEV charging	Scheduled BEV charging
ENS (GW h)	6.49	7.07	7.99	8.02	144.90	143.50	199.29	186.04
LOLE (h/year)	25	30	37	37	200	202	266	245
Renewable surplus (GW h)	0.00	0.02	0.00	0.01	774.15	700.33	630.04	374.55
Emissions (MtCO_2)	8.94	8.92	9.62	9.62	10.37	10.33	11.00	10.86
Total costs (M€)	1207	1200	1290	1278	1697	1686	1887	1842
Thermal costs (M€)	1206	1199	1279	1271	1389	1381	1463	1445

4.2.3. Environment

Scheduling of WGs and BEVs impacts the environment due to a change in power plant operation. In what follows, this impact is expressed by the amount of renewable surplus or spillage and CO_2-emissions as depicted in the third and fourth row of Table 4.

Results show that renewable surplus is zero in 2012 when no demand response is used. Towards 2025 renewable surplus increases to 774 GW h due to limited controllability and the variability of wind and solar power generation. This equals almost 1% of annual demand. By scheduling WGs, surplus is reduced by 10%. By scheduling BEVs, the decrease is even higher and amounts to 41% or 255.49 GW h compared to the unscheduled scenario.

Also CO_2-emissions are affected by the underlying production portfolio and the presence of DR. In 2012, CO_2-emissions amount to 8.94 million ton CO_2 in the reference scenario. Towards 2025, CO_2-emissions increase with 16% due to the nuclear phase out and its replacement by gas capacity. By scheduling WGs, CO_2-emissions decrease to a minor extent. Although WG scheduling decreases the loading of polluting ICE in 2012, this effect is counteracted by an increased loading of polluting coal plants. In 2025, only the loading and the amount of start-ups of gas plants are reduced. This has a limited effect on emissions. The introduction of BEVs increases CO_2-emissions from the power system significantly due to increased power generation. Emissions increase with 8% in 2012 and 6% in 2025. Although the effect is limited, the scheduling of BEVs reduces CO_2-emissions compared to the scheduled case. It should be noted that the decrease in emissions due to the electrification of transport is not accounted for.

4.2.4. Costs

Demand response influences annual operational costs. This impact is visualized in the last two rows of Table 4. Hereby, only the controllable part of the generation portfolio is considered. Operational costs and subsidies of RES and CHPs are not included. Cost results are split up into total costs and thermal costs. While thermal costs only account for operational costs, total costs also include costs for not being able to meet demand or reserve requirements.

Results show that costs are higher in 2025. In 2025, total and thermal costs increase with 41% and 15% respectively. The increase in thermal costs is mainly due to the nuclear phase out, which increases the run-time of more expensive thermal plants. Moreover, thermal costs and total costs are of the same order in 2012, while in 2025 total costs are significantly higher. This results from increased violations of demand and reserve requirements, as discussed in Section 4.2.2. By introducing DR with WGs, a yearly total cost reduction of 7 and 12 million euro is accomplished for 2012 and 2025 respectively. The cost reduction for 2025 is larger as more ENS is avoided. The thermal cost reduction mainly follows from a reduced use of other sources of flexibility, such as GTs and pumped storage hydro units. When BEVs are introduced, total costs rise substantially. The cost increase is higher in 2025, as future power generation capacity does not allow for a further increase in demand. If BEVs are introduced with scheduled charging, both total and thermal costs decrease with 10–25% compared with unscheduled charging. This ranges from 12 to 45 million euro of total yearly cost reduction and 8–18 million euro of thermal yearly cost reduction. This cost decrease is higher in 2025 as more ENS is reduced and less renewable surplus occurs.

5. Conclusions

This paper investigates the impact of demand response on power system operation by scheduling white good cycles and battery electric vehicles. A two-stage modeling approach is used on an hourly data set covering a full year. The approach allows taking into account both the variability and limited predictability of power generation from RES. Moreover, a detailed representation of flexibility at the demand side. This benefits a realistic outcome allowing to assess a potential introduction of DR.

Results show that in general DR decreases the loading of mid-peak and peak plants over the year and during peak moments. This is also reflected in the reduced number of start-ups of those plants. The renewed plant operation impacts reliability, environment and costs of power system operation. While reliability is affected to a limited extent, DR provides an efficient means to integrate RES and avoid surplus. By shifting only 2% of total consumption towards moments with an excess of generation from RES, up to 41% of renewable surplus can be avoided. Finally, DR decreases thermal costs as less peaking plants need to be operated. This paper shows that the impact of DR depends on the underlying power generation portfolio. The highest benefits of DR are accrued in a portfolio with a high amount of uncontrollable and renewable capacity.

Looking at the demand side, shifting WG cycles and BEV charging in time contributes to peak shaving. Up to 150 MW h/h and 300 MW h/h of the peak is reduced by WG and BEV scheduling respectively. BEV consumption is mainly shifted towards nighttime, while WG cycles are mainly shifted towards the night and the afternoon. Aside from these general observations, this paper shows that a large variety in shifting patterns exists. While only 8% of light-duty vehicles or 432 000 BEVs are assumed to contribute to DR, compared to 100% or over 9 million of WGs, system benefits are higher in case of BEVs. This justifies an increased attention for DR with BEVs. While an introduction of unscheduled BEV charging impedes system operation, scheduling facilitates the integration extensively.

While this paper provides insights into the impact of DR, some limitations are present in the modeling of the power system and DR. In the modeling of the power system interconnection capacity, transmission capacity, market behavior, demand uncertainty, and uncertainty in power generation from solar plants is neglected. Moreover, no stochasticity is included in the day-ahead optimization stage. In the modeling of DR, the willingness of households to provide flexibility and the cost it brings is not included. Furthermore, individual WG appliance characteristics per household are not considered. Integrating this would further benefit a realistic outcome. Other paths for future research are the inclusion of a sensitivity analysis on reserve requirements, inclusion of residential controllable generation technologies, inclusion of the provision of reserves by means of DR and inclusion of vehicle-to-grid charging.

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Appendix A

This appendix provides the specific mathematical formulation of the inclusion of demand response within the deterministic unit commitment and economic dispatch model used in this paper. Therefore, the main indices, parameters, variables, and equations are provided. A distinction is made between demand response with white good appliances (WGs) and demand response with battery electric vehicles (BEVs). A detailed description of the former can be found in [2], while the latter is thoroughly discussed in [15] and [8]. Constraints related to reserve requirements or technical characteristics of power plants are omitted for simplicity, but can be found in [2].

Indices	
General	
p, p'	Time period
g	Generators
t	Thermal plants ($\{t\} \subset \{g\}$)
h	Pumped storage hydro plants ($\{h\} \subset \{g\}$)
Inclusion WGs	
a	Types of appliances
Inclusion BEVs	
e	Types of BEVs
s, s'	State of the BEV {sc (connected to the grid), sm (moving)}
Parameters	
General	
D_p	Demand for period p (MW)
$UncG_p$	Power generation from uncontrollable capacity (wind capacity, solar, biomass, CHP, hydro run-of-river capacity) in period p (MW)
$UResC$, $DResC$	Upward and downward reserve deficit cost (€/MW h)
$NSEC$	Non-supplied energy cost (€/MW h)
FC^t	Fixed cost of thermal unit t (€/h)
VC^t	Variable cost of thermal unit t (€/MW h)
SC^t	Start-up cost of thermal unit t (€)
Inclusion WGs	
$DUpMax_a$	Maximum upward variation of demand for each appliance type a (p.u.)
$DDoMax_a$	Maximum downward variation of demand for each appliance type a (p.u.)
Inclusion BEVs	
$ECMax_p^e$	Maximum power charged by BEV e in the period p (MW)
$EEMax^e$	Maximum energy charged by BEV e (MW h)
$EP_p^{e,s}$	Percentage of BEV of type e and in the state s for each period p (p.u.)
$EPT_p^{e,s,s'}$	Percentage of BEV of type e and in the state s' that move to the state s for each period p (p.u.)
$ET_p^{e,s}$	Battery energy used in transport of each type of BEV e in each state s for each period p (MW h)
$EEfGtB^e$	Grid-to-battery efficiency for each type of BEV e (p.u.)
$EEfBtW^e$	Battery-to-wheel efficiency for each type of BEV e (p.u.)
Variables	
General	
$opcost$	Total operational cost (€)
nse_p	Non-supplied power in period p (MW)
wc_p	Wind curtailment in period p (MW)
$urdef_p$, $drdef_p$	Upward and downward reserve deficit in period p (MW)
st_p^t	Start-up thermal unit t in period p {0,1}
uc_p^t	Commitment of thermal unit t in period p {0,1}
gp_p^g	Output of generator g in period p (MW)
gc_p^h	Consumption of pumped storage hydro plant h in period p (MW)
Inclusion WGs	
$dup_{p,a}$, $ddo_{p,a}$	Upward and downward demand variation for each type of appliance in period p (MW)
Inclusion BEVs	
$soc_p^{e,s}$	State of charge (SOC) of the battery of BEV e at the end of period p in each state s (MW h)
$ec_p^{e,s}$	Consumption of BEV e in state s in period p (MW)
ch_p^e	BEV e charging indicator in period p {0,1}

Appendix B. Objective function

$$\text{Minimize opcost} = \sum_p \left[\sum_t (FC^t \cdot uc_p^t + SC^t \cdot st_p^t + VC^t \cdot gp_p^t) + NSEC \cdot nse_p + UResC \cdot urdef_p + DResC \cdot drdef_p \right] \tag{1}$$

Appendix C. Constraints related to the inclusion of WGs

Modified demand–supply balance constraint

$$D_p + dup_{p,a} - ddo_{p,a} - UncG_p - nse_p + wc_p = \sum_g gp_p^g - \sum_h gc_p^h \quad \forall\, p \tag{2}$$

Upward and downward daily demand variation balance per appliance type

$$\sum_{p \in \{1,24\}} dup_{p,a} = \sum_{p \in \{1,24\}} ddo_{p,a} \quad \forall\, a \tag{3}$$

Maximum demand shift per appliance type

$$\begin{pmatrix} DDoMax_a \\ DUpMax_a \end{pmatrix} \cdot D_p \geqslant \begin{pmatrix} ddo_{p,a} \\ dup_{p,a} \end{pmatrix} \geq 0 \quad \forall\, p, a \tag{4}$$

Appendix D. Constraints related to the inclusion of EVs

Modified demand–supply balance constraint

$$D_p + \sum_{e,s} ec_p^{e,s} - UncG_p - nse_p + wc_p = \sum_g gp_p^g - \sum_h gc_p^h \quad \forall\, p \tag{5}$$

State of charge of battery

$$soc_p^{e,s} - soc_{p-1}^{e,s} = ec_p^{e,s} \cdot EEfGtB^e - \frac{ET_p^{e,s}}{EEfBtW^e} + \sum_{s' \neq s} soc_{p-1}^{e,s'} \cdot EPT_{p-1}^{e,s,s'} \quad \forall\, p, e, s \tag{6}$$

Logical BEV constraints of BEV when moving and plugged-in

$$\begin{matrix} ec_p^{e,s} = 0 & \forall\, s \in sm \\ ET_p^{e,s} = 0 & \forall\, s \in sc \end{matrix} \quad \forall\, p, e, s \tag{7}$$

Maximum charging power

$$ec_p^{e,s} \leq (1 - ch_p^e) \cdot ECMax_p^e \cdot EP_p^{e,s} \quad \forall\, p, e, s \tag{8}$$

Maximum energy that can be charged in one period

$$ec_p^{e,s} \leq EP_p^{e,s} \cdot (EEMax^e - soc_p^{e,s}) \quad \forall\, p, e, s \tag{9}$$

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